Czech University of Life Sciences Prague
Faculty of Economics and Management

agris on-line

Papers in Economics and Informatics

http://online.agris.cz

ISSN 1804-1930
XVI, 2024, 4

International scientific journal
Prague

Agris on-line Papers in Economics and Informatics

The international reviewed scientific journal issued by the Faculty of Economics and Management of the Czech University of Life Sciences Prague.

The journal publishes original scientific contributions from the area of economics and informatics with focus on agriculture and rural development.

Editorial office

AGRIS on-line Papers in Economics and Informatics
Department of Economics of FEM CZU Prague
Kamýcká 129, 165 00 Praha-Suchdol
Czech Republic
Phone: +420 224 382 056
E-mail: agrisonline(at)pef.czu.cz

Publisher

Faculty of Economics and Management
Czech University of Life Sciences Prague
Kamýcká 129, 165 00 Praha-Suchdol
Czech Republic
Reg. number: 60460709

ISSN 1804-1930

XVI, 2024,
30th of December 2024
Prague

Agris on-line
Papers in Economics and Informatics

ISSN 1804-1930

XVI, 2024, 4

Agris on-line Papers in Economics and Informatics

Volume XVI Number 4, 2024

Content:

Volume XVI Number 4, 2024

Digital Marketing Strategy Development for Recovery Ecotourism Visit After COVID-19 Pandemic: A Comparison Study on BJBR and Kampung Blekok Mangrove Ecotourism, Indonesia

Zainal Abidin[1], Virda Faradila Rahmad[1], Siti Ngayesah Ab Hamid[2], Asyifa Anandya[3], Pudji Purwanti[1], Dwi Sofiati[3], Mentari Puspa Wardani[3], Supriadi Supriyadi[3]

[1]Faculty of Fisheries and Marine Science, Universitas Brawijaya, Indonesia

[2]Faculty of Economics and Management, Universiti Kebangsaan Malaysia, Malaysia

[3]Faculty of Fisheries and Marine Science, PSDKU Universitas Brawijaya, Kediri, Indonesia

Abstract

Ecotourism is a form of tourism that can help overcome the problem of low welfare of local communities. The digital cultural transformation that occurred in the era of revolution 4.0, especially during the COVID-19 pandemic, was able to change the entire cycle of the tourism ecosystem. Besides, several ecotourism experiences have experienced a significant decline in tourist visits, including Bee Jay Bakau Resort and Kampung Blekok ecotourism. This research aims to develop a digital marketing strategy for ecotourism at Bee Jay Bakau Resort and Kampung Blekok to restore visitation levels after the COVID-19 pandemic. This research uses a qualitative approach with SWOT analysis and is quantitatively calculated using the Quantitative Strategic Planning Matrix (QSPM). Data were collected through interviews with ecotourism managers including marketing employees, and HRD managers; visitors, local communities, Tourism Awareness Groups, and the Environmental Service (DLH). Also, direct observation of the ecotourism conditions studied, documentation, and literature studies. The research results show that the strengths and opportunities of BJBR and Kampung Blekok are greater than the weaknesses and threats, so the strategy formulated is aggressive (growth-oriented strategy). The strategic priority lies in optimizing the use of information technology and social media as promotional media, especially the frequency of promotions. The strategy used is none other than to increase the value of ecotourism as a form of growth so that it can compete with other ecotourism in returning the level of tourist visits after the COVID-19 pandemic.

Keywords

SWOT analysis, QSPM, social media, mangrove ecotourism, digital marketing.

Abidin, Z., Rahmad, V. F., Ab Hamid, S. N., Anandya, A., Purwanti, P., Sofiati, D., Wardani, M. P. and Supriyadi, S. (2024) "Digital Marketing Strategy Development for Recovery Ecotourism Visit After COVID-19 Pandemic: A Comparison Study on BJBR and Kampung Blekok Mangrove Ecotourism, Indonesia", *AGRIS on-line Papers in Economics and Informatics*, Vol. 16, No. 4, pp. 3-17. ISSN 1804-1930. DOI 10.7160/aol.2024.160401.

Introduction

Tourism is an important factor in the economic development of a region (Del P. Pablo-Romero and Molina, 2013). Ecotourism development is an alternative tourism development that can help overcome the problem of minimal welfare of local communities. It is the practice of traveling to relatively rarely exploited natural destinations to appreciate the natural environment, gain knowledge about wildlife, and enjoy the local culture in an authentic atmosphere while preserving the environment at the destination (Lee and Jan, 2019). The use of mangrove ecosystems for ecotourism is in line with the shift in tourist interest from old tourism, namely tourists who only come to do tourism without any elements of education and conservation, to new tourism, namely tourists who come to do tourism that includes elements of education and conservation (Sutjiatmi and Edy, 2018). Bee Jay Bakau Resort (BJBR) is a mangrove conservation ecotourism area located in Mayangan Fishing Port, Probolinggo and has been established since 2012. The tourist activities offered by BJBR include natural, historical, cultural, culinary, shopping, and educational tourism. Apart from offering beautiful natural views, especially the sea, BJBR also has facilities such as a multi-purpose meeting hall, cafe, swimming pool, restaurant, bungalows as a beautiful place to stay above sea level, lots of photo spots, education on flora and fauna in BJBR ecotourism, several playgrounds, and there is also a gift shop with interesting products. Meanwhile, Kampung Blekok, which is located in Klatakan Village, Situbondo Regency, is the only ecotourism site with thousands of fish birds living in the mangrove conservation area of Kampung Blekok. The types of fish birds in Kampung Blekok are very diverse, including the blekok rice field (Ardeola speciosa), the little egret (Egretta garzetta), the buffalo egret (Bubulcus ibis), the gray night kowak (Nycticorax nycticorax), the gray heron (Ardea cinerea), the cangak red (Ardea purpurea), and sea cockroach (Butorides striatus). This area is dominated by mangrove forests at 60% (Dassucik et al., 2023). This ecotourism exists as a form of awareness of the importance of mangrove conservation ecotourism which can be used as a protected forest for the surrounding community. Apart from that, the same as BJBR, the Kampung Blekok ecotourism also offers views of the beach that are no less beautiful, facilitated by a coffee shop, and craft souvenir shop, typical of the surrounding community as a shopping tour and educational tour which allows tourists to interact directly with mangroves from nurseries to making crafts.

The demand for natural tourism destinations for physical and mental relaxation has increased dramatically during and after the COVID−19 pandemic in many countries (Li et al., 2021). With the beautiful natural scenery and value that BJBR and Kampung Blekok offer to tourists, this ecotourism should be able to bring in a lot of new and old visitors after the COVID-19 pandemic. However, the number of tourists visiting BJBR has gone down since 2019 (Fattah et al., 2020). A similar thing was also experienced by the Kampung Blekok tourist attraction, where during the pandemic there was a decline in visitors. This makes it difficult for managers to improve and develop tourism and causes a reduction in the income received (Khomsah et al., 2022). In fact, in East Java, mangrove areas that contribute to conservation still lack tourist travel programs (Utami et al., 2022). The digital transformation that has occurred in the recent 4.0 revolution era has also been able to change the entire cycle of the tourism ecosystem, including being the cause of a shift in cyber and visual culture for tourists. The impact of the shift in cyber culture that can be seen from digital transformation in the era of revolution 4.0 is a change in the decision-making process for traveling (Eddyono et al., 2021). Thus, changes in travel decision-making require ecotourism destination managers to adapt in managing digital marketing aspects of ecotourism to meet tourist needs to recover the level of tourist visits.

Mkwizu (2019) considers digital marketing opportunities to be very valuable for tourism industry. Digital technology has the potential to improve performance while facilitating ecotourism marketing activities. In addition, digital technology functions as an effective medium for generating ideas that drive ecotourism toward sustainability (Bruce et al., 2023). Dassucik et al. (2023) found that tourist information and comments on social media can influence the decision to visit an ecotourism destination. The COVID-19 pandemic has increased the use of social media communication at a time when people cannot leave their homes due to lockdown policies (Mele et al., 2023). However, the current literature focuses more on various factors such as brand image, brand trust, relationship quality, and service quality (Fu and Timothy, 2021). The lack of identified research on how ecotourism destination marketing managers utilize digital media during the global health crisis (Mele et al., 2023) as one of the ecotourism digital marketing strategies, explains the current lack of research in the ecotourism marketing literature and this gap needs to be addressed urgently.

It is important to understand the relationship between marketing and ecotourism because this will impact protected areas, conservation, and local communities. Much controversy concerns the marketing of ecotourism in its efforts to consider the dual objectives of protected areas and local communities on the one hand and the objectives of the tourism industry on the other. Meanwhile, ecotourism is also related to rural development. Activities of ecotourism have the potential to promote sustainable village development through proceeds from conserving such facilities (Bonye et al., 2021). It also can be a significant driver of economic growth in rural areas. By attracting tourists interested in natural environments and cultural heritage, ecotourism generates revenue through accommodation, food services, local transportation, and guided tours (Boley and Green, 2016; Das and Chatterjee, 2015). This income can provide jobs and stimulate local businesses, reducing poverty and enhancing the overall economic well-being of rural communities (Martínez et al., 2019; Snyman, 2017). In many developing countries, ecotourism has become an essential source of income, enabling communities to diversify their economies beyond traditional agriculture (Das and Chatterjee, 2015; Cobbinah et al., 2017). The growth of ecotourism often necessitates the development of infrastructure in rural areas, such as roads, communication networks, and basic amenities (Cobbinah et al., 2017; Martínez et al., 2019). While this infrastructure is primarily intended to support tourism, it can also benefit local residents by improving access to education, healthcare, and other essential services (Snyman, 2017; Das and Chatterjee, 2015). Better infrastructure can help integrate rural communities into the broader economy and enhance their quality of life (Boley and Green, 2016; Martínez et al., 2019).

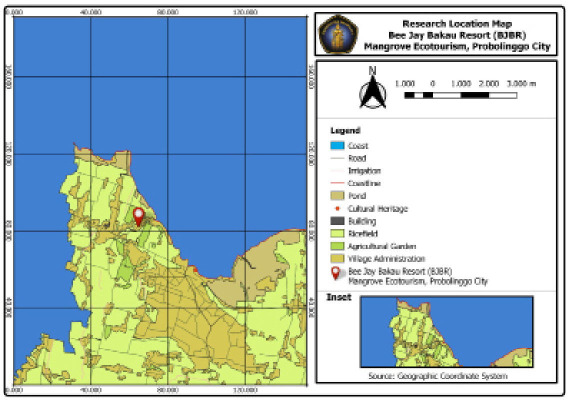
This research aims to develop an ecotourism digital marketing strategy towards appropriate sustainability with the target of increasing tourist visits after the COVID-19 pandemic using strengths, weaknesses, opportunities, and threats (SWOT) analysis. SWOT analysis uses systematic thinking and comprehensive diagnosis to prioritize solutions by considering heterogeneous stakeholders and their diverse perceptions (Joshi et al., 2018). By using SWOT analysis, we can develop appropriate ecotourism marketing strategies by considering internal and external factors. A single SWOT-TOWS-based planning tool is widely applied in planning processes in various scientific disciplines but is not sufficient for decision-making (Sahani, 2021). To overcome this problem, the Quantitative Strategic Planning Matrix (QSPM) approach was adopted for further analysis to find the best priority strategy in ecotourism planning. The QSPM method follows three steps in the decision-making process such as: i) constructing a model; ii) comparing criteria, alternatives, and weight calculations; and iii) priority synthesis (Papapostolou et al., 2020).

Materials and methods

Research location and time

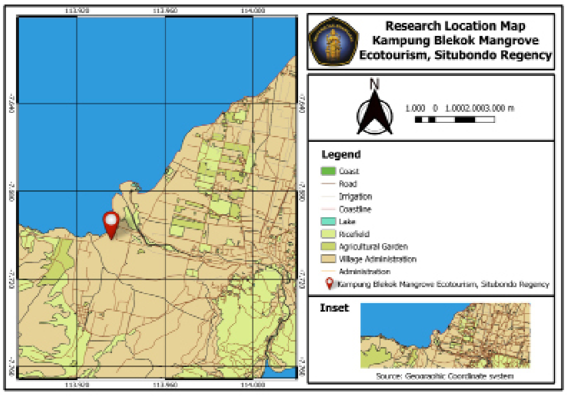
This research was carried out from July to August 2023 and conducted in two mangrove conservation ecotourism areas, namely, Bee Jay Bakau Resort (BJBR) which is located in Mangunharjo Village, Mayangan District, Probolinggo City, East Java (Figure 1) and Kampung Blekok which is located in Klatakan Village, Kendit District, Regency. Situbondo, East Java (Figure 2). Bee Jay Bakau Resort (BJBR) is located on the coast of Mayangan Fishing Port, north of the Probolinggo City square. Before it was built as a tourist spot, the coastal area was mangrove forest land that was not well maintained and full of rubbish. This mangrove forest area is the final disposal site for the Banger River, so the condition is a turbid and unhealthy environment even though it is located in a strategic area. The idea arose to create the Bee Jay Bakau Resort (BJBR) tourist attraction based on the strategic conditions of the area.

The second location is Kampung Blekok which is a new tourist attraction developed in Klatakan Village, Kendit District, Situbondo Regency. This tourism was developed through an ecotourism concept based on community-based tourism (CBT). This is because the mangrove conservation area covering an area of approximately 6 hectares is a place where Blekok birds with various species live.



Source: Dataprocessed byauthors in ArcGIS

Figure 1: Beejay Bakau Resort (BJBR) Ecotourism Research Site.



Source: Dataprocessed byauthors in ArcGIS

Figure 2: Kampung Blekok Ecotourism Research Site.

Research method

This research is descriptive research with a qualitative and quantitative approach that objectively describes the actual state of the research object and is analyzed qualitatively and quantitatively using SWOT analysis to formulate ecotourism digital marketing development strategies and QSPM to determine the priority strategies used. So, the results obtained are very reliable, can be applied practically, and increase the possibility of success of the planned strategy (Bui et al., 2020).

Expert-based assessment is a highly recommended approach in research worldwide (Paliogiannis et al., 2019; Müller et al., 2020). Therefore, interviews with experienced experts and scholars in the tourism industry to project development strategy models have broad implications (Reichstein and Härting, 2018) in determining evaluation criteria and suitability for the issues raised. The way to get research respondents is to use a purposive sampling technique, with the criteria that respondents are directly involved or have a deep understanding of ecotourism at Bee Jay Bakau Resort and Kampung Blekok, especially its marketing.

Data collection

Data was collected through a survey method using a questionnaire instrument and semi-structured interviews. Additionally, observation and documentation were carried out to gather data related to ecotourism marketing strategy. The interviewees consisted of ecotourism managers, ecotourism marketing employees, ecotourism visitors, local communities, the Kampung Blekok Tourism Awareness Group (POKDARWIS), and Situbondo Regency Environmental Service (DLH) employees. This data aims to answer research objectives on factors that can influence the sustainability of mangrove ecotourism in BJBR and Kampung Blekok, especially from a marketing perspective. The data collected is supported by literature studies such as books, articles, and other relevant information.

Data analysis

The development of a strategy or organization can be formulated after taking into account a combination of internal and external factors. Both factors must be considered in the SWOT analysis. SWOT analysis is the development of relationships or interactions between internal elements, namely strengths and weaknesses against external elements, namely opportunities and threats. The following are the steps that must be taken in a SWOT analysis according to Salim and Siswanto (2019):

1. Identifying variables related to ecotourism marketing strategies development;
2. Classify internal and external variables;
3. Determine the weight of each variable;
4. Determine the scale or rating of the variables;
5. Determine the value or score of each SWOT aspect;
6. Calculating strength posture and competitive posture;
7. Describe the strategic position in the SWOT quadrant; and
8. Determine ecotourism marketing strategies development.

Factors are assigned coefficients between 0 and 1, indicating their significance in measuring strengths, opportunities, weaknesses, and threats. This coefficient represents the importance of a factor, whether it is an internal strength/weakness or an external opportunity/threat. Each factor is rated on a scale of 1 to 4, with 1 being a basic weakness, 2 being a minor weakness, 3 being a strength, and 4 being a greater strength/opportunity/threat. The final score for each factor is determined by multiplying its weight by its rating. If the value is greater than 1.5, it implies that the weaknesses outweigh the strengths; if the value is less than 1.5, it indicates that the strengths outweigh the weaknesses (Salim and Siswanto, 2019; Mallick et al., 2020).

The Quantitative Strategic Planning Matrix (QPM) is an analytical tool used to compare alternative actions. QSPM is widely used to simplify decision-making or problem-solving processes. Most efforts select the best strategy using input from other management techniques and easy components. This analysis is introduced to identify several marketing strategies needed to increase tourist visits which are listed below with several effective and quantitative measurements. The summation of the total attractiveness score (STAS) is carried out to determine the relative attractiveness of each key factor and related individual strategies (Mallick et al., 2020).

The QSPM stages are divided into three stages to make the most objective decisions using as many facts as possible (Figure 3). The first step in the overall strategic management analysis is identifying key strategic factors. This can be done using IFAS and EFAS. The IFAS Matrix is

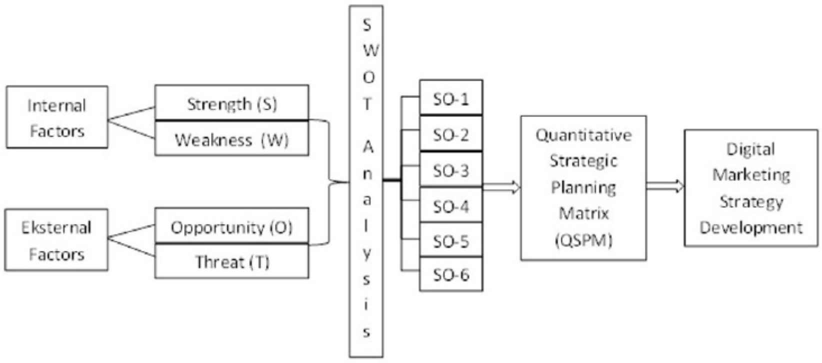


Figure 3. Stages of SWOT-QSPM analysis for digital marketing strategy development: mangrove ecotourism

Source: Authors

Figure 3: Stages of SWOT-QSPM analysis for digital marketing strategy development: mangrove ecotourism

a strategic management tool for auditing or evaluating key strengths and weaknesses in functional areas of a business. The EFAS matrix method is a strategic management tool often used to assess, visualize, and prioritize the opportunities and threats facing businesses today. The IFAS and EFAS matrices are strategy formulation tools that can be used to evaluate how a company is performing in relation to identified internal strengths and weaknesses. After identifying and analyzing key strategic factors as input to QSPM, the most attractive strategy can be formulated. This can be done using strategic management tools in stage 2 which in this research uses SWOT analysis. The strategic management method at stage 1 is carried out to determine the main strategic factors. Based on the results of the analysis in stage 2, it is used to formulate possible strategies. Next, in stage 3, through comparison of alternative QSPM strategies, the one that best suits the objectives of this research is selected. Stage 2 provides the information needed by researchers to prepare a QSPM conceptually, QSPM in stage 3 determines the relative attractiveness of the various strategies that have been created based on the extent to which external and internal key success factors are utilized or improved. The relative attractiveness of each strategy is calculated by determining the cumulative impact of each external and internal critical success factor (Ghorbani et al., 2015).

Results and discussion

Internal Factors Analysis Strategy (IFAS)

Regarding strengths and weaknesses, 7 strength factors and 7 weakness factors were identified for the internal factor analysis strategy (IFAS). The weight allocated to the BJBR strength factor is between 0.03 - 0.16 and the rating ranges between 3 and 4. The BJBR weakness factor has a rating between 1 - 3 and the allocated weight is between 0.03 - 0.10. Where the BJBR ecotourism ticket price factor has the highest score with a value of 0.48 on strengths and the lack of promotional updates via social media has the lowest score on BJBR's weaknesses with a value of 0.03. The final IFAS BJBR identification score was 2.22 for strengths and 0.82 for weaknesses (Table 1). So, the value of BJBR's internal factors shows that strengths are superior to weaknesses.

The weight allocated to the strength factor of Kampung Blekok is between 0.04 - 0.15 and the rating ranges between 3 and 4. The weakness factor of Kampung Blekok has a rating between 1 - 4 and the allocated weight is between 0.02 - 0.11. Where the Kampung Blekok ecotourism ticket price factor has the highest score with a value of 0.6 on strengths and non-routine promotion via TV and print media has the lowest score on the weaknesses of Kampung Blekok with a value of 0.02. The final IFAS identification score for Kampung Blekok was 1.89 for strengths and 1.54 for weaknesses (Table 1). So, the value of Kampung Blekok's internal factors shows that strengths are still superior to weaknesses.

Bee Jay Bakau Resort				Kampung Blekok		
Internal Factors	**Weight**	**Rating**	**Score**	**Weight**	**Rating**	**Score**
Strength			**2,22**			**1,89**
- The variety of tourist and educational objects at the BeeJay Bakau Resort/Blekok Village ecotourism	0.09	4	**0.36**	0.07	4	**0.28**
- There are per-season promos as part of the content on social media	0.09	4	**0.36**	0.06	3	**0.18**
- The service of the tour crew at the BeeJay Bakau Resort/ Blekok Village ecotourism is carried out in a friendly manner	0.03	3	**0.09**	0.04	4	**0.16**
- Ecotourism BeeJay Bakau Resort/Kampung Blekok provides event and gathering venues for visitors	0.07	3	**0.21**	0.07	3	**0.21**
- The managers and employees are committed to promoting ecotourism at BeeJay Bakau Resort/Blekok Village (online and offline)	0.09	4	**0.36**	0.06	3	**0.18**
- BeeJay Bakau Resort/Kampung Blekok Ecotourism has wide-reaching promotional media in the form of Instagram, Facebook, YouTube, & Website	0.09	4	**0.36**	0.07	4	**0.28**
- BeeJay Bakau Resort/Blekok Village ecotourism ticket prices are relatively affordable	0.16	3	**0.48**	0.15	4	**0.60**
Weakness			**0.82**			**1.54**
- Less intensive promotions carried out	0.02	1	**0.02**	0.07	3	**0.21**
- Customer surveys still use traditional methods	0.02	1	**0.02**	0.04	2	**0.08**
- Don't have a professional marketing team yet	0.07	2	**0.14**	0.11	4	**0.44**
- Lack of promotional updates via social media	0.03	1	**0.03**	0.08	3	**0.24**
- Promotion via TV and print media is not routine (incidental)	0.05	2	**0.10**	0.02	1	**0.02**
- Limited funding to support marketing activities	0.07	3	**0.21**	0.07	4	**0.28**
- The use of information technology and social media has not been optimal to promote ecotourism at BeeJay Bakau Resort/ Blekok Village	0.10	3	**0.30**	0.09	3	**0.27**

Source: Author computation, 2023

Table 1: Internal Factors Analysis Strategy (IFAS) on BJBR and Kampung Blekok Ecotourism.

External Factors Analysis Strategy (EFAS)

There are 7 factors related to opportunities and 7 factors identified as threats in the external factor analysis strategy (EFAS). Regarding the opportunities for BJBR and Kampung Blekok both weight 0.07 - 0.13 with a rating of between 3 and 4. The back-to-nature tourism trend is the influence of the opportunity with the highest ore (0.52) as an opportunity for BJBR and Kampung Blekok which can be used to develop marketing strategies. Meanwhile, the BJBR threat weights 0.02 and 0.09 with a rating of between 1 - 4. This is different from Kampung Blekok where the threat weight is between 0.02 - 0.08 with a rating of between 1 - 3. The emergence of ecotourism competitors who have objects A more innovative and attractive tourist attraction is a threat that does not affect the ecotourism of BJBR and Kampung Blekok with the lowest score (0.03) (Table 2). The final EFAS BJBR identification score is 2.44 for opportunities and 0.84 for threats, while 2.73 is the final score for Kampung Blekok's opportunities and threats with a score of 0.68. So, the value of the external factors of BJBR and Kampung Blekok shows that the influence of opportunities is higher than the influence of threats.

Bee Jay Bakau Resort				Kampung Blekok		
External Factors	**Bobot**	**Rating**	**Skor**	**Bobot**	**Rating**	**Skor**
Opportunity			**2.44**			**2.73**
- There is digital marketing technology in the 5.0 era that can support ecotourism promotion activities	0.1	4	**0.4**	0.07	3	**0.21**
- The availability of social media for massive and cheap dissemination of ecotourism information	0.1	4	**0.4**	0.1	4	**0.4**
- There is a back-to-nature tourism trend	0.13	4	**0.52**	0.13	4	**0.52**
- here are accommodation facilities available around the Bee Jay Bakau Resort/Kampung Blekok ecotourism location	0.09	3	**0.27**	0.1	4	**0.4**
- Availability of facilities for promotion through broadcast media (TV, radio)	0.08	3	**0.24**	0.1	4	**0.4**
- Availability of facilities for promotion through print media	0.07	3	**0.21**	0.1	4	**0.4**
- Easy internet access to search for and share information related to ecotourism in real-time	0.1	4	**0.4**	0.1	4	**0.4**
Threat			**0.84**			**0.68**
- The marketing technology developed by competing ecotourists is superior	0.03	2	**0.06**	0.02	2	**0.04**
- The emergence of ecotourism competitors who have more innovative and attractive tourist attractions	0.03	1	**0.03**	0.03	1	**0.03**
- In short, the length of stay or the length of stay of tourists in the area around the Bee Jay Bakau Resort/Kampung Blekok ecotourism area	0.03	2	**0.06**	0.03	2	**0.06**
- Minimal investment in supporting activities in the tourism sector at Bee Jay Bakau Resort/Kampung Blekok	0.02	2	**0.04**	0.02	2	**0.04**
- There are few ecotourism visitors on days other than weekends	0.07	4	**0.28**	0.05	3	**0.15**
- There is a tendency for tourists to turn to other more popular tourist attractions	0.09	3	**0.27**	0.08	3	**0.24**
- Varying people's understanding of the importance of ecotourism	0.05	2	**0.1**	0.06	2	**0.12**

Source: Author computation, 2023

Table 2. External Factor Analysis Strategy (EFAS) on BJBR and Kampung Blekok Ecotourism.

Development of Ecotourism Marketing Strategy

SWOT analysis is used effectively after selecting and evaluating the most important internal and external factors for developing a mangrove ecotourism marketing strategy. To analyze SWOT, it is necessary to determine strength posture and competitive posture first. The SWOT model analysis is shown by the SO, ST, WO, and WT pairwise matrices which determine the validation of the SWOT model for marketing strategies in the research area (Table 3). The results of the SWOT analysis show that the strength the weaknesses and the influence of opportunities for BJBR and Kampung Blekok is also greater than the threats, so it can be concluded that the position of the mangrove ecotourism marketing strategy of BJBR and Kampung Blekok is in quadrant I, where in this position the strategy is appropriate. used is the S-O strategy, namely using current strengths to take advantage of existing opportunities. Specifically, you can use the SWOT analysis calculations in Table 3 to see the SWOT coordinates of each ecotourism where the BJBR coordinates are at points x = 1.4 and y = 1.6 while Kampung Blekok is at coordinates x = 0.35 and y = 2.05.

This condition is a very favorable situation where this position has positive strengths and opportunities. So, the strategy implemented is to support aggressive policies (growth-oriented strategy). This indicates a very strong and potential strategy. Therefore, researchers use a SWOT model based on strategic planning that utilizes existing strengths and opportunities, namely by creating a strength-opportunity (SO) strategy:

SO-1: Upgrading ecotourism digital promotional media to follow 5.0 technology which continues

IFAS				EFAS			
BJBR		Kampung Blekok		BJBR		Kampung Blekok	
Categories	**Total Score**	**Categories**	**Total Score**	**Categories**	**Total Score**	**Categories**	**Total Score**
Strength (S)	2.22	Strength (S)	1.89	Opportunity (O)	2.44	Opportunity (O)	2.73
Weakness (W)	0.82	Weakness (W)	1.54	Threat (T)	0.84	Threat (T)	0.68
Total (S-W)	1.4		0.35	Total (O-T)	1.6		2.05

Source: Author computation, 2023

Table 3: SWOT Analysis of Marketing Strategy on BJBR and Kampung Blekok.

to develop and current trends. The continuous introduction of technological evolution, especially new trends such as the Internet of Things, into the daily lives of tourists has broken down barriers such as geographical or time boundaries. Digital marketing allows marketers to measure the results of their actions accurately (even in real time). This facilitates any changes to energy promotional materials or consumer targeting to optimize communications or advertising (Dimitrios et al., 2023).

SO-2: Optimize the use of information technology and social media as promotional media, especially the frequency of promotions. Digital marketing allows travelers to engage with destinations and local communities. Social media applications such as Facebook, YouTube, Twitter, Instagram, Snapchat, LinkedIn, Telegram, and WhatsApp Business are often used as digital marketing interactions to encourage consumers to research and plan their travel destinations (Toral et al., 2018; Stylidis, 2022).

SO-3: Conduct many comparative studies with other ecotourists to learn from each other regarding digital marketing. The challenge for ecotourism marketing regarding digital marketing, is staffing the digital marketing department with the right professionals, as the staff must know how to manage digital communication and advertising channels, and will be systematically informed about the new possibilities constantly offered by technology (Ahmed et al., 2017). By conducting many comparative studies with other ecotourists who have implemented digital marketing, there will be many things that can be learned from each other and applied to the digital marketing of each ecotourism that perhaps have not been implemented so far and have the potential to increase the level of tourist visits without having to spend a large budget. This comparative study activity can be carried out offline or online to reduce costs, such as joint IG live, podcast content and the like. Apart from comparative studies, this activity can also be used as a form of promotion and establishing cooperation between ecotourists.

SO-4: Highlight the strengths and uniqueness of each ecotourism as interesting marketing content. Using digital marketing with relevant and interesting content to promote a destination through high-quality images, videos and blog posts can influence potential tourists to choose a destination over others (Toral et al., 2018; Kim and Kim, 2020).

SO-5: Establish and strengthen cooperation with local ecotourism, surrounding communities, and local government agencies or institutions in creating new programs such as education and tourism packages. Nickerson et al. (2016) linked sustainable tourist behavior to other important attributes for destination marketers, revealing that sustainable tourists spend more money, stay longer, and contribute to the tourist destination's triple bottom line.

SO-6: Utilize other electronic media (TV, radio and print media) in promoting ecotourism. Promoting a positive image of a destination through social media and other channels can help create positive perceptions among tourists (Fu and Timothy, 2021) and therefore reflect the level of individual feelings (positive or negative) towards a behavior of interest (Armutcu et al., 2023).

Quantitative Strategic Planning Matrix (QSPM)

The QSPM strategy is formulated based on Strength and Opportunity (SO) and arranged using the SWOT matrix method. It is calculated by adding up the total attractiveness scores in each category (by column) of the QSPM (Table 4). The calculated STAS score shows which score is the most attractive considering all external and internal factors. Where the Attractiveness Score (AS) and Total Attractiveness Scores (TAS) in QSPM consist of how attractive each factor is in relation to each alternative strategy. The range of attractive scores (AS) includes 1 = not interesting, 2 = not interesting, 3 = quite interesting, and 4 = interesting.

Factors	Bobot	Strategy											
		SO 1		SO 2		SO 3		SO 4		SO 5		SO 6	
		AS	TAS	AS	TAS	AS	TAS	AS	TAS	AS	TAS	AS	TAS
S1	0.09	4	0.36	3	0.27	3	0.27	4	0.36	4	0.36	3	0.27
S2	0.09	3	0.27	3	0.27	4	0.36	4	0.36	4	0.36	3	0.27
S3	0.03	4	0.12	4	0.12	4	0.12	4	0.12	4	0.12	3	0.09
S4	0.07	4	0.28	3	0.21	3	0.21	4	0.28	3	0.21	3	0.21
S5	0.09	3	0.27	4	0.36	4	0.36	4	0.36	3	0.27	3	0.27
S6	0.09	3	0.27	4	0.36	3	0.27	4	0.36	4	0.36	3	0.27
S7	0.16	4	0.64	4	0.64	3	0.48	4	0.64	3	0.48	4	0.64
W1	0.02	3	0.06	3	0.06	4	0.08	3	0.06	4	0.08	3	0.06
W2	0.02	3	0.06	3	0.06	4	0.08	3	0.06	3	0.06	3	0.06
W3	0.07	3	0.21	3	0.21	4	0.28	4	0.28	4	0.28	3	0.21
W4	0.03	3	0.09	4	0.12	4	0.12	3	0.09	4	0.12	3	0.09
W5	0.05	4	0.2	4	0.2	4	0.2	4	0.2	4	0.2	3	0.15
W6	0.07	4	0.28	4	0.28	3	0.21	3	0.21	3	0.21	3	0.21
W7	0.1	3	0.3	3	0.3	3	0.3	3	0.3	3	0.3	3	0.3
O1	0.1	4	0.4	4	0.4	3	0.3	3	0.3	3	0.3	4	0.4
O2	0.1	3	0.3	4	0.4	3	0.3	3	0.3	3	0.3	3	0.3
O3	0.13	4	0.52	3	0.39	4	0.52	4	0.52	3	0.39	3	0.39
O4	0.09	3	0.27	3	0.27	4	0.36	4	0.36	3	0.27	3	0.27
O5	0.08	4	0.32	3	0.24	3	0.24	3	0.24	4	0.32	4	0.32
O6	0.07	4	0.28	3	0.21	3	0.21	3	0.21	4	0.28	4	0.28
O7	0.1	3	0.3	3	0.3	3	0.3	4	0.4	4	0.4	3	0.3
T1	0.03	3	0.09	3	0.09	3	0.09	4	0.12	4	0.12	4	0.12
T2	0.03	4	0.12	3	0.09	3	0.09	4	0.12	4	0.12	4	0.12
T3	0.03	4	0.12	4	0.12	3	0.09	4	0.12	4	0.12	4	0.12
T4	0.02	4	0.08	4	0.08	3	0.06	3	0.06	3	0.06	3	0.06
T5	0.07	3	0.21	4	0.28	3	0.21	3	0.21	3	0.21	3	0.21
T6	0.09	3	0.27	3	0.27	3	0.27	4	0.36	3	0.27	3	0.27
T7	0.05	3	0.15	3	0.15	3	0.15	3	0.15	3	0.15	3	0.15
Priority index			**6.84**		**6.75**		**6.53**		**7.15**		**6.72**		**6.41**

Note: Description: S1 (1st Strength), S2 (2nd Strength), S3 (3rd Strength), S4 (4th Strength), S5 (5th Strength), S6 (6th Strength), S7 (7th Strength), W1 (1st Weakness), W2 (2nd Weakness), W3 (3rd Weakness), W4 (4th Weakness), W5 (5th Weakness), W6 (6th Weakness), W7 (7th Weakness), O1 (1st Opportunity), O2 (2nd Opportunity), O3 (3rd Opportunity), O4 (4th Opportunity), O5 (4th Opportunity -5), O6 (6th Opportunity), O7 (7th Opportunity), T1 (1st Threat), T2 (2nd Threat), T3 (3rd Threat), T4 (4th Threat), T5 (5th Threat), T6 (6th Threat), T7 (7th Threat), SO1(1st Strength-Opportunity), SO2 (2nd Strength-Opportunity), SO3 (Strength- 3rd Opportunity), SO4 (4th Strength-Opportunity), SO5 (5th Strength-Opportunity), SO6 (6th Strength-Opportunity).

Source: Author compilation, 2023

Table 4: Quantitative Strategic Planning Matrix (QSPM) for Digital Marketing Strategy Development on BJBR and Kampung Blekok.

The BJBR and Kampung Blekok mangrove ecotourism marketing strategies development are classified according to their priorities and strategic weights in the SWOT matrix and attractiveness scores in the QSPM approach. The strategy with the highest appeal is highlighting the strengths and uniqueness of each ecotourism as one of the attractive marketing content with a score of 7.15, followed by upgrading ecotourism digital promotional media following technology 5.0 which continues to develop with a total attraction value of 6.84 and in third place. The top position is occupied by the strategy of optimizing the use of information technology and social media as promotional media, especially promotional frequency (6.75). Even though all of these strategies look real, the SO-4, SO-1, and SO-2 strategies which obtained the highest total attractiveness score could be the best strategy for developing a mangrove ecotourism marketing strategy to increase the number of tourist visits after the COVID-19 pandemic. In addition, the SO-5, SO-3, and SO-6 strategies are interesting but require more feasibility to achieve sustainability goals in the field of mangrove ecotourism marketing strategies development in the future. In other words, SO-4, SO-1, and SO-2 strategies can be implemented as soon as possible as short-term marketing strategies and using SO-5, SO-3, and SO-6 strategies as long-term marketing strategies that can be implemented after seeing the results of developments in the main strategies that must be carried out first.

While the QSPM method offers a systematic approach to prioritizing strategies by evaluating attractiveness scores for each factor, it has certain limitations that must be acknowledged. First, the method is highly dependent on the subjectivity of the attractiveness scores (AS) and the Total Attractiveness Scores (TAS), which may vary based on the evaluator's judgment or bias. The weighting of factors is also subjective and may not always reflect their true relative importance in real-world scenarios. Additionally, the QSPM method does not account for the dynamic and evolving nature of external environments or unforeseen changes in market conditions, which could influence the actual success of a given strategy. For example, external threats such as sudden changes in tourism trends or technological disruptions could alter the feasibility and attractiveness of the strategies identified in this study. Furthermore, the QSPM does not fully consider the practical challenges and resource constraints that may affect the implementation of the identified strategies, particularly for smaller or less-resourced ecotourism businesses.

Therefore, while the strategies identified in this analysis, especially the SO-4, SO-1, and SO-2 strategies show promise, it is important to recognize that their actual effectiveness may depend on various uncontrollable factors. To mitigate these limitations, it is recommended that future studies incorporate more.

Discussion

This study aims to design a relevant digital marketing strategy for mangrove ecotourism in the post-COVID-19 era, considering the unique empirical situation of each ecotourism site. The findings highlight a significant downturn in visitor numbers at coastal ecotourism sites like BJBR and Kampung Blekok, particularly during non-weekend days, as well as a decline in promotional activities, both online and offline. This disruption in visitation and marketing efforts underscores the challenges faced by these ecotourism destinations, many of which were already struggling with a lack of professionalism and inconsistent promotional strategies.

SWOT analysis of BJBR and Kampung Blekok reveals that these ecotourism destinations still possess considerable strengths, such as picturesque natural attractions, affordable ticket prices, community involvement in lodging, and the availability of social media platforms. However, these strengths are underutilized, and the primary strategic opportunity identified is the need to optimize the use of information technology and social media. Enhancing the frequency and quality of digital promotions, particularly through targeted social media campaigns, emerges as the most critical priority to revitalize tourism post-pandemic.

This study's findings are consistent with broader global trends in the tourism industry, particularly the growing importance of digital marketing in influencing travel decisions. Numerous global studies have shown that a significant portion of travel decisions is influenced by information found on digital platforms. Research by Magano and Cunha (2020); Islam (2021); de Amorim et al. (2022); Khan et al. (2022) emphasizes the critical role of online travel websites and social media in shaping traveler choices. The ease of access to information on platforms such as websites and social media is an essential factor that drives tourists to select particular destinations. For example, Lam et al. (2020) discuss the positive impact of online co-creation platforms on enhancing destination attractiveness and customer satisfaction, which directly supports the case for utilizing digital marketing strategies in ecotourism.

Moreover, Racherla and Friske (2012), highlight that easy-to-access content about tourist attractions plays a key role in tourists' decision-making process, facilitating the re-selection of destinations. This research supports the notion that digital presence is paramount in fostering repeat visits and brand loyalty. Our findings align with this perspective, reinforcing the importance of developing a digital marketing strategy that not only increases visibility but also engages travelers in interactive ways.

The integration of Information and Communication Technology (ICT) into tourism marketing has been recognized globally as a critical driver for post-pandemic recovery. By digitizing promotional activities, such as utilizing social media for targeted campaigns, ecotourism destinations can reach a broader audience more efficiently and cost-effectively. This shift to digital platforms enables the promotion of tourism products and services, facilitates the booking of travel packages, and allows for the collection of valuable data on tourists' preferences and behaviors. Such digital transformations have been linked to improved engagement, as evidenced by studies from Yuniarta et al. (2023) and Sujono et al. (2023) which confirm that enhanced online interactions lead to higher customer acquisition and satisfaction, ultimately generating greater revenue for ecotourism operators.

In line with global best practices, the research by Armutcu et al. (2023) calls for developing an online content strategy that resonates with tourists' psychological needs, influences social media usage, and confirms their expectations. This comprehensive approach not only drives visitor satisfaction but also stimulates a higher intention to visit, which is particularly crucial for destinations recovering from the downturn caused by the COVID-19 pandemic.

The findings of this study suggest that optimizing digital marketing efforts, particularly through social media platforms, and integrating Information and Communication Technology (ICT) into operations can help BJBR and Kampung Blekok ecotourism destinations leverage global digital trends to enhance visitor engagement, facilitate recovery, and foster sustainable growth in the post-pandemic era. The significant potential for digital interactions to revitalize ecotourism underscores the broader implication that digital marketing strategies are no longer optional but essential for ensuring the sustainability of ecotourism worldwide.

Moreover, these findings are not only relevant to BJBR and Kampung Blekok but also align with broader global trends in ecotourism marketing. They highlight the growing importance of digital platforms and social media in driving tourism recovery, as destinations around the world increasingly rely on digital marketing strategies to engage a global audience. Research has shown that an active digital presence and online engagement are critical for destinations to remain competitive and attract international visitors (Magano and Cunha, 2020; Lam et al., 2020). The strategies proposed for these local ecotourism sites—particularly the emphasis on optimizing information technology and social media—reflect these global trends, emphasizing the necessity of embracing digital transformation in tourism marketing.

Additionally, the study reinforces the importance of sustainability in ecotourism marketing, a key priority for ecotourism destinations worldwide. As travelers increasingly seek environmentally responsible experiences, effectively communicating sustainability efforts through digital channels becomes vital. By integrating both local and global trends, this study not only offers a roadmap for enhancing the marketing strategies of BJBR and Kampung Blekok but also contributes to the broader conversation on how digital marketing can help ecotourism destinations improve visibility, engage diverse audiences, and promote sustainable tourism practices. These findings provide valuable insights for ecotourism stakeholders globally, illustrating how digital marketing strategies can address local challenges while aligning with global tourism trends.

The identified trends, particularly the growing reliance on digital marketing and social media in ecotourism, also have important practical implications for strategic planning and marketing activities. Ecotourism managers can leverage these trends to design more targeted and cost-effective marketing campaigns, using digital platforms to reach a global audience and foster stronger customer engagement. By aligning their strategies with these digital trends, ecotourism destinations can not only enhance their competitiveness but also ensure long-term sustainability through increased visibility and stronger connections with potential tourists. This approach will be crucial for adapting to the evolving tourism landscape and securing the future growth of ecotourism in the digital era.

In addition to the findings on digital marketing trends, it is important to recognize the growing global interest in sustainable tourism and the need for climate change adaptation in ecotourism. As tourists increasingly prioritize environmental responsibility, there is a strong demand for ecotourism destinations to integrate sustainability into their offerings. This shift presents an opportunity for destinations like BJBR and Kampung Blekok to align their marketing strategies with sustainable tourism practices, such as promoting eco-friendly activities, supporting conservation efforts, and showcasing their commitment to climate adaptation.

The integration of sustainability into digital marketing strategies can not only attract a more conscientious traveler but also enhance the long-term viability of ecotourism destinations. As climate change increasingly affects coastal regions and ecosystems, ecotourism destinations must adapt to these changes by implementing resilience measures and promoting them in their marketing. By focusing on sustainability and climate change adaptation in their marketing messages, these destinations can strengthen their brand and appeal to a global audience that values environmental stewardship.

Conclusion

This study provides valuable insights into the development of digital marketing strategies for mangrove ecotourism at BJBR and Kampung Blekok, with a focus on enhancing visitor numbers in the post-pandemic era. By applying the SWOT analysis, we identified that both ecotourism sites are positioned in quadrant I, which indicates a favorable situation for utilizing strengths to capitalize on available opportunities. The findings suggest that the most effective approach for developing digital marketing strategies is the application of aggressive and vertical integrity strategies, allowing these ecotourism sites to compete with other destinations. Among the six Strength-Opportunity (S-O) strategies identified, the highest priority is optimizing the use of information technology and social media as promotional media, particularly increasing the frequency of promotions.

These findings contribute to the existing body of knowledge by emphasizing the critical role of digital marketing in the recovery and growth of ecotourism, especially after the COVID-19 pandemic. The research highlights the importance of leveraging digital platforms, such as social media, to effectively engage potential tourists and increase brand visibility. Moreover, it underscores the relevance of Information and Communication Technology (ICT) in creating dynamic, cost-effective marketing campaigns tailored to the needs of modern travelers.

Furthermore, this study aligns with global trends in the tourism sector, where digital marketing and social media have become key drivers of travel decisions (Magano & Cunha, 2020; Islam, 2021; de Amorim et al., 2022). It contributes to the literature on ecotourism by proposing actionable strategies for ecotourism destinations to enhance their competitive advantage and visitor engagement in the digital era. Practically, the study provides a roadmap for ecotourism managers to implement strategies that not only boost short-term tourist visits but also establish long-term sustainability in the marketing of mangrove ecotourism.

Overall, this research contributes to the understanding of digital marketing's impact on ecotourism, offering both theoretical insights and practical guidance for future marketing strategies. It suggests that, by effectively utilizing digital tools and focusing on strategic promotions, mangrove ecotourism can recover and thrive in an increasingly competitive and digitalized tourism market.

Acknowledgments

The authors would like to express their deepest gratitude to the Institute of Research and Community Services, Universitas Brawijaya for the financial support from the Distinguished Research Grant Program in 2023.

Corresponding author:
Dr. Zainal Abidin, S.Pi, M.P, M.B.A.
Faculty of Fisheries and Marine Science, Universitas Brawijaya
Veteran Street, Malang, Indonesia, 65145
Phone: +62 8123478891, E-mail: z_abidin@ub.ac.id

References

[1] Ahmed, E., Yaqoob, I., Hashem, I. A. T., Khan, S. F., Ahmed, A., Imran, M. and Vasilakos, A. V. (2017) "The role of big data analytics in Internet of Things", *Computer Network*s, Vol. 129, pp. 459-471. ISSN 1389/1286. DOI 10.1016/j.comnet.2017.06.013.

[2] Armutcu, B., Tan, A. Amponsah, M., Parida, S. and Ramkissoon, H. (2023) "Tourist behaviour: The role of digital marketing and social media", *Acta Psychologic*a, Vol. 240(June). E-ISSN 1873-6297. DOI 10.1016/j.actpsy.2023.104025

[3] Bonye, S. Z., Yiridomoh, G. Y. and Dayour, F. (2021) "Do ecotourism sites enhance rural development in Ghana? Evidence from the Wechiau Community Hippo Sanctuary Project in the Upper West Region, Wa, Ghana", *Journal of Ecotourism*, Vol. 21, No. 2, pp. 121-146. E-ISSN 1747-7638. DOI 10.1080/14724049.2021.1922423.

[4] Bruce, E., Shurong, Z., Ying, D., Yaqi, M., Amoah, J. and Egala, S. B. (2023) "The Effect of Digital Marketing Adoption on SMEs Sustainable Growth: Empirical Evidence from Ghana", *Sustainability*, Vol. 15, No. 6, p. 4760. ISSN 2071-1050. DOI 10.3390/su15064760.

[5] Bui, T. D., Tsai, F. M., Tseng, M. L. and Ali, M. H. (2020) "Identifying sustainable solid waste management barriers in practice using the fuzzy Delphi method", *Resources, Conservation and Recycling,* Vol. 154, p. 104625. E-ISSN 1879-0658. DOI 10.1016/j.resconrec.2019.104625.

[6] Dassucik, D., Rasyidi, A. H., Iqbal, M. A. and Agus, R. P. (2023) "Pengaruh atribut produk wisata dan word of mouth terhadap keputusan berkunjung pada objek wisata Kampung Blekok Desa Klatakan Situbondo", *Jurnal IKA PGSD (Ikatan Alumni PGSD) UNARS*, Vol. 13, No. 1, pp. 241–256. E-ISSN 2656-4459. DOI 10.36841/pgsdunars.v13i1.3143 . (In Indonesian).

[7] de Amorim, L. A., Sousa, B. B., Dias, A. L. and Santos, V. R. (2022) "Exploring the outcomes of digital marketing on historic sites´ visitor behaviour", *Journal of Cultural Heritage Management and Sustainable Developmen*t, Vol. 14, No. 6, pp. 934-949. E-ISSN 2044-1274, ISSN 2044-1266. DOI 10.1108/JCHMSD-11-2021-0202.

[8] Del P. Pablo-Romero, M. and Molina, J. A. (2013) "Tourism and economic growth: A review of empirical literature", *Tourism Management Perspectives*, Vol. 8, pp. 28-41. ISSN 2211-9736. DOI 10.1016/J.TMP.2013.05.006.

[9] Dimitrios, B., Ioannis, R., Angelos, N. and Nikolaos, T. (2023) "Digital Marketing: The Case of Digital Marketing Strategies on Luxurious Hotels", *Procedia Computer Science*, Vol. 219, pp. 688-696. ISSN 1877-0509. DOI 10.1016/j.procs.2023.01.340.

[10] Eddyono, F., Darusman, D., Sumarwan, U. and Sunarminto, F. (2021) "Optimization model: the innovation and future of e-ecotourism for sustainability", *Journal of Tourism Futures*, pp. 1-18. ISSN 2055-5911. DOI 10.1108/JTF-03-2021-0067.

[11] Fattah, M., Utami, T. N. and Sofiati, D. (2020) "Tourist Visits Forecasting and Carrying Capacity of Bee Jay Bakau Resort Probolinggo", *Jurnal Analisis Kebijakan Kehutana*n, Vol. 17, No. 2, pp. 153-163. E-ISSN 2502-6267. DOI 10.20886/jakk.2020.17.2.151-161.

[12] Fu, Y. and Timothy, D. J. (2021) "Social media constraints and destination images: The potential of barrier-free internet access for foreign tourists in an internet-restricted destination", *Tourism Management Perspectives*, Vol. 37, pp. 100771. ISSN 2211-9736. DOI 10.1016/j.tmp.2020.100771.

[13] Ghorbani, A., Raufirad, H. and Jafarian, M. (2015) "Ecotourism sustainable development strategies using SWOT and QSPM model: A case study of Kaji Namakzar Wetland, South Khorasan Province, Iran", *Tourism Management Perspectives*, 16, pp. 290-297. ISSN 2211-9736. DOI 10.1016/j.tmp.2015.09.005.

[14] Islam, Md. T. (2021) "Applications of Social Media in the Tourism Industry: A Review", *SEISENSE Journal of Management*, Vol. 4, No. 1, pp. 59-68. ISSN 2617-5770. DOI 10.33215/sjom.v4i1.556.

[15] Joshi, O., Parajuli, R., Kharel, G., Poudyal, N. C. and Taylor, E. (2018) "Stakeholder opinions on scientific forest management policy implementation in Nepal", *PLOS ONE*, Vol. 13, No. 9, p. e0203106. ISSN 1932-6203. DOI 10.1371/journal.pone.0203106.

[16] Khan, M. M., Siddique, M., Yasir, M., Qureshi, M. I., Khan, N. and Safdar, M. Z. (2022) "The Significance of Digital Marketing in Shaping Ecotourism Behaviour through Destination Image", *Sustainability*, Vol. 14, No. 12, p. 7395. E-ISSN 2071-1050. DOI 10.3390/su14127395.

[17] Khomsah, N. R., Carolina, A. and Abrori, R. (2022) "Faktor Internal Organisasi Dan Pencegahan Fraud Pada Pengelolaan Wisata Mangrove Di Madura", *Ultimaccounting Jurnal Ilmu Akuntansi*, Vol. 14, No. 2, pp. 295-311. ISSN 2541-5476. DOI 10.31937/akuntansi.v14i2.2867.

[18] Kim, M. and Kim, J. (2020) "Destination Authenticity as a Trigger of Tourists" Online Engagement on Social Media", *Journal of Travel Research*, Vol. 59, No. 7, pp. 1238–1252. E-ISSN 1552-6763. DOI 10.1177/0047287519878510.

[19] Lam, J. M. S., Ismail, H. and Lee, S. (2020) "From desktop to destination: User-generated content platforms, co-created online experiences, destination image and satisfaction", *Journal of Destination Marketing and Management*, Vol.18, p. 100490. E-ISSN 2212-5752. DOI 10.1016/j.jdmm.2020.100490.

[20] Lee, T. H. and Jan, F. H. (2019) "Can community-based tourism contribute to sustainable development? Evidence from residents´ perceptions of the sustainability", *Tourism Management*, 70, pp. 368-380. ISSN 0261-5177. DOI 10.1016/j.tourman.2018.09.003.

[21] Li, J., Wang, G., Wang, Z., Wang, W., Chen, H. and He, M. (2021) "Comparative study of the physiological and psychological effects of forest and urban auditory stimulus on humans", *International Journal of Geoheritage and Parks*, Vol. 9, No. 3, pp. 363-373. E-ISSN 2577-445X, ISSN 2577-4441. DOI 10.1016/j.ijgeop.2021.09.001.

[22] Magano, J. and Cunha, M. N. (2020) "Digital marketing impact on tourism in Portugal: A quantitative study", *African Journal of Hospitality, Tourism and Leisure,* Vol. 9, No. 1, pp. 1-19. ISSN. 2223814X. {Online]. Available: https://www.ajhtl.com/uploads/7/1/6/3/7163688/article_75_vol_9_1__2020_portugal.pdf [Accessed: Sept. 20, 2024].

[23] Mallick, S. K., Rudra, S. and Samanta, R. (2020) "Sustainable ecotourism development using SWOT and QSPM approach: A study on Rameswaram, Tamil Nadu", *International Journal of Geoheritage and Parks*, Vol. 8, No. 3, pp. 185-193. E-ISSN 2577-445X, ISSN 2577-4441. DOI 10.1016/j.ijgeop.2020.06.001.

[24] Mele, E., Filieri, R. and De Carlo, M. (2023) "Pictures of a crisis. Destination marketing organizations´ Instagram communication before and during a global health crisis", *Journal of Business Research*, Vol. 163, p. 113931. ISSN 0148-2963. DOI 10.1016/j.jbusres.2023.113931.

[25] Mkwizu, K. H. (2019) "Digital marketing and tourism: opportunities for Africa", *International Hospitality Review*, Vol. 34, No. 1, pp. 5-12. E-ISSN 2516-8142 . DOI 10.1108/ihr-09-2019-0015.

[26] Müller, F., Bicking, S., Ahrendt, K., Bac, D. K., Blindow, I., Fürst, C., Haase, P., Kruse, M., Kruse, T., Ma, L., Perennes, M., Ruljevic, I., Schernewski, G., Schimming, C.-G., Schneiders, A., Schubert, H., Schumacher, J., Tappeiner, U., Wangai, P., Windhorst, W. and Zeleny, J. (2020) "Assessing ecosystem service potentials to evaluate terrestrial, coastal and marine ecosystem types in Northern Germany: An expert-based matrix approach", *Ecological Indicators*, Vol. 112, p. 106116. ISSN 1470-160X. DOI 10.1016/j.ecolind.2020.106116.

[27] Nickerson, N. P., Jorgenson, J. and Boley, B. B. (2016) "Are sustainable tourists a higher spending market?", *Tourism Management*, Vol. 54, pp. 170-177. ISSN 0261-5177. DOI 10.1016/j.tourman.2015.11.009.

[28] Paliogiannis, C., Koedam, N. and Cliquet, A. (2019) "The impact of the economic crisis on the implementation of the EU Nature Directives in Greece: An expert-based view", *Journal for Nature Conservation*, Vol. 48, pp. 36-46. ISSN 1617-1381. DOI 10.1016/j.jnc.2018.12.003.

[29] Papapostolou, A., Karakosta, C., Apostolidis, G. and Doukas, H. (2020) "An AHP-SWOT-Fuzzy TOPSIS approach for achieving a cross-border RES cooperation", *Sustainability*, Vol. 12, No. 7, p. 2886. ISSN 2071-1050. DOI 10.3390/su12072886.

[30] Racherla, P. and Friske, W. (2012) "Perceived 'usefulness' of online consumer reviews: An exploratory investigation across three services categories", *Electronic Commerce Research and Applications*, Vol. 11, No. 6, pp. 548-559. E-ISSN 1873-7846, ISSN 1567-4223. DOI 10.1016/j.elerap.2012.06.003.

[31] Reichstein, C. and Härting, R.C. (2018) "Potentials of changing customer needs in a digital world - A conceptual model and recommendations for action in tourism", *Procedia Computer Science*, Vol. 126, pp. 1484-1494. E-ISSN 1877-0509. DOI 10.1016/j.procs.2018.08.120.

[32] Sahani, N. (2021) "Application of hybrid SWOT-AHP-FuzzyAHP model for formulation and prioritization of ecotourism strategies in Western Himalaya, India", *International Journal of Geoheritage and Parks*, Vol. 9, No. 3, pp. 349–-62. E-ISSN 2577-445X, ISSN 2577-4441. DOI 10.1016/j.ijgeop.2021.08.001.

[33] Salim*, M. A. and Siswanto, A. B. (2019)* "Analisis SWOT Dengan Metode Kuesioner - Google Books", Pilar Nusantara, (November 2019), pp. 1-81. ISBN 9786237590101.

[34] Stylidis, D. (2022) "Exploring Resident–Tourist Interaction and its Impact on Tourists´ Destination Image", *Journal of Travel Research*, Vol. 61, No.1, pp. 186-201. E-ISSN 1552-6763, ISSN 0047-2875. DOI 10.1177/0047287520969861.

[35] Sujono, S., Juliati, R., Pramuja, R. A. and Nurul, M. (2023) "Assessing the impact of digital marketing optimization on the self-sustainability of agrotourism in Sumbergedang Village", *Journal of Enterprise and Development*,Vol. 5, No. 2. E-ISSN 2685-8258, ISSN 2715-3118. DOI 10.20414/jed.v5iSpecial-Issue-2.8210.

[36] Sutjiatmi, S. and Edy, S. (2018) "Strategi Komunikasi Pemasaran Ekowisata Hutan Mangrove Pandansari Brebes", *Jurnal Egaliter*, Vol. 2, No. 3, pp. 1-13.

[37] Toral, S. L., Martínez-Torres, M. R. and Gonzalez-Rodriguez, M. R. (2018) "Identification of the Unique Attributes of Tourist Destinations from Online Reviews", *Journal of Travel Researc*h, Vol. 57, No. 7, pp. 908-919. E-ISSN 1552-6763, ISSN 0047-2875. DOI 10.1177/0047287517724918.

[38] Utami, T. N., Fattah, M. and Intyas, C.A. (2022) "The System Dynamic of Mangrove Ecotourism of 'Kampung Blekok' Situbondo East Java Indonesia: Economic and Ecological Dimension", *Environmental Research, Engineering and Management*, Vol. 78, No. 2, pp. 58-72. ISSN 2029-2139. DOI 10.5755/j01.erem.78.2.30322.

[39] Yuniarta, G. A., Purnamawati, I. G. A. and Suwena, K. R. (2023) "The Effect of Using Digital Marketing Platforms, Optimizing Potential Assets on the Inclusive and Sustainable Economy Improvement", *International Journal of Organizational Behavior and Policy*, Vol. 2, No. 1, pp. 3544. E-ISSN 2961-9548. DOI 10.9744/ijobp.2.1.35-44.

Agris on-line Papers in Economics and Informatics

Volume XVI Number 4, 2024

Impact of Livelihood Diversification on the Economic Performance of Rural Households in Nasarawa State, Nigeria

Roseline Ojoromiwa Anyachukwudinarum[1], Waheed Mobolaji Ashagidigbi[2], Jimoh Atanda Afolabi[2], Olumide Akinrinola[2]

[1] National Universities Commission, Directorate of Research and Innovation, Maitama, Abuja, Nigeria

[2] Department of Agricultural and Resource Economics, Federal University of Technology Akure, Ondo State, Nigeria

Abstract

This study examined the impact of livelihood diversification on the economic performance of rural households in Nasarawa state, Nigeria. Multistage sampling procedure was used to select 390 respondents. Endogenous switching regression model was employed to carry out the impact analysis of diversified agricultural and non-agricultural activities on rural households' economic performance of which income, poverty gap, and severity were indicators. The empirical findings revealed that rural household's age, gender, level of education, access to market, membership of cooperatives, access to public transport and rural-urban seasonal migration significantly influenced income, while gender, level of education, household size, access to farmland, access to market, membership of cooperative and entrepreneurial skills significantly influenced rural households' poverty gap and severity. Improved income of rural households in the study area promotes agricultural activities which is the mainstay of their economy. In conclusion, livelihood diversification improves living standard and reduces poverty for rural families and their communities.

Keywords

Livelihood diversification, economic performance, rural households.

Anyachukwudinarum, R. O., Ashagidigbi, W. M., Afolabi, J. A. and Akinrinola, O. (2024) "Impact of Livelihood Diversification on the Economic Performance of Rural Households in Nasarawa State, Nigeria", *AGRIS on-line Papers in Economics and Informatics*, Vol. 16, No. 4, pp. 19-32. ISSN 1804-1930. DOI 10.7160/aol.2024.160402.

Introduction

Agriculture is the mainstay of the economy of the rural households in the study area as it plays a great role in the development of the area. Diversifying agriculture results to enhancing the welfare and income of the rural households. But exacerbating climatic conditions such as erratic rainfall, rising temperatures (Cooke and Jonathan, 2016), over grazing in the far north, desertification, incessant violent clashes between herdsmen and farmers and prevailing Boko Haram insurgency in the North-Central and North East (International Crisis Group, 2017) pushes poorer smallholders to seek alternative incomes in the non/off farm sector. These alternative incomes are used to revive the fallen agricultural activities in the study area. It was reported that coping with the changing situation, smallholder farmers in the North Central and North East in Nigeria are adopting both on-farm (planting drought-tolerant crops and mixed farming) and off/non-farm diversification strategies. According to Baird and Hartter (2017), households across the developing countries are trying to diversify their livelihood activities to secure from risks and cope with economic and environmental shocks. Diversified livelihood combines both agricultural and non-agricultural activities to survive and improve the standard of living. Livelihood diversification plays a crucial role in promoting economic growth and reducing rural poverty in developing countries (Loison, 2019). It is the process of providing alternative job. It marks a vital role in sustainable ecological development and rural poverty reduction (Liu and Lan, 2015).

Rural livelihood diversification is the process by which rural households construct an increasingly diverse portfolio of activities and assets in order to survive and to improve their standard of living (Khatun and Roy 2012). The rural livelihood diversification into farming, off- farming and non-farming is one of the rural households' strategies for boosting agricultural activities and for survival in the study area. The rural people diversify into farm and non-farm activities to explore opportunities through which they increase and stabilize their incomes or to supplement farming in order to improve the welfare or living standard of their household (Wondim, 2019). Rural people have diversified their livelihood means and income earning portfolio across farm, non-farm and off-farm activities. Thus, non-farm income generating activities have become an essential component of livelihood strategies among rural households ((Bezu, Barret and Holden, 2012; Khatun and Roy 2012; Agyeman, Asuming-Brempong and Onumah, (2014). According to Ovwigho (2014), the rural farm families usually engage in different non-farm income generating activities apparently to balance the shortfall of income due to the seasonality of primary agricultural production and create a continuous stream of income to cater for the various household needs. The rural households in the study area survive farm productivity crisis by engaging in a variety of activities, thus generating income and other consumption goods to meet the needs of the family. The Nigerian rural households may have enough reasons to diversify their income. Firstly, factors such as inconsistent government policies, poor processing techniques, poor storage facilities, bad road networks and natural disasters which negatively impact on farmers' productivity, drives income diversification in Nigeria so as to boost agriculture (Msoo and Goodness, 2014). Secondly, Cooke and Jonathan (2016) argued that Nigerian farmers finds it very difficult to access quality agricultural inputs, such as seeds, pesticides, fertilizer and credit needed to scale up their farm operations. Thirdly, the Nigerian labour productivity per worker is about three times higher in the non-farm sector than the farm sector and the non-farm sector boast of higher average income than incomes from the farm sector (Djido and Shiferaw, 2018).

To the best of my knowledge, empirical studies on the impact of livelihood diversification on rural households' economic performance using income, poverty gap and severity appear to be infrequent in the North central area of Nigeria. Therefore, there was the need to carry out this study in Nasarawa State, which developed a structure that measured the impact of diversified farming, off-farming and non-farming activities looking at improving income which will help support the mainstay of their economy. Endogenous switching Regression model approach (Lokshin and Sajaia, 2004) was used in this study to examine the impact. Also examined were the determinants of livelihood diversification where the parameters for economic performance considered in this study were income, poverty gap and severity. This paper adds to the literature by giving recent information on the impact of livelihood diversification on economic performance in North Central part of Nigeria using income, poverty gap and severity as measurement. There has not been detailed impact analysis of livelihood diversification on economic performance of rural households of recent using parameters like income, poverty gap and severity as measurement which this study has given proper attention.

The interesting research topic examined livelihood diversification as a survival strategy and a means to improve economic performance of rural households with the following research questions. Firstly, what are the determinants responsible for livelihood diversification amongst rural households in Nasarawa State, Nigeria? What is the impact of livelihood diversification on rural households' income, poverty gap and poverty severity in the study area? The specific objectives of this research are to analyse the impact estimate of determinants on livelihood diversification, also, impact estimate of livelihood diversification on income, poverty gap and poverty severity using Endogenous Switching Regression (ESR) model. The remaining sections of this paper include materials and methods, results and discussion, and conclusions

Materials and methods

Study area

The study was carried out in Nasarawa State, North Central Nigeria. The State has Latitude 80° - 90°30'N (approx.) and longitude 70° - 90°30'E (approx) and covers a land area of about 32,500 km^2 (Nasarawa State Ministry of Information, 2012) with a population of about 2.13 million (National Population Commission, 2016) with average growth rate of 2.5%. Agriculture is the mainstay of its economy with the production of varieties of cash crops throughout the year. Some of the inhabitants of the State are fish farmers while most of them cultivate food crops such as grains and legumes, root and tubers, vegetables and fruits.

Data collection and sampling procedure

Data used for this study were collected from primary source through administration of a well-structured questionnaire on rural households in the study area. A multistage sampling technique was adopted for the study. The thirteen (13) Local Government Areas (LGAs) of the state were selected. At the first stage, three (3) communities were randomly selected from each of the LGAs in the state, making a total of thirty nine (39) communities. Thereafter, at the second stage, a random sampling technique was used to select eleven (11) rural households from each community to give a sample size of four hundred and twenty nine (429) rural households. Out of the 429 responses, 390 were valid and complete.

Data analytical procedure

Endogenous Switching Regression Model was used for the analysis of the data.

Empirical specifications

Endogenous Switching Regression (ESR) model

In the process of estimating the impact of livelihood diversification on the economic performance of rural households using ESR framework, a two-stage estimation procedure is involved. In the first stage, the model for the determinants of livelihood diversification is estimated that is the adoption decision to diversify is estimated in order to determine the factors that influenced diversification. The second stage involved the estimation of relationship between the outcome variables and a set of explanatory variables specified for two regimes of diversified and non-diversified rural households. The diversified and non-diversified rural households are represented by y_{1i} and y_{2i} respectively, while the unobserved is denoted by $I_i^* = y_{1i} - y_{2i}$. The function that specifies the households is:

$$I_i = \begin{cases} 1 \; if \; I_i^* > 1 \\ 0 \; otherwise \end{cases} \quad (1)$$

The basic relationship used is income, poverty gap and poverty severity from diversification status and it is stated in relation to a vector of household independent variables (Z_i) in a latent variable framework. The relationship, which is the determinants of livelihood diversification in the first stage, is expressed as follows;

$$I_i^* = \alpha Z_i + \mu_i \quad (2)$$

where l_i is a dichotomous variable with 1= diversified rural households and 0 otherwise, Z represents all observable determinants rural households, for example, household characteristics, α is a vector of parameters to be estimated, μ is the error term with mean zero. The relationship being considered in examining the impact of livelihood diversification on income, poverty gap and poverty severity assumes that vector of outcome variable is a linear function of a vector of explanatory variables (Z_i) and diversification status which is a dichotomous variable explanatory variables (l_i). The relationship can be expressed as follows;

$$y_i = k_i\beta + l_i\gamma + \mu_i \quad (3)$$

where variable y_i is a vector of outcome variable, K_i is a vector of farm and household characteristics, l_i is the diversification status, μ_i is a random error term while β and γ are vector of parameters estimated.

In the course of carrying out impact evaluation, the study was only aware of the observed attributes declared by the respondents, while other unobservable factors are known to only the respondents. In view of this, selection bias ensues if error terms of the outcome equation, (μ) in the Equation 2 and selection equation (ε) in the Equation 1 are influenced by unobservable factors. Endogenous Switching Regression model approach which was developed by Lokshin and Sajaia (2004) was employed in order to concurrently estimate the determinants and impact of livelihood diversification with consideration being given to observable and unobservable factors. The specifications for the two regimes in the second stage are as follows;

Regime 1 (Diversification):

$$y_{1i} = \beta_1 x_{1i} + \varepsilon_{1i} \quad (4a)$$

Regime 2 (Non-Diversification):

$$y_{2i} = \beta_1 x_{2i} + \varepsilon_{2i} \quad (4b)$$

where y_{1i} and y_{2i} are outcome variables for rural households that diversified and did not diversify respectively; x is a vector of household characteristics; β is a vector of parameters to be estimated and ε is the error term.

The structure of the ESR model gives room for an intersection (overlap) of Z in the Equation 2 and β of the Equations (4a) and (4b). However, it is important that at least one variable in Z does not appear in β for the purpose of identification. Therefore, this suggests that the same set of variables are used to estimate selection and outcome equation but with additional one variable in the former. Access to non-farm and off-farm job information is used as a valid instrument as it is expected to affect diversification status and not the outcomes.

As explained by Heckman (1979), the selectivity terms used in the selection equation which represent λ_1 and λ_2 for rural household that diversified and did not diversify respectively, covariance terms σ_{12} and $\sigma_{1\varepsilon}$ are included in the Equation 4a and 4b which resulted to equation 5a and 5b below;

$$y_{1i} = x_1\beta + \sigma_{1\varepsilon}\lambda_1 + \emptyset_{i1} \text{ if } l_i = 1 \tag{5a}$$

$$y_{2i} = x_2\beta + \sigma_{2\varepsilon}\lambda_2 + \emptyset_{i2} \text{ if } l_i = 0 \tag{5b}$$

The ESR model was used to examine the impact of livelihood diversification on rural households' outcome variables (income, poverty severity and poverty gap) by comparing the expected outcomes of rural households who are diversified with the expected outcomes of the counterfactual hypothetical cases that rural households who were diversified are not diversified. The expected values of the outcome Y on diversified and non-diversified can be expressed as follows:

$$E(Y_{i1}/l = 1) = x\beta_{i1} + \sigma_1\varepsilon\lambda_1 - \emptyset_{i1} \tag{6a}$$

$$E(Y_{i2}/l = 1) = x\beta i2 + \sigma_{2\varepsilon}\lambda 2 - \emptyset_{ii2} \tag{6b}$$

According to Lokshin and Sajaia (2004), Average Treatment effect on the Treated (ATT) is a change in the outcome due to diversification adoption. In this case, ATT is expressed in terms of livelihood diversification status, which is expressed as follows in the Equation 7 as the difference in the expected outcomes from equations 6a and 6b.

$$\text{ATT} = E(Y_{i1}/l = 1) - E(Y_{i2}/l = 1) = x(\beta_{i1} - \beta_{i2}) + + \lambda(\sigma 1\varepsilon - \sigma 2\varepsilon) \tag{7}$$

Table 1 shows the list of variables in the Econometric Analysis.

Results and discussion

The Full Information Maximum Likelihood (FIML) results of the Endogenous Switching Regression Model (ESRM) for income, poverty gap and poverty severity are presented

Variable	Description	Measurement
Dependent variables		
Livelihood Diversification (LD)	If household engages in livelihood diversification	(Yes =1; No= 0)
Income	Income per household	Naira
Poverty gap	Poverty gap per household	Number
Poverty severity	Poverty severity per household	Number
Independent variables		
Personal characteristics		
Gender	Gender of household head	(Male=1, Female=2)
Age	Age of respondents	Years
Level of education	Education of respondents	Years
Membership of cooperative societies	Household membership of cooperatives	(Yes =1; No= 0)
Household size members	Number of household members working	Number
Access to farmland	If had access to farmland	(Yes=1; No= 0)
Institutional Variables		
Access to credit	If had received informal credits	(Yes =1; No= 0)
Access to market	If had access to market	(Yes =1; No= 0)
Access to public transport	If had access to public transport	(Yes=1; No=0)
Access entrepreneurial skills	If had received entrepreneurial skills	(Yes =1; No= 0)
Access to jobs information.	If had access to jobs information	(Yes =1; No= 0)
Rural-urban seasonal migration opportunity	If had experienced seasonal migration	(Yes =1; No= 0)
Environmental factors		
Bad weather occurrence	Weather shock experience such as late onset of rains, rises in temperature, heavy rainfall and other unseasonable weather which are as a result of the consequences of climate change experienced in the previous year	(Yes=1, No=0)

Source: Own processing

Table 1: List of variables in the Econometric Analysis.

in Table 2, 3 and 4. The Wald tests confirmed joint significance of the error correlation coefficients in both selection and outcome equations. The significant correlation coefficients of the selection equation and the outcome equations (Income, Poverty gap and Poverty severity) for participants in livelihood diversification indicated the presence of self-selection in engaging in livelihood diversification. Table 5 presents expected values of various outcomes under actual and counterfactual conditions and resulting treatment effects.

The likelihood ratio tests for joint independence of the equations in endogenous switching regression model revealed that the equations are dependent. This implies that the models were not jointly independent and not estimated differently, which explains the empirical approach applied in this study. Therefore, the use of ESR model, which accounts for both observable and unobservable factors, was suitable for this study as explained by (Lokshin and Sajaia, 2004). The estimated coefficients of the correlation term (r1 and r2) were statistically significant in all the regimes. The result showed that there was selection bias due to unobservable factors in livelihood diversification. The negative and significant sign for ‘r’ implies that there was a positive selection bias which suggests that rural households that diversified have higher probability of having increased income and reduced poverty gap and severity.

Determinants of adoption

The results from the selection equation are presented in Tables 2, 3 and 4 together due to the fact that the empirical results in the selection equation can be interpreted as normal probit coefficients. It is worthy of note that estimates for variables with the same name in the selection equation (probability of adopting livelihood diversification) have similar effects on the dependent variable. Results of the estimation of the determinants of livelihood diversification in the study area suggest that level of education, membership of cooperatives and rural to urban seasonal migration are the main drivers behind rural households’ engagement in livelihood diversification. The factors are positive and statistically significant at 1% which shows that, the claim of these factors promoting livelihood diversification cannot be rejected. It was also observed that gender and access to market were found to be significantly positive at 5%. Other factors such as access to farmland, entrepreneurial skills and bad weather were observed to have positive correlation with engagement with livelihood diversification. 1% (highly statistically significant) and 5% (statistically significant) significance level do not have enough evidence to reject the claim that determinants of rural households improve livelihood diversification.

As shown in the results, level of education implies that the probability of being diversified tends to increase as level of education increases. This means that increase in the level of education by 1% enables the rural dwellers to have improved agricultural practices and also engage in various livelihood activities as some non-farm and off-farm jobs demand a minimal level of education. This is in line with Amare and Shiferaw (2017), that said empirical literature shows that education allows households to overcome barriers to diversification and provides incentives for expansion of livelihood options both within and outside agriculture. Membership of cooperative indicates that being a member of cooperative society increases the probability of diversifying livelihood amongst the households. This is possible because cooperative societies in the rural areas help to enhance and establish livelihood activities. Cooperative societies distribute farming inputs and also, introduce their members to sustainable agricultural practices and business opportunities and gives loan to start-up businesses. This is supported by Oloyede (2008) who said the recognition of cooperatives as self-help organizations with capacity to improve livelihood is global and wide spread. Rural to urban seasonal migration exposes rural households’ farmers to different technology which helps to improve agricultural practices and also influence diversification into off-farm and non-farm activities. This seasonal migration is mostly during the dry season, off farming season. This is in line with Barrett al et. (2001), who said rural households in Nigeria engage in economic activities when migrated. However, gender was found to significantly and positively influence the decision of livelihood diversification in the study area at 5% level. The implication of this scenario is that being a male rural household’s head increases the probability of having livelihood diversification. This may be as a result of the cultural practices among the respondents that give men power over and access to productive resources. This confirms the report of Mulwa et al. (2017) that gender variable is a positive and significant factor in rural household decision making in the adoption innovative practices, such as household income improvement. Also, access to market was found to be positive and significant to influence the decision to diversify livelihood in the study area at 5%. The implication of the result is that access to market increases the likelihood of being diversified. However, improved market accessibility will enhance diversification into production of different crops, rearing of animals and involvement in various economic activities by the respondents. Prowse (2015) asserted that distance to markets determines and influences income diversification in rural areas.

Age is a major negative driver in engaging in livelihood diversification as increase in age significantly reduces the likelihood to engage in livelihood diversification by 1%. Age of the household's head had a negative and significant coefficient with rural households' decisions to livelihood diversification, suggesting that increase in age of the respondent decreases the probability of choosing diversified livelihood. This concurs with Asfir (2016) who reported the effect of age of the rural farmers on diversification and pointed out that as the farmers get older, they become more resistant to new ideas, information and technology to better farming activities. Job information about livelihood diversification into on-farm, off-farm and non-farm by rural households tends to increase the likelihood of having diversified livelihood. However, it is worthy to note that the aim of the selection equation is not to perfectly explain diversified livelihood but to account for unobserved heterogeneity that could course bias. It is for this reason that one or more valid instruments must be included in the selection equation and the instrument used in his study is job information about livelihood diversification. The instrument variable, access to job information was found to be positive and influenced the choice of diversification significantly. Job information about livelihood diversification in farming, off-farm and non-farm by rural households tends to increase the likelihood of having diversified livelihood. This implies that having access to job information on farming and non/off farm activities increases the likelihood of livelihood diversification as there are job opportunities. This is in line with Shujaat Farooq and Zunaira Younais (2018) who said access to employment information are provided for more than half of the rural population, contributing to reduction in poverty and equity.

Impact estimate of determinants on rural households' income

The estimates in the outcome equation in the columns for diversified and non-diversified in Table 2 generally show the impact of livelihood diversification on rural household income. The impact estimates showed that the key variables behind rural households' increased income for diversified rural households are gender, level of education and rural to urban seasonal migrations which are significantly positive at 1% while access to market and membership of cooperative are significantly positive at 5%. Age was found to be the major negative driver that reduces income in the study area. The key variables for increased income of non-diversified rural households is access to market which is significantly positive at 1% while age is at 5% and gender at 10%. The negative main driver for income of non-diversified rural households' is rural to urban seasonal migration, found negative at 1% and significant. 1% (highly statistically significant) and 5% (statistically significant) significance level do not have enough evidence to reject the claim that the determinants increase income of rural households. 10% significance level has enough evidence to reject the claim that determinants increase income.

The result of the impact estimates states that age had negative but significant relationship with the income of the diversified respondents while the income of non-diversified respondents was positive and significantly influenced by age. This implies that, as the age of the rural households' increases, the income of diversified respondents falls while the income of non-diversified respondents rises. This finding concurs with Roslan and Siti (2011) and Ike (2015) who separately noted that the older the farmer, the less the probability for him/her to participate in any employment. The positive and statistically significant coefficients of gender of both diversified and non-diversified respectively showed that male household heads in the study had more income than their female counterparts in the two groups (diversified and non-diversified livelihoods). Level of education of diversified rural households tends to increase income. This showed that the more educated the rural households the better they participate in employment opportunities. This is in accordance with McMichael (2008) who stated that the new agriculture for development replaces smallholder knowledge with corporate inputs for development. Also, households with higher education are more likely to participate in wider employment opportunities offered by the non-farm and urban sectors. The positive and statistically significant coefficients of access to market increases income for diversified and non-diversified households.

Variables	Selection		Income of Diversified Households		Income of Non-Diversified Households	
	Coefficient	Z-Value	Coefficient	Z-Value	Coefficient	Z-Value
Age	-0.055***	2.91	-0.010*	1.95	0.019**	2.27
Gender	0.294**	2.15	0.688***	6.7	0.009*	1.89
Level of Education	0.797***	3.34	0.034***	3.15	-0.042	0.33
Household Size	-0.001	0.02	0.012	0.73	-0.015	0.67
Access to farmland	0.004	1.12	0.187	0.84	0.003	0.23
Access to Market	0.123**	2.07	0.354**	2.23	0.938***	4.52
Membership of Cooperatives	0.714***	2.56	0.147**	2.01	-0.114	0.93
Access to Credit	-0.229	0.53	0	0	0.034	0.16
Access to Public transport	-0.043	0.09	0.043	0.26	-0.005	1.82
Rural- Urban Seasonal Migration	4.097***	6.31	1.059***	6.09	-0.059***	2.45
Entrepreneurial Skills	0.246	0.57	0.012	0.08	-0.294	1.26
Bad Weather	0.45	1.04	0.233	1.39	-0.079	0.3
Access to Job Information	0.296**	2.02				
Constant	-0.411	0.33	10.899	36.7	10.121	23.19
Insl			-0.652***	14.92		
Ri			-0.311***	4.98		
Ins2					-0.569***	9
r2					0.15	0.48
LR test of independent: chi^2 (1) = 30.49***						
Log likelihood = -115.681						

Note: ***, **,* means significant at 1%, 5% and 10% respectively
Source: Own processing

Table 2: Full information maximum likelihood estimates of endogenous switching regression model for livelihood diversification and impact on rural households' income.

Abdiassa (2017) reported a similar result that rural household heads having access to market centres has higher involvement in livelihood diversification and could diversify their sources of income.

However, being a member of the cooperative increases the income of the respondents that diversified livelihood. This is in accordance with ILO (2014) who reported that the services of cooperatives help pull members out of poverty. While rural-urban seasonal migration increases income of diversified respondents and increases the likelihood of non-diversified income to fall. It can be interpreted that the more the respondents migrate the higher the income and the lower the income of non-diversified households. The results show that migration is a source of income to the rural households because seasonal migration to urban areas is driven by search for work to earn cash as they see no visible options for moving out poverty within their locality.. This is in agreement with Clement and Timothy (2014) that said migration is one of the households' sources of income used to alleviate unforeseen shocks.

Impact estimate of determinants on rural households' poverty gap

As indicated in Table 3, the impact estimate of determinants on rural households' poverty gap shows that the main drivers of the diversified rural households are level of education and rural to urban seasonal migration which increases the probability of reducing poverty gap at 1% while membership of cooperative increases the probability of reducing poverty gap by at 5% and access to farmland at 10%. The main drivers for non-diversified rural households that increase the probability of reducing poverty gap at 1% are gender and level of education while access to farmland is at 5% and access to market at 10% respectively. Household size was found to be positive and significant at 1% and a main driver which reduces the probability of poverty severity. 1% and 5% significance level do not have enough evidence to reject the claim that the determinants increase the reduction of poverty gap amongst the rural households. 10% significance level has enough evidence to reject the claim that

Variables	Selection		Poverty Gap of Diversified Households		Poverty Gap of Non-Diversified Households	
	Coefficient	Z-Value	Coefficient	Z-Value	Coefficient	Z-Value
Age	-0.055***	2.91	0.004	0.91	-0.005	1.28
Gender	0.294**	2.15	0.023	0.65	0.763***	3.64
Level of Education	0.797***	3.34	0.173***	3.38	-0.056***	2.42
Household Size	-0.001	0.02	0.008	0.74	0.030***	2.65
Access to farmland	0.004	1.12	-0.101*	1.82	-0.583**	2.25
Access to Market	0.123**	2.07	-0.648	1.44	-0.038*	1.91
Membership of Cooperatives	0.714***	2.56	0.104**	2.19	0.085	1.40
Access to Credit	-0.229	0.53	0.021	0.20	-0.128	1.22
Access to Public transport	-0.043	0.09	0.144	1.34	-0.159	0.86
Rural- Urban Seasonal Migration	4.097***	6.31	-3.302***	6.63	0.034	0.14
Entrepreneurial Skills	0.246	0.57	-0.004	0.04	-0.194*	1.84
Bad Weather	0.450	1.04	0.114	1.05	-0.027	0.21
Access to Job Information	0.296**	2.02				
Constant	-0.411	0.33	3.377***	6.39	0.359	1.65
Insl			-0.081***	3.70		
Ri			0.792***	2.39		
Ins2					-0.071**	2.17
r2					-0.128**	2.18
LR test of independent: chi^2 (1) = 15***						
Log likelihood = -137.872						

Note: ***, **,* means significant at 1%, 5% and 10% respectively
Source: Own processing

Table 3: Full information maximum likelihood estimates of endogenous switching regression model for livelihood diversification and impact on rural households' poverty gap.

determinants reduce poverty gap.

The impact estimate of determinants on rural households' poverty gap shows that gender disparity amongst the non-diversified rural household negatively affects the household economic success to a significant degree. This shows that gender differences in access to resources and status usually favour men and often institutionalized through tradition and social norms. This is in agreement with Joe-Ukamuke (2019) who reported that promoting gender equality is widely recognised globally in contributing to agricultural productivity and food security. The level of education increases the probability of reducing poverty gap. This implies that the fall in the level of education widens the poverty gap of the respondents as rural farmers find it difficult to accept new technology. The results denote that education is an important factor to reduce poverty in the study area. This is in accordance with Omodero and Azubike (2016) who said education is way out of economic problem in the rural areas. Also, increase in household size increases poverty gap for the non-diversified in the study area. The result explains that poverty levels increases with larger size of households that have not diversified farming, off-farm and non-farm activities. This study is in accordance with Anyanwu (2014) who said there is a positive correlation between the levels of poverty and the size of the household. Poverty is lowest among single-person households and increases with the number of members of the households.

Farmland increases the likelihood of reducing poverty. The reason for this could be attributed to inherited farmland or farmland owned by the family as essential means of livelihood for rural households but is also one of the most important assets that can be the principal source of poverty reduction. This is in accordance with Akinyemi, B.E,, Mushunje, A., and Sinnett, D. (2019) who explained that land availability is fundamentally crucial to efficient agricultural production, food security and poverty alleviation in Sub-Saharan Africa where rural households have limited access to productive land. Access to farmland is essential to improving the rural farming households in Nigeria. Market accessibility increases the likelihood of reducing poverty gap for the non-diversified in the study. The result explains that non-diversified respondents who are into farming need to be able to access markets to sell their products. Unavailability of this market increases the poverty gap for the non-diversified respondents in the study area. According to Akaakohol and Aye (2014), distance to market is negatively related to diversification. Reliable market access boosts farm productivity, increases incomes and strengthens food security. It can contribute to reducing poverty and hunger for rural families and their communities.

Being a member of the cooperative increases the likelihood of reducing poverty gap. The results showed that, rural households whose livelihoods are diversified or not diversified should be members of the cooperatives so as to have access to financial support to secure farming inputs and also to do other businesses. This is in accordance with Ma and Abdulai (2016) who said existing studies suggest that cooperatives can help reduce market failures and improve access to financial resources without stringent interest rates or harsh conditions. Rural-urban seasonal migration tends to increase the likelihood of reducing poverty gap in the study area if they diversify on-farm, off-farm and non-farm activities. The results show that to have diversified livelihoods may be as a result of migration from rural to urban in search of job when there is low agricultural productivity. Amrevurayire and Ojeh (2016) contrary reported that migration reduces the availability of skilled professionals to work on developmental projects aimed at developing rural areas, furthermore, the notion that better working conditions are only found in major cities, entices unskilled people to leave rural areas, hence prominent rural sector industries such as agriculture and extraction may find it cumbersome to attract the required labour, especially with the notion that rural salaries are not in line with those of urban areas. Having acquired skills for other kinds of job reduces poverty gap of non-diversified respondents when faced with challenges on farm. This is in line with Naudes (2008) who said that the role of rural entrepreneurship in the development process is an effective entrepreneurship venture which fosters the production of wealth for a nation, creates jobs that utilise human resources and also reduces economic waste.

Impact estimate of determinants on rural households' poverty severity

As indicated in Table 4, the impact estimate of determinants on rural households' poverty severity shows the negative main drivers that decrease the probability of reducing poverty severity of diversified rural households by 1% which are level of education and rural to urban seasonal migration while access to farmland and membership of cooperative negatively and significantly reduce poverty level by 5%. Household size and membership of cooperative from non-diversified rural households on poverty severity was found significant and positive at 5% while the main driver which is unavailability of market increases the probability of poverty severity at 5%. However, gender and level of education were found to be 10% significant. 1% and 5% significance level do not have enough evidence to reject the claim that the determinants increase the reduction of poverty severity amongst the rural households. 10% significance level has enough evidence to reject the claim that determinants reduce poverty severity.

The impact estimates of determinants on rural households' poverty severity showed that gender outcome equation of the non-diversified respondents was found to be significant but negative which means that, male non-diversified respondents experienced less poverty severity than their female colleagues. This is in accordance with Beyene (2008) that stated male headed households have more access to opportunities than female headed households. The probability of diversifying is expected to be positive for the former. The level of education was seen to be negative and significant for the diversified and non-diversified respondents. This implies that increase in the level of education reduces poverty severity of the respondents. This is in accordance with Yizengaw et al., (2015) who said the more educated households' heads are the more diversified activities they would have. The positive and significant effect of households size on poverty severity for non-diversified indicates that increase in household size increases poverty severity for the non-diversified respondents. The result explains that the more the household size, the more likely is the burden of the jobless household members on those employed and hence poverty increases with increased household size. This is in accordance with a study by Orbeta (2005) who revealed that extra children have a negative impact on the welfare of household, especially in the case of poor households. Another result indicates that access to farmland was significant but negative for diversified and undiversified rural households. This implies that, poverty severity increases for respondents that do not acquire farmland. This result explains that, availability of farmland is also a source of income distribution

Variables	Selection		Poverty Severity of Diversified Households		Poverty Severity of Non-Diversified Households	
	Coefficient	Z-Value	Coefficient	Z-Value	Coefficient	Z-Value
Age	-0.055***	2.91	0.001	0.17	-0.006	1.68
Gender	0.294**	2.15	-0.012	0.72	-0.338*	2.00
Level of Education	0.797***	3.34	-0.155***	3.10	-0.020*	1.88
Household Size	-0.001	0.02	-0.015	1.47	0.019**	2.00
Access to farmland	0.004	1.12	-0.009**	2.12	-0.065	0.87
Access to Market	0.123**	2.07	-0.083	2.10	-0.012**	2.16
Membership of Cooperatives	0.714***	2.56	-0.101**	2.19	0.074**	2.46
Access to Credit	-0.229	0.53	-0.026	0.26	-0.095	1.10
Access to Public transport	-0.043	0.09	0.154	1.48	-0.188	1.25
Rural- Urban Seasonal Migration	4.097***	6.31	-2.491***	6.21	0.129	0.71
Entrepreneurial Skills	0.246	0.57	0.016	0.16	0.138	1.49
Bad Weather	0.450	1.04	0.093	0.88	-0.021	0.19
Access to Job Information	0.296**	2.02				
Constant	-0.411	0.33	2.709***	6.42	0.357*	1.99
Insl			-0.111***	2.11		
Ri			0.209***	9.20		
Ins2					-0.456***	2.17
r2					-0.012***	3.28
LR test of independent: chi2 (1) = 68.87***						
Log likelihood = -161.365						

Note: ***, **,* means significant at 1%, 5% and 10% respectively
Source: Own processing

Table 4: Full information maximum likelihood estimates of endogenous switching regression model for livelihood diversification and impact on rural households' poverty severity.

and very necessary for the diversified respondents who solely rely on non-farm. The results show that farmland is not only for farming but can be used for other economic activities. Meanwhile, Ali and Deininger (2015) stated that empirical research suggests that land availability and tenure security are important factors in the growth of rural economies. Land ownership motivates investments labour and other resources in land so as to diversify sustain productivity and maintain the value of that land.

The estimate of market accessibility was found to be significant but negative for the non-diversified rural households. The result explains that non-diversified respondents who are into farming need to be able to access markets to sell their products. Unavailability of this market increases the poverty severity for the non-diversified. This is in agreement with Frelat et al., (2016) who said greater market access through better quality road infrastructure is central to advancing the well-being of rural farming populations in many developing countries. Also, the coefficient of membership of cooperatives was found to be statistically significant but negative for both the diversified and non-diversified respondents. This implies that membership of cooperatives tends to reduce poverty severity. The results showed that, member of cooperatives experience the ease of funding their businesses and obtaining inputs for farming. This is in accordance with Sugden et al., (2021) who said cooperative facilitate collective purchase of inputs and marketing of produce, which lower the cost of production, enhance bargaining power for favourable prices and build resilience. While rural-urban seasonal migration was found to be significant to poverty severity of the diversified respondents. This means that migration was identified as a survival strategy utilized by the rural dwellers. This is in agreement with Ajaero and Onokala (2013) who stated that the regression analysis carried out showed that rural-urban migration contributes significantly towards the development of rural communities.

Endogenous Switching Regression: Average Treatment Effects (ATT)

In Table 5, the case of the impact of livelihood diversification on income showed that livelihood diversification increased income for both diversified

Variables	Diversified	Non-diversified	ATT
Income			
Diversified Households	8.430	4.410	ATT = 4.02***
Non- Diversified Households	6.538	3.202	ATU = 3.33
Poverty Gap			
Diversified Households	0.440	0.615	ATT = -0.175**
Non- Diversified Households	0.386	0.461	ATU = -0.075
Poverty Severity			
Diversified Households	0.283	0.489	ATT = - 0.206**
Non- Diversified Households	0.123	0298	ATU = -0175

Source: Own processing

Table 5: Expected Outcome, Treatment and Heterogeneity Effects.

and non-diversified rural households. For instance, diversification of livelihood increased the income of the respondents as indicated by the positive and significant value of ATT. This shows how important livelihood diversification is among the respondents.

In the case of poverty gap, the results show that being diversified is capable of reducing the poverty gap. The ATT was negatively significant which implies that diversification of livelihood would reduce poverty gap among the respondents that diversified their livelihood. The positive value of base heterogeneity implies that there is the existence of some sources of heterogeneity that make diversified respondents less productive than non-diversified respondents.

While in the case of poverty severity, the results show that being diversified is capable of reducing the poverty severity. The ATT was negatively significant, which implies that diversification of livelihood would reduce poverty severity among the respondents that diversified their livelihood. The positive value of base heterogeneity implies that there is the existence of some sources of heterogeneity that makes diversified respondents less productive than non-diversified respondents.

Conclusion

Endogenous Switching Regression model was used to estimate livelihood diversification and impact of diversification on rural households' economic performance. It is indicated in this study that livelihood diversification strategies had positive and statically significant influence on the rural households' economic performance. The empirical findings revealed that rural household's age, gender, level of education, access to market, membership of cooperatives, access to public transport and rural urban-migration significantly influenced income of rural households while gender, level of education, household size, access to farmland, access to market, membership of cooperative and entrepreneurial skills significantly influenced rural households poverty gap and severity.

Following the empirical findings from this study, the following conclusions are made:

1. Livelihood diversification should be encouraged among rural households in Nasarawa State of Nigeria because of its positive effect on household income, poverty gap and severity.
2. Government and NGOs should give more support in protecting the rural households' life and properties and also support the development of formal and informal capacity building at the local level to enhance human assets of rural households and make them adopt new technology in agriculture which will promote Climate Smart Agriculture, off-farm and non-farm opportunities;
3. Government should ensure that rural development programmes are effectively implemented, monitored and evaluated. This will go a long way in ensuring an enabling rural environment in terms of provision of adequate rural infrastructure that is very important for livelihood diversification;
4. Private investors and development partners should be encouraged to invest in rural areas. This will help tremendously in the fight against unemployment among rural households during off-season of agriculture and;
5. Enabling rural environment should also

be provided by the government and NGOs in terms of extension worker services, establishment of cooperative society, access to other livelihood assets, reduction in vulnerability, training, provision of infrastructural facilities such as good roads, electricity, communication networks and farm inputs, marketing facilities, agrometeorological services as well as other programmes that will enable rural households to sustain their livelihoods at both seasons of the year.

Corresponding author:
Roseline Ojoromiwa Anyachukwudinarum, Ph.D.
National Universities Commission, Directorate of Research and Innovation
26, Aguiyi Ironsi street PMB 237 Garki GPO, Maitama, Abuja, Nigeria
Email: rayomoh@yahoo.com

References

[1] Abdiassa, N. (2017) "Determinants of Rural livelihood strategies: The case of rural Kebeles of Dire Dawa administration", *Research Journal of Finance Accounting*, Vol. 8, No. 15, pp. 1-14. E-ISSN 2222-2847, ISSN 2222-1697.

[2] Agyeman, B. A. S., Asuming-Brempong, S. and Onumah, E. E. (2014) "Determinants of income diversification of farm households in the western region of Ghana", *Quarterly Journal of International Agriculture*, Vol. 53, No. 1, pp. 55-72. ISSN 0049-8599.

[3] Ajaero, C. K. and Onokala, P. C. (2013) "The Effects of Rural-Urban Migration on Rural Communities of Southeastern Nigeria", *International Journal of Population Research*, Vol. 2013, Article ID 610193, pp. 10. ISSN 2090-4037. DOI 10.1155/2013/610193.

[4] Akaakohol, M. A. and Aye, G. C. (2014) "Diversification and farm household welfare in Makurdi, Benue State, Nigeria", *Development Studies Research*, Vol. 1, No. 1, pp. 168-175. E-ISSN 2166-5095. DOI 10.1080/21665095.2014.919232.

[5] Akinyemi, B. E., Mushunje, A. and Sinnett, D. (2019) "Land Ownership and Usage for Agriculture: Empirical Evidence from South African Living Conditions Survey", *Cogent Social Sciences*, Vol. 5, pp. 1-17. E-ISSN 2331-1886. DOI 10.1080/23311886.2019.1663691.

[6] Ali, D. A. and Deininger, K. (2015) "Is There a Farm Size – Productivity Relationship in African Agriculture? Evidence from Rwanda", *Land Economic*, Vol. 91, No. 2, pp. 317-343. E-ISSN 1543-8325. DOI 10.3368/le.91.2.317.

[7] Amare, M. and Shiferaw, B. (2017) "Nonfarm employment, agricultural intensification, and productivity change: Empirical findings from Uganda", *Agricultural Economics*, Vol. 48, No. S1, pp. 59-72. ISSN 0169-5150. DOI 10.1111/agec.12386.

[8] Amrevurayire, E. O. and Ojeh, V. N. (2016) "Consequences of rural-urban migration on the source region of Ughievwen clan Delta State Nigeria", *European Journal of Geography*, Vol. 7, No. 3, pp. 42-57. ISSN 1792-1341.

[9] Asfir, S. (2016) "Determinants of Rural Households Livelihood Strategies: Evidence from Western Ethiopia", *Journal of Economics and Sustainable Development*, Vol. 7, No. 15, E-ISSN 2222-2855, ISSN 2222-1700.

[10] Anyanwu, J. C. (2014) "Marital Status, Household Size and Poverty in Nigeria: Evidence from the 2009/2010 Survey Data", *African Development Review*, Vol. 26, No. 1, pp. 118-137. ISSN 1017-6772. DOI 10.1111/1467-8268.12069.

[11] Baird, T. D. and Hartter, J. (2017) "Livelihood diversification, mobile phones and information diversity in Northern Tanzania", *Land Use Policy*, Vol. 67, pp. 460-471. ISSN 0264-8377. DOI 10.1016/j.landusepol.2017.05.031.

[12] Barrett, C. B., Reardon, T. and Webb, P. (2001) "Nonfarm income diversification and household livelihood strategies in rural Africa: Concepts, dynamics, and policy implications", *Food Policy*, Vol. 26, No. 4, pp. 315-331. ISSN 0306-9192. DOI 10.1016/S0306-9192(01)00014-8.

[13] Beyene, A. D. (2008) "Determinants of off-farm participation decision of farm households in Ethiopia", *Agrekon,* Vol. 47, No. 1, pp. 140-161. ISSN 2078-0400. DOI 10.1080/03031853.2008.9523794.

[14] Bezu, S., Barrett, C. B. and Holden, S. T. (2012) "Does the Nonfarm Economy Offer Pathways for Upward Mobility? Evidence from a Panel Data Study in Ethiopia", *World Development*, Vol. 40, No. 8, pp. 1634-1646. ISSN 0305-750X. DOI 10.1016/j.worlddev.2012.04.019.

[15] Clement, M. and Ogden, T.(2014) "*Migration as a Strategy for Household Finance: A Research Agenda on Remittances, Payments, and Development - Working Paper 354*", Working Papers 354, Center for Global Development. [Online]. Available: https://ideas.repec.org/p/cgd/wpaper/354.html [Accessed: Jan. 15, 2024].

[16] Cooke, J. G. and Jonathan, E. (2016) "*Tracing the Roots of Nigeria's Agricultural Decline*", Center for Strategic and International Studies, Washington, D.C. [Online]. Available: https://www.csis.org/analysis/tracing-roots-nigerias-agricultural-decline [Accessed: Jan. 15, 2024].

[17] Djido, A. I. and Shiferaw, B. A. (2018) "Patterns of labor productivity and income diversification: Empirical evidence from Uganda and Nigeria", *World Development*, Vol. 105, pp. 416-427. ISSN 0305-750X. DOI 10.1016/j.worlddev.2017.12.026.

[18] Frelat, R., Lopez-Ridaura S. and Giller, K. (2016) "Drivers of household food availability in sub-Saharan Africa based on big data from small farms", *Proceedings of the National Academy of Sciences*, Vol. 113 No. 2, pp. 458-463. ISSN 0027-8424. DOI 10.1073/pnas.1518384112.

[19] Heckman, J. J. (1979) "Sample selection bias as a specification error", *Econometrica*, Vol. 47, pp. 153-161. ISSN 1468-0262. DOI 10.2307/1912352.

[20] Ike, P. C. (2015) "Determinants of participants in non-farm economic activities in South East Nigeria: A tobit analysis approach", *Journal of Biology, Agriculture and Healthcare*, Vol. 5, No. 2, pp. 102-108. E-ISSN 2225-093X, ISSN 2224-3208.

[21] International Crisis Group (2017) "*Herders against Farmers: Nigeria's expanding Deadly Conflict*", Africa Report N° 252. [Online]. Available: https://www.ecoi.net/en/file/local/1410340/1226_1505986246_252-nigerias-spreading-herder-farmer-conflict.pdf [Accessed: Jan. 10, 2024].

[22] International Labour Organisation ILO (2014) "*Social and Solidarity Economy: Towards Inclusive and Sustainable Development*", 28th July – 1st August 2014, Campinas, Brazil. ISBN 978-92-9049-713-4.

[23] Khatun, D. and Roy, B. C. (2012) "Rural livelihood diversification in West Bengal: Determinants and constraints", *Agricultural Economics Research Review*, Vol. 25, pp. 115-124. ISSN 0971-3441. DOI 10.22004/ag.econ.126049.

[24] Liu, Z. and Lan, J. (2015) "The sloping land conversion program in China: Effect on the livelihood diversification of rural households", *World Development*, Vol. 70, pp. 147-161. ISSN 0305-750X. DOI 10.1016/j.worlddev.2015.01.004.

[25] Loison, S. A. (2019) "Household livelihood diversification and gender: Panel evidence from rural Kenya", *Journal of Rural Studies*, Vol. 69, pp. 156-172. ISSN 0743-0167. DOI 10.1016/j.jrurstud.2019.03.001.

[26] Lokshin, M. and Sajaia Z. (2004) "Maximum likelihood estimation of endogenous switching regression models", *Stata Journa*l, Vol. 4, No. 3, pp. 282-289. ISSN 1536-8734. DOI 10.1177/1536867X0400400306.

[27] Ma, W. and Abdulai, A. (2016). "Does cooperative membership improve household welfare? Evidence from apple farmers in China", *Food Policy*, Vol. 58, pp. 94-102. ISSN 0306-9192. DOI 10.1016/j.foodpol.2015.12.002.

[28] Msoo, A. A. and Goodness, C. A. (2014) "Diversification and farm household welfare in Makurdi, Benue State, Nigeria", *Development Studies Research*, Vol. 1, No. 1, pp. 168-175. ISSN 2166-5095. DOI 10.1080/21665095.2014.919232.

[29] Mulwa, C., Marenya, P. and Kassie, M. (2017) "Response to climate risks among smallholder farmers in Malawi: A multivariate probit assessment of the role of information, household demographics, and farm characteristics", *Climate Risk Management*, Vol. 16, pp. 208-221. DOI 10.1016/j.crm.2017.01.002.

[30] Naude, W. A. (2008) "Entrepreneurship in Economic Development", WIDER Research Paper, RP 2008/20, United Nations University, Helsinki.

[31] Oloyede, J. A. (2008) "Informal Financial Sector, Savings Mobilization and Rural Development in Nigeria: Further Evidence from Ekiti State of Nigeria", *African Economic and Business Review,* Vol. 6, No.1, pp. 35-63. E-ISSN 1750-4562, ISSN 1750-4554.

[32] Omodero, C. O. and Azubike, J. U. (2016) "Empirical review of government expenditure on education and economic development in Nigeria (2000-2015)", *International Journal of Development and Economic Sustainability*, Vol. 4, No. 5, pp.13-25. E-ISSN 2053-220, ISSN 2053-2199.

[33] Orbeta, Jr. and Aniceto, C. (2005) "Poverty, Vulnerability and Family Size: Evidence from the Philippines", Asian Development Bank Institute, Research Paper Series, No. 68. [Online]. Available: https://www.adb.org/sites/default/files/publication/157217/adbi-rp68.pdf [Accessed: Jan. 15, 2024]. DOI 10.4337/9781847203168.00012.

[34] Ovwigho, B. O (2014) "Factors Influencing Involvement in Nonfarm Income Generating Activities among Local Farmers: The Case of Ughelli South Local Government Area of Delta State, Nigeria", *Sustainable Agriculture Research*, Vol. 3, No. 1. E-ISSN 1927-050X, ISSN 1927-0518. DOI 10.5539/sar.v3n1p76.

[35] Prowse, M. (2015) "The Determinants of Non-Farm Income Diversification in Rural Ethiopia", *Journal of Poverty Alleviation and International Development*, Vol. 6, No. 1, pp. 109-130. ISSN 2586-2537.

[36] Roslan, A.-H. and Siti, H. Ch.-M. (2011) "Does farmers' diversification into non-farm employment reduce their likelihood of poverty? Evidence from Malaysia", *Journal of Business and Political Research*, Vol. 6, No.1, pp. 145-155. Corpus ID: 56061784.

[37] Shujaat, F. and Younais, Z. (2018) "Do Non-farm Enterprises Offer Pathways for Upward Mobility in Rural Pakistan? Evidence from Panel Dataset", *The Pakistan Development Review*, Vol. 57, No. 2, pp. 203-221. ISSN 0030-9729. DOI 10.30541/v57i2pp.203-221.

[38] Sugden, F., Agarwal, B., Leder, S., Saikia, P., Raut, M., Kumar, A. and Ray, D. (2021) "Experiments in farmers' collectives in Eastern India and Nepal: Process, benefits, and challenges", *Journal of Agrarian Change*, Vol. 21 No. 1, pp. 90-121. ISSN 1471-0366. DOI 10.1111/joac.12369.

[39] Joe-Nkamuke, U., Olagunju, K. O., Njuguna-Mungai, E. and Mausch, K. (2019) "Is there any gender gap in the production of legumes in Malawi? Evidence from the Oaxaca–Blinder decomposition model", *Review of Agricultural, Food and Environmental Studies,* Vol. 100, No. 1, pp. 69-92. ISSN 2425-6870. DOI 10.1007/s41130-019-00090-y.

[40] Wondim, A. K. (2019) "Determinants and challenges of rural livelihood diversification in Ethiopia: Qualitative review", *Journal of Agricultural Extension and Rural Development*, Vol. 11, No. 2, pp. 17-24. ISSN 2141-2170. DOI 10.5897/JAERD2018.0979.

[41] Yizengaw, S., Okoyo, E. and Fekadu B. (2015) "Determinants of livelihood diversification strategies: The case of smallholder rural farm households in Debre Elias District, East Gojjam Zone, Ethiopia", *African Journal of Agricultural Research*, Vol. 10, No. 19, pp. 1998 - 2013. ISSN 1991-637X. DOI 10.5897/AJAR2014.9192.

[42] McMichael, P. (2009) "Banking on Agriculture: A Review of the World Development. Report 2008". *Journal of Agrarian Change,* Vol. 9, No. 2, pp. 235-246. ISSN 1471-0366. DOI 10.1111/j.1471-0366.2009.00203.x.

Volume XVI Number 4, 2024

Image-Based Solutions for Precision Food Loss Evaluation

Adrián Csordás

Faculty of Economics and Business, University of Debrecen, Hungary

Abstract

The high amount of food loss and waste significantly challenges the sustainable development. The agriculture needs rapid and fundamental transformation to enhance its efficient and sustainabile operation. However, to measure precisely the effect of the new policies and practices is also difficult. The present study analyses the applied methods' data sources, as one of the key factors regarding the effective estimation of food loss and waste. By conducting a systematic literature review using the PRISMA approach, a lack of scientific focus was found related to the new data collection methods. Based on the selected articles reasonably slight amount joined the application of image processing to food loss estimation related purposes. The reviewed studies principally used the image-based solutions for the prevention and reduction of on-farm food loss. This recognition lighted up the application of image processing in agriculture, but only the thematic map analysis revealed the privileged status of "plant disease detection" within the studied area. The results suggest the possibility of applying image-based data sources to quantify food loss. Even though the limitations of agricultural image processing, the application of new data sources, and methods could considerably improve the accuracy of food loss and waste quantification in addition to the operation on farm level in short term.

Keywords

Computer vision, sustainable development, data collection, smart farming, innovation, digitalisation.

Csordás, A. (2024) "Image-Based Solutions for Precision Food Loss Evaluation", *AGRIS on-line Papers in Economics and Informatics*, Vol. 16, No. 4, pp. 33-43. ISSN 1804-1930. DOI 10.7160/aol.2024.160403.

Introduction

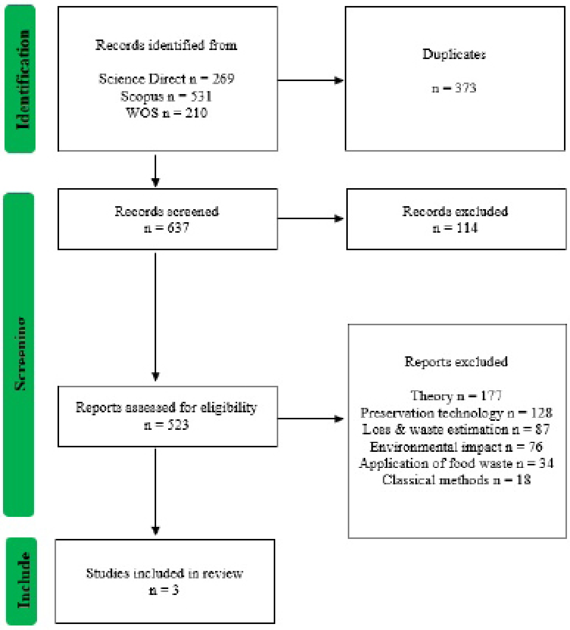
The issue of food loss and waste (FLW) is a critical global concern, that presents considerable obstacles to sustainability, food security, and economic development. Based on the estimation of the Food and Agriculture Organization of the United Nations (FAO) one-third of all food produced for human consumption is lost or wasted globally (FAO, 2011). FLW contributes among others to greenhouse gas emissions (Abbade, 2023; Guo et al., 2020; Khatri-Chhetri et al., 2022; Zhu et al., 2023) water pollution (Abbade, 2020; Marston et al., 2021; Sun et al., 2022) and land degradation (Capone et al., 2020; Pagani et al., 2020; Sun et al., 2022). Its economic costs are also significant, estimated to exceed USD 400 billion from harvest up to, but not including retail (FAO, 2019). The share of FLW along the value chain differ significantly related to the various crop (Corrado and Sala, 2018; Dal' Magro and Talamini, 2019; Hartikainen et al., 2018) and the geographical location (Anriquez et al., 2021; Ishangulyyev et al., 2019; KC et al., 2016). The usage of different concepts and approaches also makes the navigation in the field of FLW more complicated (Boiteau and Pingali, 2023; Chaboud and Daviron, 2017; Ellison et al., 2019), in addition, some studies often combine and analyze the different stages of the food supply chains together (Chauhan et al., 2021; Luo et al., 2022). The above briefly mentioned issues are some of the reasons why, accurate and comprehensive quantification of FLW remains a complicated task. Various methodologies are utilized to measure FLW (Shee et al., 2022), including field surveys (Johnson et al., 2018), household interviews (Redlingshöfer et al., 2017), data analysis (Garcia-Herrero et al., 2018), economic modeling (Soltani et al., 2020) or development of own methods (Delgado et al., 2021). Although these approaches are tailored to specific products and stages of the supply chain, the challenges related to quantification are still significant. The lack of standardized methodologies, the quality data, and the complexity of the topic demands the adoption of innovative approaches and research strategies. The development of new and more robust quantification methods, the integration of data from diverse sources, and the use of advanced statistical techniques are all avenues for enhancing the understanding of FLW. The current study is focused on the preharvest and harvesting loss. These stages cover the losses in crops caused among others by pests, weather, weeds, crops left in the field, or poor harvesting techniques before and during harvesting (Delgado et al., 2017). The present research aimed to discover and propose a new data collection method for the precision evaluation of food loss based on published scientific works, in addition to fostering the scientific discussion of the new data collection and quantification methods.

Materials and methods

To gain a deep insight into food loss, a comprehensive collection of relevant articles was gathered from three respected online databases; Science Direct, Scopus, and Web of Science. The possibilities related to the keywords were restricted, while in Science Direct the application of astrix is not allowed anymore, and the utilization of more than eight operators is also prohibited. Considering the constraints, the following search query could cover the widest range of relevant results ("food loss") AND ("estimate" OR "measure" OR "calculate" OR "evaluate" OR "declare" OR "method" OR "technique"). The title, abstract, or keywords must contain the previously mentioned expressions. The study focused exclusively on English-language research. References from the studied works were also examined, but no relevant studies were found. This could be due to the specialized nature of the topic. The selected articles had to significantly differ in the data collection method compared to the traditional (survey, interview, weighing) approach. Other sources (grey literature) could not be involved.

Related to the determination of food loss various methods are defined, although given stages like preharvest are often out of their range (Boiteau and Pingali, 2023). Proposed and widely implemented estimations focus on the post-harvest stages (Koester and Galaktionova, 2021), but even associated with these activities modern image-based solutions are not broadly studied. The well-known organizations (FAO, World Business Council for Sustainable Development, World Resources Institute, United Nations Environment Programme, World Health Organization, International Food Policy Research Institute) either do not address this or seek to provide more accurate estimation methods by refining traditional data collection practices, methods. Connected to the current concepts (FAO, 2011) numerous criticisms have stressed their inaccuracy. Spang et al., (2019) identified inconsistencies and gaps in the definitions of FLW, noting substantial data deficiencies, particularly regarding food types and stages of the food supply chain. Redlingshöfer et al., (2017) expressed skepticism regarding FLW quantification databases and methodologies. A part of their concerns lies in the application of FAO and USDA definitions, which exclusively pertain to edible, safe, and nutritious food. Xue et al., (2017) also stressed the significant discrepancies in nationally-focused estimates of food loss and waste. Among the estimates they examined, numerous did not conduct new measurements; rather they applied outdated or surrogate data from other countries. The authors emphasize that the deficiency of data is not solely a global concern; the majority of countries lack comprehensive food loss and waste data. However new data collection approach has not been suggested.

To reveal innovative alternatives a systematic literature review was conducted. Among the scientific databases, 1010 articles fulfilled the above-described criteria. The systematic literature review was managed by Rayyan (Rayyan, 2023) – an online platform for this purpose –, applying the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) methodology. The aim of it is to recognize the motivation, method, and result of the examined article. Initially, it was introduced in 2009, and later in 2020, it was extended (Page et al., 2021). The first stage is pinpointing the research query, succeeded by the formulation of a search strategy to locate relevant databases. In the next phase the publications' title, abstract, or in given cases full text is checked. Based on the defined conditions, the studies are categorized (Moher, 2009). In the final analysis, a detailed evaluation of the selected articles is undertaken, and the most pertinent publications to the research aim are carefully separated (Swartz, 2011). Based on the above briefly demonstrated approach, multi-round screening (Figure 1) was applied.



Source: own elaboration, 2023

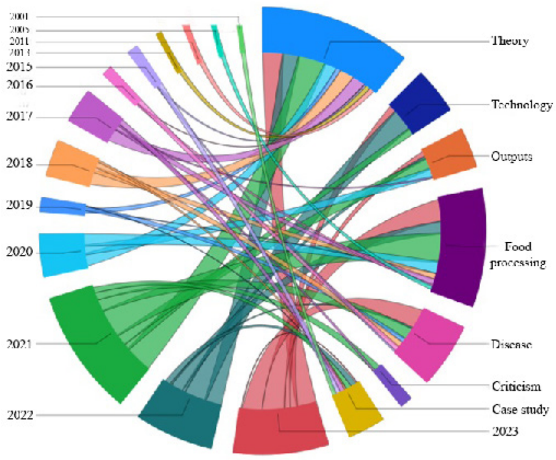
Figure 1: Pathway of the research.

In the first round, the duplicates were selected. This resulted in the elimination of 373 works, so 637 studies created the base of the analysis. After these were filtered out by Rayyan (Rayyan, 2023) started the initial screening which resulted in 114 excluded articles. This stage was followed by the in-depth analysis of the remaining 523 studies, to identify the diverse areas within the estimation of food loss. Considering the growing number of articles related to the Sustainable Development Goals (SDGs) in addition the recent rise in food prices could stimulate high interest related to this topic. These phenomena could explain why a large number of weakly connected works were excluded from the further study. Within the analyzed works the following main research directions were identified: theory (177), preservation technology (128), food loss and waste estimation (87), environmental impact (76), application of food waste (34), and classical methods (18). The present study covers all the related publications until 14 November 2023. Although PRISMA is a widely used research method, it, and therefore this article, has its limitations. The work relies on three major academic databases and using a restricted set of keywords. As a result, some significant studies on food loss estimation might have been overlooked, particularly those that use alternative phrasing or published in journals that are not indexed by these sources. Grey literature often provides valuable insights and data that are not available in peer-reviewed academic publications. However, finding these is challenging. Moreover, the exclusive focus on English-language studies, potentially excluding relevant research conducted in other languages. Finally, the study's time constraint, which only covers publications up until 14 November 2023, limits its ability to capture the most recent developments in this rapidly evolving field.

Results and discussion

Related reviews

To justify the relevance and growing interest related to food loss, the published reviews were analyzed in depth. The search method was similar to the one explained above, but this time reviews were included only. The high number of publications provides the opportunity for proper classification to reveal the main directions within the studied area. However, a review of innovative data-collecting methods has not been published as seen in Figure 2.



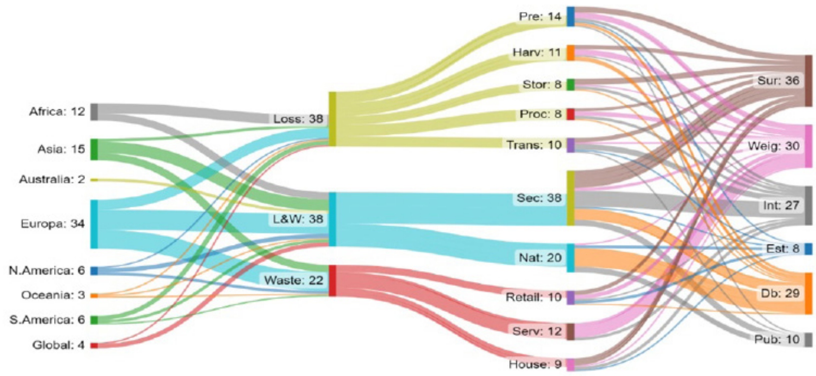
Source: own elaboration, 2023

Figure 2: The distribution of review articles by year and topic.

The emerging interest could be traced back to 2017, a year after the SDGs came into force. The sorted works rather focus on areas like food processing or theory, where often the challenges and obstacles in addition to the good and bad practices are presented. The need for a proper dataset has not been critically reviewed.

Academic papers

The articles excluded from the in-depth review and grouped into the cluster of "food loss and waste estimation" were screened to expose the most widely applied methods. The mapping of these articles in Figure 3. showed the leading position of the European studies.



Note: abbreviations: N. America: North America, S. America: South America, L&W: loss and waste, Pre: preharvest, Harv: harvesting, Stor: storage, Trans: transportation, Sec: sector/supply chain, Nat: countrywide, Serv: services, Sur: survey, Weig: weighing, Int: interview, Est: estimation, Db: database, Pub: publication
Source: own elaboration, 2023

Figure 3: The share of applied methods in the FLW studies.

The high number of sector/supply chain and countrywide (in addition to international) studies in L&W can suggest the endeavor of generalizability, although these rough estimations are mostly based on mathematically improved estimations (database), publications, or surveys. The high number of these works distorts the diagram since the L&W studies involved all the stages of the chain and were based on more than one source of information. From the food loss-related studies the high share of the preharvest, and harvest phase is distinct. The application of questionnaires is quite common, albeit many of the studies are frequently founded on weighing. The resource intensity of the latter technique is unquestionable, but to date, no other method of comparable effectiveness has been used in the reviewed studies.

While traditional methods such as weighing and questionnaires are prevalent in food loss studies, there is growing opportunities in more advanced, data-driven approaches. Although precision agriculture has been widely studied, the use of computer vision specifically for food loss estimation has not been comprehensively explored. One of the few relevant studies in this field is written by is Hassanzadeh et al., (2022), where unmanned aerial systems (UASs) made images were analyzed to evaluate pod size crop maturity. This work aimed to facilitate identifying the optimal harvesting date, to reduce food loss at farm level. The study was conducted in Geneva, NY, USA for the summer 2019, and in Seneca, NY for the summer 2020. There were 18 plots in the latter-mentioned area, while in the other location, 24 were created. The size of each plot was 1.5 m long and 0.75 m wide, where six different cultivar of snap bean was cultivated. They were sowed around 4 cm deep and 20-26 plants were placed per meter. The images were made by the hyperspectral imager ("Nano Hyperspec", Headwall Photonics, USA) was equipped on a DJI Matrice-600 quadcopter that flew five times each year during the crop pod formation. In the study, five key stages were defined and utilized to preprocess and analyze the gathered data. The preprocessing phase involved activities such as calibrating to reflectance, extracting plots and identifying vegetation, reducing noise, and preparing the data. In the analysis phase, the preprocessed data underwent the application of a feature selection library. The authors contrasted their method's outcomes to the top-performing test (RF-Kaiser-B3) on simulated annealing, comparing it with eight frequently utilized vegetation indices. Where their findings demonstrated superior performance compared to the others. So, this research demonstrated that accurately evaluating the maturity of snap beans in the growth stage for large-sieve cultivars (based on unmanned aerial systems made images), such as Huntington and Venture, is feasible when distinguishing between those ready for harvest.

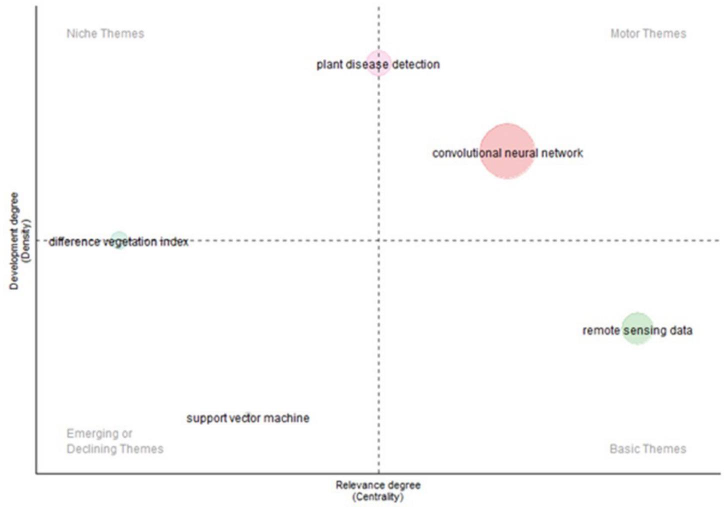
Similarly to the previous work, the study of Wang et al., (2023) focused on (drone)image-based harvest data prediction of broccoli. The research was conducted on the farm of the Institute for Sustainable Agro-ecosystem Services (ISAS), Tokyo, Japan in 2020 and 2021. Throughout the two-year trial, the identical broccoli variety (Jet dome) was cultivated, with the same field management practices. However, the plot size was reduced in the second year from 0.2 ha to 0.1 ha.

In conformity with the commercial regimes through the machine planting the seedlings were 35 cm apart from each and rows of seedlings were separated by a distance of 70 cm. The images were made by DJI Phantom 4 v2 and, DJI Mavic 2 Pro in 2020 while in 2021 DJI Phantom 4 RTK was used. The resolution of all the pictures was 5472x3648 pixels. After the data collection and data preprocessing, broccoli position detection, broccoli head segmentation, and broccoli head size calculation were conducted. Compared to the previous work the researchers even developed a model to predict the optimal harvest time, so maximize the income, and minimize the food loss. In the studied case one day shift in harvest date (compared to the forecasted one) could have led to a significant income loss of up to 20%. Even though this study concentrated on broccoli, according to the authors the framework lightly could be adopted to similar vegetables like cabbage, cauliflower, or artichoke. Although this outstanding work shows up several technical improvements it has some limitations too. Plant phenotyping is a big challenge in image processing, and this issue can be seen here too. To solve temporarily this problem only those broccoli heads were studied in the research that were clearly visible. Some manual inspection is also needed for seedling position detection, detection of omissions, duplications, and drifts. Although many farmers own some general IT knowledge, this model is neither fully automated nor app-based which requires some more background in the field of computer science. As the source code is open-access, the further development of this work is supported and encouraged by the authors.

Not only vegetable cultivations were studied by image processing. The research of Assunção et al., (2022) applied a deep learning approach to detect peaches supporting the yield estimation. The analyzed pictures were made by an Eken H9R camera (5472x3648 pixels). All the photos were taken in the same orchard - whose fruits were yellowish - located in Beira Interior, Portugal. To train the model 200 photos with 1934 annotated fruits were used. To test it 40 pictures with 410 annotated peaches from the same farm and some images from another orchard with reddish peaches were taken to see the generalisability of the R-CNN based model. The study revealed the great potential of using the R-CNN model for peach detection. The difficulties belonging to an uncontrolled environment like light changes, occluded or bunches of fruits were well managed. In addition, the change of fruit and leave colors was handled by this robust deep learning technique too.

The examination revealed a scarce existence of relevant literature applying new data collection methods for food loss evaluation purposes. According to the studied works and their references, the recent image-based approach is being studied in agriculture. However, the focus of these articles differs from the current research's direction. The studies focus on preventing and reducing on-farm food loss, rather than quantifying it. The very small number of connected studies suggests that the application of image processing in this area is still in its early stages.

To examine the landscape of the image-based research directions related the farming issues a thematic map was made. The purpose of this figure is to understand the current state and reveal the future of the studied field. By analyzing the connections between groups of abstracts, thematic analysis revealed underlying themes, that have specific attributes, namely, density and centrality (Aria and Cuccurullo, 2017). The latter measures how closely related different topics are to each other, while density measures how interconnected the nodes within the topic are. These two properties together determine a topic's development and importance. The more connections a topic has, the more important it is. Similarly, the more interconnected the nodes, the more cohesive the research field is (Agbo et al., 2021). On the map, each circle symbolizes a group of related terms, and the circle's size reflects the number of terms it encapsulates. The map could be divided into sections (Q1-Q4). The driving themes are located in the upper right quadrant (Q1). The highly specialized matters are found in the upper left corner (Q2). The emerging or disappearing issues are presented in the lower left area (Q3), and the lower right section (Q4) shows the underlying themes (Yu and Muñoz-Justicia, 2020). To collect relevant studies the "image-based" AND "agriculture" search query was used in the same scientific databases. After the data cleaning, 433 work created the base of the thematic map (Figure 4).



Source: own elaboration, 2023

Figure 4: The thematic map of image-based studies in the agriculture.

The analysis of more than four hundred articles outlined the most relevant factors. The map made visible in the Q4 section the essential need for ”remote sensing data”, which is the basis and very important for the further development of the studied field. It is not surprising, since this is the information source of the studies. In section Q3 the emerging or declining themes are presented. In the current case the extremely small circle of ”support vector machine” is located here. The support vector machines (SVMs) are supervised machine learning algorithms dedicated to classification and pattern recognition tasks (Otchere et al., 2021). These functions make them ideal for analyzing agricultural images. The widespread of drones, satellites, and other imaging technologies (Hall and Wahab, 2021), the development of machine learning algorithms (Alzubi et al., 2018), the growing demand for precision agriculture (Sishodia et al., 2020), and even the decreased computational costs (Xie et al., 2021) rather support the rise, than the fall of the cluster. At the junction of highly specialized matters (Q2) and emerging or disappearing issues (Q3) located a bit bigger circle, the so-called ”difference vegetation index”. The DVIs (difference vegetation indices) are a type of vegetation index that measures the disparity in reflectance between two different wavelengths of light (Huang et al., 2021). In agriculture this ability is utilized among others for monitoring crop growth and development (Mandal et al., 2020), detecting and mapping vegetation (Rokni and Musa, 2019), estimating crop yield (Ji et al., 2021), or identifying areas of nutrient deficiency (Sharifi, 2020). This group has less centrality but is compensated with a relatively higher level of interconnection. In the top right corner (Q1) positioned the biggest cluster. According to the thematic map "convolutional neural network" is the driving theme in the studied field. The centrality and the density of CNN (convolutional neural network) are fairly high, which could be explained by the excellent suitability for for image-based analysis of this deep learning algorithm (Indolia et al., 2018). The sandwiched lay of the "plant disease detection" cluster on the borders of the niche (Q2) and driving (Q1) sections shows up the one indeed agricultural related matter of the analyzed studies. Even though "plant disease detection" is prioritized, the results further support the assumption that image-based data sources could also be applied to quantify food loss. However, the new data collection method has not only great potential but also significant hurdles. One of the primary barriers lies in the complex nature of plant phenotyping. Not only adapting the method to different types of plants can be challenging, but also analysing the plants belonging to a particular species. Given that the visual characteristics of a species can vary significantly due to factors such as genetic diversity, environmental conditions, diseases or pests. These variations can make it difficult for image processing algorithms to accurately identify and classify different plant stages or anomalies. Another challenge is the potential for errors in data collection and processing. Despite advancements in UAS technology, factors such as atmospheric conditions, camera calibration, and image quality can introduce noise and distortions into the collected data. These errors can impact the accuracy of subsequent analyses and predictions. Moreover, the development of robust image processing algorithms requires extensive training data, which can be time-consuming and resource-intensive to acquire. Furthermore, the practical implementation of image-based food loss estimation systems in real-world agricultural settings can be hindered by factors such as cost, technical expertise, and infrastructure requirements. While the initial investment in UASs and image processing software may be substantial, the ongoing operational costs associated with data collection and analysis must also be considered. The successful deployment of these systems often requires specialized technical knowledge and skills, which may not be readily available to all farmers. A key concern in the use of image processing particularly related to data ownership, privacy, and security. As drones and advanced imaging systems capture vast amounts of detailed data from farms, questions arise about who controls this information. Farmers may face challenges in ensuring their data remains secure, especially when third-party platforms or cloud services are involved in data processing. Some of the arguments pro and con the new data collection method are presented in Table 1.

	Pro	Con
Labor	It reduces the labor need, through provides a remote and fast tool for food loss assessment.	It requires some IT skills, and may some on-site checks.
Accuracy	It can achieve high accuracy in quantifying food loss.	Accuracy can be affected by various factors (e.g. crop, weather).
Scalability	It can be easily scaled to cover large areas and multiple crops.	It depends on the quality and quantity of training data.
Implementation	It can provide insights into the causes of food loss, which can inform targeted interventions.	It requires specialized equipment and raises data privacy concerns.

Source: own elaboration, 2023

Table 1: Some advantages and disadvantages of the image-based food loss quantification.

However, it is crucial to consider the farms' characterisitcs before the implementation of the proposed image-based solution. Since, applying image processing to different agricultural systems, such as mixed cropping or agroforestry, presents unique challenges. In such systems, multiple crops or trees are grown in close proximity, making it harder to isolate and analyze individual plants. In mountainous regions or hilly landscapes, capturing consistent, high-quality aerial images can be more difficult due to elevation changes and shadows cast by the terrain. Moreover, a different approach could be needed for certain species (e.g. wheat, rice, and maize), as their development based on internal characteristics, rather than purely visual ones. Over time the hardware and software-related challenges could be mitigated, further improving the adequacy of the image-based approach. But to do so consideration and consistent research of the addressed area would be needed.

Conclusion

Agriculture has a critical role in achieving the Sustainable Development Goals. Through its effective operation, multiple SDGs could be neared and addressed simultaneously. However, to measure proper the effect of the new practices and policies adequate methodologies are needed. Lately, the widely adapted approaches are rethought, developed, and discussed, but the information sources of the food loss and waste estimations are sporadically studied. The traditional methods such as weighing and surveys, are often inaccurate or labor-intensive. Directly the studied articles did not reveal new data collection methods related to food loss and waste quantification. However, through the smart farming concept, the application of image processing in the preharvest, and harvesting phases gets identified for food loss reduction purposes. The comprehensive exploration of the newly specified area highlighted its infancy. The driving theme in this field seems to be the "convolutional neural networks", which is a deep learning algorithm dedicated to image analysis. However, the rise of "support vector machines" is also visible. Related to the farming issues, only "plant disease detection" appeared, thus designating the main research direction in the studied area. Even though the proposed method is in its early stage, it can be highly beneficial for farmers to monitor crop health, estimate food loss, and optimize harvesting processes. The latest technology enables more accurate and real-time data collection, which can lead to better decision-making on the farm. So the overall yield and profit of the farmers could be improved. By integrating image-based data collection, agriculture becomes more data-driven, reducing the labour involved in farming and enhancing sustainability. The ability to prevent food loss at the preharvest stage is critical for improving efficiency and reducing the environmental impact of agriculture. These advancements can help the agricultural sector meet the growing global demand for food while minimizing resource consumption and environmental damage. However, several areas warrant further research to fully realize the benefits of this technology. It is essential to explore the potential of image-based food loss estimation for a wider range of crops and agricultural systems. While the studies focused on specific crops, the future's principles and techniques have to be suitable to apply on other agricultural commodities too. The development of more robust and accurate plant phenotyping algorithms is critical for the success. Even the studies made significant strides, there is still room for improvement in distinguishing between different plant stages, detecting anomalies, and accounting for variations in plant appearance. Another important research direction is to focus on addressing the practical challenges associated with implementing image-based food loss estimation systems in real-world agricultural settings. This includes developing user-friendly interfaces, reducing the cost of hardware and software -what would be particularly relevant for developing regions-, and ensuring the reliability and scalability of these systems. Additionally, efforts should be made to address data privacy concerns and develop secure and ethical data management practices. Policymakers play a crucial role in creating an enabling environment for this method. By providing funding for research and development, and implementing supportive regulations, they could facilitate the widespread use of this method.

Corresponding author
Dr. Adrián Csordás
Faculty of Economics and Business University of Debrecen
Debrecen, Böszörményi út 138 4032, Hungary
Email: csordas.adrian@econ.unideb.hu

References

[1] Abbade, E. B. (2020) "Land and water footprints associated with rice and maize losses in Brazil", *Land Use Policy,* Vol. 99, p. 105106. ISSN 0264-8377. DOI 10.1016/j.landusepol.2020.105106.

[2] Abbade, E. B. (2023) "Land footprint and GHG emissions from global food loss", *Journal of the Science of Food and Agriculture*, Vol. 103, No. 9, pp. 4430–4440. ISSN 1097-0010. DOI 10.1002/jsfa.12524.

[3] Agbo, F. J., Oyelere, S. S., Suhonen, J. and Tukiainen, M. (2021) "Scientific production and thematic breakthroughs in smart learning environments: a bibliometric analysis", *Smart Learning Environments*, Vol. 8, No. 1, p. 1. ISSN 2196-7091. DOI 10.1186/s40561-020-00145-4.

[4] Alzubi, J., Nayyar, A. and Kumar, A. (2018) "Machine Learning from Theory to Algorithms: An Overview", *Journal of Physics: Conference Series"*, Vol. 1142, p. 012012. ISSN 1742-6596. DOI 10.1088/1742-6596/1142/1/012012.

[5] Anriquez, G., Foster, W., Ortega, J. and Santos Rocha, J. (2021) "In search of economically significant food losses: Evidence from Tunisia and Egypt", *Food Policy*, Vol. 98, p. 101912. ISSN 0306-9192. DOI 10.1016/j.foodpol.2020.101912.

[6] Aria, M. and Cuccurullo, C. (2017) "bibliometrix: An R-tool for comprehensive science mapping analysis", *Journal of Informetrics*, Vol. 11, No. 4, pp. 959-975. ISSN 1751-1577. DOI 10.1016/j.joi.2017.08.007.

[7] Assunção, E. T., Gaspar, P. D., Mesquita, R. J. M., Simões, M. P., Ramos, A., Proença, H. and Inacio, P. R. M. (2022) "Peaches Detection Using a Deep Learning Technique—A Contribution to Yield Estimation, Resources Management, and Circular Economy", *Climate*, Vol. 10, No. 2, p. 11. ISSN 2225-1154. DOI 10.3390/cli10020011.

[8] Boiteau, J. M. and Pingali, P. (2023) "Can we agree on a food loss and waste definition? An assessment of definitional elements for a globally applicable framework", *Global Food Security*, Vol. 37, p. 100677. ISSN 2211-9124. DOI 10.1016/j.gfs.2023.100677.

[9] Capone, R., Berjan, S., El Bilali, H., Debs, P. and Allahyari, M. S. (2020) "Environmental implications of global food loss and waste with a glimpse on the Mediterranean region", *International Food Research Journal*, Vol. 27, No. 6. ISSN 1985-4668.

[10] Chaboud, G. and Daviron, B. (2017) "Food losses and waste: Navigating the inconsistencies", *Global Food Security*, Vol. 12, pp. 1-7. ISSN 2211-9124. DOI 10.1016/j.gfs.2016.11.004.

[11] Chauhan, C., Dhir, A., Akram, M. U. and Salo, J. (2021) "Food loss and waste in food supply chains. A systematic literature review and framework development approach", *Journal of Cleaner Production"*, Vol. 295, p. 126438. ISSN 0959-6526. DOI 10.1016/j.jclepro.2021.126438.

[12] Corrado, S. and Sala, S. (2018) "Food waste accounting along global and European food supply chains: State of the art and outlook", *Waste Management*, Vol. 79, pp. 120-131. ISSN 0956-053X. DOI 10.1016/j.wasman.2018.07.032.

[13] Dal' Magro, G. P. and Talamini, E. (2019) "Estimating the magnitude of the food loss and waste generated in Brazil", *Waste Management & Research*, Vol. 37, No. 7, pp. 706-716. ISSN 0734-242X. DOI 10.1177/0734242X19836710.

[14] Delgado, L., Schuster, M. and Torero, M. (2017) "Reality of food losses: A new measurement methodology", [Online]. Available: https://www.oneplanetnetwork.org/sites/default/files/the_reality_of_food_losses_a_new_measurement_methodology.pdf [Accessed: Dec. 2, 2023].

[15] Delgado, L., Schuster, M. and Torero, M. (2021) "Quantity and quality food losses across the value Chain: A Comparative analysis", *Food Policy*, Vol. 98, p. 101958. ISSN 0306-9192. DOI 10.1016/j.foodpol.2020.101958.

[16] Ellison, B., Muth, M.K. and Golan, E. (2019) "Opportunities and Challenges in Conducting Economic Research on Food Loss and Waste", *Applied Economic Perspectives and Policy*, Vol. 41, No. 1, pp. 1-19. ISSN 2040-5804. DOI 10.1093/aepp/ppy035.

[17] FAO (2011) "*Global food losses and food waste – Extent, causes and prevention*", Food and Agricultural Organisation of the United Nations. ISBN 978-92-5-107205-9.

[18] FAO (2019) "*The state of food and agriculture 2019. Moving forward on food loss and waste reduction*", FAO, Rome, pp. 2-13. ISBN 978-92-5-131789-1.

[19] Garcia-Herrero, I., Hoehn, D., Margallo, M., Laso, J., Bala, A., Batlle-Bayer, L., Fullana, P., Vazquez-Rowe, I., Gonzalez, M. J., Durá, M. J., Sarabia, C., Abajas, R., Amo-Setien, F. J., Quiñones, A., Irabien, A. and Aldaco, R. (2018) "On the estimation of potential food waste reduction to support sustainable production and consumption policies", *Food Policy*, Vol. 80, pp. 24-38. ISSN 0306-9192. DOI 10.1016/j.foodpol.2018.08.007.

[20] Guo, X., Broeze, J., Groot, J. J., Axmann, H. and Vollebregt, M. (2020) "A Worldwide Hotspot Analysis on Food Loss and Waste, Associated Greenhouse Gas Emissions, and Protein Losses", *Sustainability*, Vol. 12, No. 18, p. 7488. ISSN 2071-1050. DOI 10.3390/su12187488.

[21] Hall, O. and Wahab, I. (2021) "The Use of Drones in the Spatial Social Sciences", *Drones*, Vol. 5, No. 4, p. 112. ISSN 2504-446X. DOI 10.3390/drones5040112.

[22] Hartikainen, H., Mogensen, L., Svanes, E. and Franke, U. (2018) "Food waste quantification in primary production – The Nordic countries as a case study", *Waste Management*, Vol. 71, pp. 502-511. ISSN 0956-053X. DOI 10.1016/j.wasman.2017.10.026.

[23] Hassanzadeh, A., Zhang, F., Murphy, S.P., Pethybridge, S. J. and van Aardt, J. (2022) "Toward Crop Maturity Assessment via UAS-Based Imaging Spectroscopy—A Snap Bean Pod Size Classification Field Study", *IEEE Transactions on Geoscience and Remote Sensing*, Vol. 60, pp. 1-17. ISSN 0196-2892. DOI 10.1109/TGRS.2021.3134564.

[24] Huang, S., Tang, L., Hupy, J. P., Wang, Y. and Shao, G. (2021) "A commentary review on the use of normalized difference vegetation index (NDVI) in the era of popular remote sensing", *Journal of Forestry Research*, Vol. 32, No. 1, pp. 1-6. ISSN 1007-662X. DOI 10.1007/s11676-020-01155-1.

[25] Indolia, S., Goswami, A. K., Mishra, S. P. and Asopa, P. (2018) "Conceptual Understanding of Convolutional Neural Network- A Deep Learning Approach", *Procedia Computer Science*, Vol. 132, pp. 679-688. ISSN 1877-0509. DOI 10.1016/j.procs.2018.05.069.

[26] Ishangulyyev, R., Kim, S. and Lee, S. (2019) "Understanding Food Loss and Waste—Why Are We Losing and Wasting Food?", *Foods*, Vol. 8, No. 8, p. 297. ISSN 2304-8158. DOI 10.3390/foods8080297.

[27] Ji, Z., Pan, Y., Zhu, X., Wang, J. and Li, Q. (2021) "Prediction of Crop Yield Using Phenological Information Extracted from Remote Sensing Vegetation Index", *Sensors*, Vol. 21, No. 4, p. 1406. ISSN 1424-8220. DOI 10.3390/s21041406.

[28] Johnson, L. K., Dunning, R. D., Gunter, C. C., Bloom, J. D. Boyette, M. D. and Creamer, N. G. (2018) "Field measurement in vegetable crops indicates need for reevaluation of on-farm food loss estimates in North America", *Agricultural Systems*, Vol. 167, pp. 136-142. ISSN 0308-521X. DOI 10.1016/j.agsy.2018.09.008.

[29] KC, K., Haque, I., Legwegoh, A. and Fraser, E. (2016) "Strategies to Reduce Food Loss in the Global South", *Sustainability*, Vol. 8, No. 7, p. 595. ISSN 2071-1050. DOI 10.3390/su8070595.

[30] Khatri-Chhetri, A., Costa Jr. C. and Wollenberg, E. (2022) "Greenhouse gas mitigation co-benefits across the global agricultural development programs", *Global Environmental Change*, Vol. 76, p. 102586. ISSN 0959-3780. DOI 10.1016/j.gloenvcha.2022.102586.

[31] Koester, U. and Galaktionova, E. (2021) "FAO Food Loss Index methodology and policy implications", *Studies in Agricultural Economics*, Vol. 123.1, pp. 1-7. ISSN 2063-0476. DOI 10.7896/j.2093.

[32] Luo, N., Olsen, T., Liu, Y. and Zhang, A. (2022) "Reducing food loss and waste in supply chain operations", *Transportation Research Part E: Logistics and Transportation Review*, Vol. 162, p. 102730. ISSN 1366-5545. DOI 10.1016/j.tre.2022.102730.

[33] Mandal, D., Kumar, V., Ratha, D., Dey, S., Bhattacharya, A., Lopez-Sanchez, J. M., McNairn, H. and Rao, Y. S. (2020) "Dual polarimetric radar vegetation index for crop growth monitoring using sentinel-1 SAR data", *Remote Sensing of Environment,* Vol. 247, p. 111954. ISSN 0034-4257. DOI 10.1016/j.rse.2020.111954.

[34] Marston, L. T., Read, Q. D., Brown, S. P. and Muth, M. K. (2021) "Reducing Water Scarcity by Reducing Food Loss and Waste", *Frontiers in Sustainable Food Systems*, Vol. 5. ISSN 2571-581X. DOI 10.3389/fsufs.2021.651476.

[35] Moher, D. (2009) "Preferred Reporting Items for Systematic Reviews and Meta-Analyses: The PRISMA Statement", *Annals of Internal Medicine*, Vol. 151, No. 4, p. 264. ISSN 1743-9191. DOI 10.1016/j.ijsu.2010.02.007.

[36] Otchere, D. A., Arbi Ganat, T. O., Gholami, R. and Ridha, S. (2021) "Application of supervised machine learning paradigms in the prediction of petroleum reservoir properties: Comparative analysis of ANN and SVM models", *Journal of Petroleum Science and Engineering*, Vol. 200, p. 108182. ISSN 0920-4105. DOI 10.1016/j.petrol.2020.108182.

[37] Pagani, M., De Menna, F., Johnson, T. G. and Vittuari, M. (2020) "Impacts and costs of embodied and nutritional energy of food losses in the US food system: farming and processing (Part A)", *Journal of Cleaner Production,* Vol. 244, p. 118730. ISSN 0959-6526. DOI 10.1016/j.jclepro.2019.118730.

[38] Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E. A., Brennan, S. E., Chou, R., Glanville, J., Grimshaw, J. M., Hróbjartsson, A., Lalu, M. M., Li, T., Loder, E. W., Mayo-Wilson, E., McDonald, S., Luke A McGuinness, L. A., Stewart, L. A., Thomas, J., Tricco, A. C., Welch, V. A., Whiting, P. and Moher, D. (2021) "The PRISMA 2020 statement: an updated guideline for reporting systematic reviews", *BMJ*, Vol. 371, No. 71. ISSN 1756-1833. DOI 10.1136/bmj.n71.

[39] Rayyan (2023) "Faster systematic reviews" [Online]. Available: https://www.rayyan.ai/[Accessed: Dec. 2, 2023].

[40] Redlingshöfer, B., Coudurier, B. and Georget, M. (2017) "Quantifying food loss during primary production and processing in France", *Journal of Cleaner Production*, Vol. 164, pp. 703/714. ISSN 0959-6526. DOI 10.1016/j.jclepro.2017.06.173.

[41] Rokni, K. and Musa, T. A. (2019) "Normalized difference vegetation change index: A technique for detecting vegetation changes using Landsat imagery", *CATENA*, Vol. 178, pp. 59-63. ISSN 0341-8162. DOI 10.1016/j.catena.2019.03.007.

[42] Sharifi, A. (2020) "Remotely sensed vegetation indices for crop nutrition mapping", *Journal of the Science of Food and Agriculture*, Vol. 100, No. 14, pp. 5191-5196. ISSN 1097-0010. DOI 10.1002/jsfa.10568.

[43] Shee, A., Parmar, A., Raut, S., Strum, B. and Bennett, B. (2022) "Assessing the measurement methods of post-harvest food loss and waste: opportunities and challenges", *Enterprise Development & Microfinance*, Vol. 33, No. 4. ISSN 1755-1986. DOI 10.3362/1755-1986.22-00062.

[44] Sishodia, R. P., Ray, R. L. and Singh, S. K. (2020) "Applications of Remote Sensing in Precision Agriculture: A Review", *Remote Sensing*, Vol. 12, No. 19, p. 3136. ISSN 2072-4292. DOI 10.3390/rs12193136.

[45] Soltani, A., Alimagham, S. M., Nehbandani, A., Torabi, B., Zeinali, E., Zand, E., Vadez, V., van Loon, M. P. and van Ittersum, M. K. (2020) "Future food self-sufficiency in Iran: A model-based analysis", *Global Food Security*, Vol. 24, p. 100351. ISSN 2211-9124. DOI 10.1016/j.gfs.2020.100351.

[46] Spang, E. S., Moreno, L. C., Pace, S. A., Achmon, Y., Donis-Gonzalez, I., Gosliner, W. A., Jablonski-Sheffield, M. P., Momin, M. A., Quested, T. E., Winans, K. S. and Tomich, T. P. (2019) "Food Loss and Waste: Measurement, Drivers, and Solutions", *Annual Review of Environment and Resources,* Vol. 44, No. 1, pp. 117-156. ISSN 1543-5938. DOI 10.1146/annurev-environ-101718-033228.

[47] Sun, H., Sun, Y., Jin, M., Ripp, S. A., Sayler, G. S. and Zhuang, J. (2022) "Domestic plant food loss and waste in the United States: Environmental footprints and mitigation strategies", *Waste Management*, Vol. 150, pp. 202-207. ISSN 0956-053X. DOI 10.1016/j.wasman.2022.07.006.

[48] Swartz, M. K. (2011) "The PRISMA Statement: A Guideline for Systematic Reviews and Meta-Analyses", *Journal of Pediatric Health Care*, Vol. 25, No. 1, pp. 1-2. ISSN 0891-5245. DOI 10.1016/j.pedhc.2010.09.006.

[49] Wang, H., Li, T., Nishida, E., Kato, Y., Fukano, Y. and Guo, W. (2023) "Drone-Based Harvest Data Prediction Can Reduce On-Farm Food Loss and Improve Farmer Income", *Plant Phenomics*, Vol. 5. ISSN 2643-6515. DOI 10.34133/plantphenomics.0086.

[50] Xie, G., Ma, W., Peng, H., Li, R. and Li, K. (2021) "Price Performance-Driven Hardware Cost Optimization Under Functional Safety Requirement in Large-Scale Heterogeneous Distributed Embedded Systems", *IEEE Transactions on Industrial Electronics*, Vol. 68, No. 5, pp. 4485-4497. ISSN 1557-9948. DOI 10.1109/TIE.2019.2905815.

[51] Xue, L., Liu, G., Parfitt, J., Liu, X., Van Herpen, E., Stenmarck, Å., O'Connor, C., Östergren, K. and Cheng, S. (2017) "Missing Food, Missing Data? A Critical Review of Global Food Losses and Food Waste Data", *Environmental Science & Technology*, Vol. 51, No. 12, pp. 6618-6633. ISSN 0013-936X. DOI 10.1021/acs.est.7b00401.

[52] Yu, J. and Muñoz-Justicia, J. (2020) "A Bibliometric Overview of Twitter-Related Studies Indexed in Web of Science", *Future Internet*, Vol. 12, No. 5, p. 91. ISSN 1999-590. DOI 10.3390/fi12050091.

[53] Zhu, J., Luo, Z., Sun, T., Li, W., Zhou, W., Wang, X., Fei, X., Tong, H. and Yin, K. (2023) "Cradle-to-grave emissions from food loss and waste represent half of total greenhouse gas emissions from food systems", *Nature Food*, Vol. 4, No. 3, pp. 247-256. ISSN 2662-1355. DOI 10.1038/s43016-023-00710-3.

Agris on-line Papers in Economics and Informatics

Volume XVI Number 4, 2024

Renewable Energy Intentions in Indonesian Agriproduct Purchasing: Exploring Product Quality, Customer Orientation, Perceived Environmental Knowledge, and Farmers' Knowledge with a Moderation Effect

Evi Feronika Elbaar, Masliani

Department of Agribusiness, Faculty of Agriculture, Palangka Raya University, Palangka Raya, Central Kalimantan, Indonesia

Abstract

The smallholder farmers come across various constraints in cultivation of agriproducts and face number of challenges in marketing the agrifoods in Indonesia that assists in sustaining the market position. This research effort entails the product quality, customer orientation, farmers' knowledge and perceived environment knowledge with moderation role of intention to use renewable energy to explain the purchase decisions of agriproducts locally-produced in Indonesia. The study was quantitative in nature and sample of 308 respondents of customers of agriproducts in different regions of Indonesia was collected that depicted interesting results. The results show that hypothesis H1, H2, H4 and H5 reported statistically significant, but hypothesis H3 was rejected. The moderation effect of intention to use renewable energy reported between product quality, customer orientation, perceived environment knowledge and purchase decision, and no moderation effect was reported between farmers' knowledge and purchase decisions. The study suggested to devise the effective marketing initiatives for agriproducts specifically to ensure the quality, customers' feedback, and needs to focus on enhancing the knowledge of farmers towards adoption of innovative initiatives for implementation of renewable energy.

Keywords

Renewable energy, product quality, customer orientation, farmers' knowledge, innovation and purchase decision.

Elbaar, E. F. and Masliani (2024) "Renewable Energy Intentions in Indonesian Agriproduct Purchasing: Exploring Product Quality, Customer Orientation, Perceived Environmental Knowledge, and Farmers' Knowledge with a Moderation Effect", *AGRIS on-line Papers in Economics and Informatics*, Vol. 16, No. 4, pp. 45-67. ISSN 1804-1930. DOI 10.7160/aol.2024.160404.

Introduction

In contemporary times, there is an increasing trend towards renewable energy, even in Indonesia's agricultural sector (Raihan, 2023). Renewable energy has taken on an increasingly important role in maintaining the environment and agriculture itself (Nendissa et al., 2022). When discussing the purchase of sustainable agricultural products in Indonesia, understanding consumer intentions regarding the use of renewable energy becomes very important (Avicenna & Febriani, 2021). Renewable energy can be a key catalyst in encouraging consumers to support sustainable agricultural products.

Furthermore, the global challenges related to Renewable Energy Intentions in the Purchase of Agricultural Products in Indonesia are an urgent issue that requires immediate attention (Syamni et al., 2021). In Indonesia, the agricultural product sector plays a significant role in the country's economy but often relies on conventional energy sources that have a significant environmental impact (Tiawon & Miar, 2023). The use of fossil fuels at various stages of production, processing, and distribution of agricultural products in Indonesia contributes to greenhouse gas emissions and potential air pollution. Moreover, the high dependence on fossil energy sources makes Indonesia vulnerable to fluctuations in global energy prices and supplies, which threatens the country's economic stability and food security (Faizah & Husaeni, 2018).

However, there are substantial opportunities in adopting renewable energy sources in the context of Indonesia's agricultural product sector (Zulkifli et al., 2019). The potential use of renewable resources such as solar energy and biomass promises to reduce environmental impact, decrease dependence on fossil resources, and enhance economic resilience (Silalahi et al., 2021).

The implementation of renewable energy in Indonesia can create job opportunities, stimulate green technology innovation, and improve international reputation in environmental sustainability (Langer et al., 2021). This research is important to understand how the intention to use renewable energy influences the purchasing decisions of agricultural products, which can shape sustainable policies in this sector (Udin, 2020). The European Union seeks to reduce its climate footprint through common agricultural policies (Schiermeier, 2019). About 38% of the global land surface is used for cultivation, but the demand for agricultural products is expected to increase by 100%. Economic growth adds pressure to agricultural systems, resulting in biodiversity loss (Beckmann et al., 2019). Land intensification and chemical use threaten species, with the main challenge being to meet biomass demand while preserving ecosystems (Seppelt et al., 2016).

Economic activity and development lead to market participation by farmers, indicating better income and improved food security in rural communities (Kennedy, 2018). Small farmers have sought to increase their market access in the face of existing markets and can attract agricultural and economic development. Market access must be enhanced due to its significant importance in increasing small farmers' market participation. The agricultural sector is one of the most prominent in terms of income and job provision, with 70% of the world's poor in rural areas related to agriculture. Small farmers contribute significantly to food security, equitable income distribution, and economic growth (Poole, 2017).

Farmers face constraints such as physical access to markets and lack of market information (Sambodo et al., 2022). Traditional food crops rely on market information due to weak connections with formal markets, thus increasing small farmers' income requires expanding relationships with formal markets. Small farmers' participation in rice markets is shrinking due to constraints such as remote areas, poor transportation, weak market infrastructure, high transaction costs, and lack of quick access to major markets. Lack of information between exchange partners also hinders agricultural success, thus reliable market information access needs to be improved for effective decision-making (Makhura et al., 2001). Small farmers have small production surpluses, high exposure to risk, and high transaction costs, so most sell their products in local markets. Lack of marketing knowledge leads to the sale of harvests at lower prices (Gyau et al., 2016). In South Asia and Sub-Saharan Africa, 60% of farmers own less than 1 hectare of land, and 80% own less than 2 hectares (Kyaw et al., 2018). Urgent action is needed to enhance small farmers' economic activities to ensure higher competitiveness, such as in Myanmar where many small farmers produce rice on less than 5 hectares of land (Lowder et al., 2016).

Studies assessing global and domestic drivers of the agri-food sector show that international markets face challenges and unexpected changes due to unsustainability in production, distribution, and consumption, as well as poor food governance. This hampers agricultural sustainability and access to sufficient, safe, and nutritious food. Issues faced include globalization, economic turbulence, climate change, population growth, food security, malnutrition, resource scarcity, and ecosystem loss. Improved market connections, trade initiatives, and consumer awareness of quality food are needed. The WTO criticizes subsidy reductions affecting small farmers, but governments in China, India, and Indonesia support their agricultural sectors to increase domestic supply (Borsellino et al., 2020).

Previous literature highlights factors influencing farmers' market orientation intentions, impacting market participation and economic activity. Vegetable crops, which are more profitable than cereal crops, contribute to market participation and economic development in Indonesia. The agricultural sector supports economic achievement, growth, and poverty reduction, thus urgent policies for this sector in developing countries are needed (Tiawon & Miar, 2023). Effective use of agricultural land and supportive agricultural products require proper planning and development. Farmers must change practices and crops to high-value crop production to increase profits and face challenges. Innovative initiatives are needed to develop the agricultural sector, reduce economic burdens, consider ecological risks, and increase profit ratios (Ikerd, 2011).

Vegetable production increases global agribusiness productivity and is more profitable than rice or cereal. In Indonesia, vegetables such as tomatoes, shallots, and chili peppers are important in the diet and economy, with many farmers shifting from rice to chili due to higher profits (Mariyono, 2018). Although vegetable production is increasing, its global market share is still low, requiring improvements in cultivation, plant availability, and irrigation. Production expansion can be achieved by promoting a commercial mindset and intensive farming methods (Mariyono, 2019b). This research investigates the relationship between product quality, customer orientation, farmer knowledge, and the environment on purchasing decisions in Indonesia's agricultural sector, and the moderating role of intentions to use renewable energy. This expands the understanding of sustainable agricultural product purchasing and the importance of environmental preservation, offering insights into the interaction of these factors and innovation in agricultural sustainability.

Literature review

The Indonesian economy depends upon the agriculture sector, so therefore there is need to consider the innovative initiatives in agriculture sector and needs to implement the creative ideas for development of agrifoods and expansion of businesses. The reduction of locally produced agriproducts has weakened the innovation and innovative initiatives, the consumers found to be concerned with quality and safety for local products. The absence of interest of consumers in purchasing of local goods are due to poor or low quality agrifood products, the lower level of differentiation, inappropriate segment identification and developmental aspect towards the products and clients (Chamhuri and Batt, 2015). The local agriproducts found to be of lower quality in Indonesia as compare to imported goods, the government and businesses must align their strategy for ensuring the quality of agriproducts and integrate the interest of community and prioritize the quality issues of local products. The Indonesian government has to regulate the policies for agriproducts due to presidential instructions, and Minister of Economic Affairs strengthened the policies for utilization of local products. The government initiated the trend and projected the slogan of ACI (I Love Indonesian Products to improve the understanding and manufacture the quality goods for locally-produced products, that also enable the government to create the jobs and domestic production (Wahyudi et al., 2019).

Product quality and purchase decision

The manufacturing sector of Indonesia has become an important pillar for the economy of the country as automobiles open their offices worldwide to increase production capacity and bring significant contributions to the national economy. The excellent efforts and progress shown in Indonesia's automobile industry have resulted in increased car production and a growing sales market, which in turn has contributed to the gross domestic product ((Lertkornkitja, 2017, Hidayatno et al., 2019). Southeast Asia controls 43% of automobile sales, and Indonesia is ranked second with a 34% market share (Negara and Hidayat, 2021). It is predicted that Indonesia has the capacity to grab market share at a higher pace and the capability to emerge as a leading market share holder in Southeast Asia (Susilo, 2018). The quality must be improved and a strong brand name established to maintain both domestic and international business expansion (Reschiwati et al., 2021). Competitors have significant market shares in Indonesia, with Japanese companies dominating the market. Studies have examined purchase decisions in Indonesia related to automotive firms, indicating that product quality tends to increase purchase decisions, influenced by perceived value (Budiono et al., 2021). The quality of the product affects customers' perception and perceived flow, which in turn influences their satisfaction and intentions (Sarjono et al., 2021). The performance of the product that matches the expectations of customers to a specific satisfaction level is influenced by the quality of the product (Nagaraja, 2012, Dhanani and Hasnain, 2002). The features of the quality of a specific product have the ability to satisfy consumers by fulfilling their needs (Amri, 2022).

The agriculture sector of Indonesia produces the large-scale agriproducts that are different in quality and quantity perspective, there is specific appearance of such agriproducts of Indonesia in terms of different aspects such as water contents, duration of cultivation, storage of agriproducts, maturity of industry, size of products and outputs, the firms face challenges related to all aspects in local as well as in international markets. The unique flavor of Indonesian agriproducts attracts the customers and they pay the primum price for such high-quality agriproducts. The consumers prefer the quality of such agrifoods and pay for freshness and quality. Moreover, the consumer prefers specific products that relates to the culture and taste including fruits and rice. The purchase decision of consumers depends upon the various factors including culture, psychological perspective and lifestyle factor that also influenced by the trends in food industry (Campbell, 2013). Rice is considered as staple food in Indonesian market and is an important in food security, the production of rice has increased the annual average 2.34% during last decade due to enhancement in production and due to government policies, such as direct support. The production of rice in Indonesia must be capable of meeting the need and demand of consumers in terms of safety, quantity and quality, the increased income of consumers lead to increase the demand for quality. On the other hand, there are other factors including education, female labor force, urbanization and along with current transportation and communications advances, influence consumer preferences. The consumers focused on the balance of quality, aesthetics, nutrition, and participation of the workforce, which encourages the consumers to adopt food from specific brands. The current marketing competitive strategy for the production of rice in Indonesia is very keen and includes the rice producers, the traders of rice around the world, and the distribution of imported rice (Timmer, 1974). The higher production of rice and superior varieties of rice have been focused on spreading in the market to meet customer demand (Simatupang and Timmer, 2008). The diversification of such varieties of rice leads towards the nature and quality of rice production intended to be sold in the market (Panuju, Mizuno and Trisasongko, 2013). The study has been conducted on the consumers of agriproducts of Indonesia in Jakarta province to assess the factors that influence the locally-produced agriproducts (Wahyudi et al., 2019). The study revealed that a number of factors gained attention in such a scenario, including gender, age, occupation, education, income, product characteristics, price, and promotion, all of which influenced the frequency of buying by the consumer (Mucharam et al., 2020). There is a need to increase the quality of locally-produced agriproducts and devise effective and appropriate marketing strategies by lowering the price of products compared to imported rice. The promotion must be attractive to increase the frequency of purchases of such agriproducts in Indonesia (Moslehpour, Kien and Danyfisla, 2014).

The above literature assists in devising the following hypothesis:

H1: The product quality of Agriproducts in Indonesia influences the purchase decisions of consumers in Indonesian markets

Customer orientation and purchase decisions

The degree to which a firm implement the marketing approach and concept for strategic development and tactical marketing decisions in expressed as the market orientation. The superior customer value can be achieved through the effective implementation of market and customer orientation. The competitive capacity is also considered that play role in assessing the market situation and effective market orientation enhance the financial performance. The prior literature has explored the relationship between effective market orientation and value chain, that found to be influential that effective marketing approach increase the value for customers and influence the performance. The customer orientation is considered as a philosophy within value chain that suggest various factors to create the value by serving the ultimate customers' need and strategically coordination with other participants for creation of superior value. The literature has explained that effective coordination enables firms to generate and share the benefits, the competitiveness of whole chain that influenced by the market intelligence (Ayele et al., 2012).

The are various number of research papers have been conducted to explore the impact of market and customer orientation, it has been reported that innovation is necessary for being high performance organizations (Nasution et al., 2011). The positive relationship has been occurred in literature between customer and performance, the market orientation found to be impactful on innovative capabilities by understanding the they need of customers that increase the efficiency and enhances the sales and profitability. The studies have been found that expressed the customer and competitor orientation that positively associated with innovative capabilities (Grinstein, 2008). The customer and competitors have the tendency to increase the willingness of firm for development of newly emerging products. It has been found that strong relationship has been reported between customer orientation and innovation initiated by the firm for achievement of specific performance standards (Newman et al., 2016).

The studies have also expressed that customer orientation and inter-functional that influence the financial chain performance, the information acquisition process is necessary for knowledge creation about the markets to spread the accurate information related to potentially important issues. It has been reported that inter-functional coordination and communication enable the firms to gain the knowledge that assist the firms to gain insight the markets through utilization of effective knowledge management. The inter-function coordination has the tendency to establish the various functional units to create the conditions for applying the market information through business initiatives. The study has reported that competitive orientation, customer orientation and inter-functional coordination influence the innovation and enhances the performance of organizations (Ho et al., 2018).

There is scarcity of research on exploring the relationship between customer orientation and purchase decisions, the researcher hasn't come across any study that has already explained the relationship, so therefore, this study found to be one of the pioneers to explain the role of customer orientation and purchase decisions. The following hypothesis is derived:

H2: Customer Orientation significantly influences the Purchase Decisions of customers in Indonesian markets

Farmer's knowledge and purchase decision

The emerging economies depends upon the strong sectors such as the strengthen and sustainable agriculture sector to be consistent, the poor population dominate the other population, the agribusiness and agriproducts has the tendency to move the economic circle of the country due to its significant importance. The large number of people found to be engaged with agricultural business and activities, the huge population is engaged in agriculture industry specifically related to the farming. The smallholder farmers are found in huge number that are engaged in agricultural activities to contributes in the economy and play crucial role in fulfilling the need for food, vegetable and food related items for whole population in Indonesia. The research studies have been conducted that assessed the impact of different farming commodity on welfare of the farmers, the socio-economic, the technical aspect and the institutional factors that influence the farmer's decision for engaging in intensive farming Java, Indonesia. The Indonesian economy largely depends upon the agriproducts, this is also a motivation to conduct this present study as well, that appropriate marketing tactics may enable the firms and countries to harvest the large-scale benefits. The agriculture sector provides the employment and dominate with 58% population associated with agriculture and 75% people are poor (McCulloch, 2008). The agriculture sector constituted 24.5% of gross domestic product and employed 54.8% of total workforce. The sector significantly contributes in economic strength of the country. The Indonesia is famous for five vegetables that are cultivated and grown in Indonesia including production of chilli. The highest share of chilli in Indonesian agriproducts that value and contribute the existing financial strength (Statistik and Pokok, 2019).

This study incorporated the farmers' knowledge that is referred as age, education, experiences and training. The family size, farming size and land tenancy and fragmentation is also considered as important factor in economic wellbeing of the farmers that further contribute in gross domestic products. The prior literature has also expressed the role of credit access, the technological adoption, intensive farming and farmer's welfare, that further leads to the performance and financial wellbeing of farmers. The study focused on the telephones, marketplace, credit sources, traders, market information, farmers' knowledge, and household endowment that play significant roles in the welfare of farmers (Matouš, Todo and Pratiwi, 2015, Rahayu and Riyanto, 2020). The direct and indirect influences of various variables explain the farmers' welfare through intensive farming (Mariyono, 2019a). Access to credit and financial services significantly impacts agricultural productivity and farmers' welfare (Nuryartono, 2007, Wibowo, 2015). Improved market information and the use of mobile phones are associated with better market outcomes and increased welfare for farmers (Matouš, Todo and Pratiwi, 2015). Furthermore, household endowments such as education and land ownership have been found to significantly affect farmers' welfare (Skoufias and Olivieri, 2013). These factors highlight the complex interplay of resources and information in enhancing the economic conditions of farming households (Nuryati et al., 2019), Achmad and Diniyati, 2018).

This study incorporated the farmers' knowledge that influence the intention of individuals to purchase the specific goods, this study argues that farmers' knowledge expected to the important and striking factor in explaining the purchase decision. There is scarcity of research on farmers' knowledge, the farmers' knowledge also includes the knowledge about the marketing policies and marketing approach to attract the customers. The following hypothesis is derived on the base of above literature.

H3: Farmers' knowledge influences the ppurchase decision related to the agricultural sector of Indonesia

Perceived environmental knowledge and purchase decisions

This study incorporates the environmental concern and knowledge about environment among the farmers to assess their concerns towards environmental protection and adopt the renewable energy resources. It is expected that requirement for energy predicted to be increased by 30% up to year 2035 due to rapid increase in population, requirement and due to rapid economic growth. The fossil fuels met the existing demand and one-quarter of demand is fulfilled that causes destruction of ozone layer (Scheffran et al., 2020). The carbon emission has been increased by 50% due to heavy industrialization, and now decarbonizing is necessary as well as agricultural production system that mitigate the greenhouse gas emission and limit the or reduce the global warning while ensuring the climate stabilization (Rissman et al., 2020). The current energy usage that is being utilized by food system is not sustainable, the usage of fossil fuels in agriculture affects and put long-lasting consequences on the environment (Zafeiriou et al., 2018).

The governments are striving for goal achievement for implementation of energy-smart food system that helps to remove the dependency on fossil fuels for energy security and assists in higher production of agriproducts. The increasing demand of energy for production and reduction in pollution can be fulfilled by the green energy resources, the solar energy is considered as sustainable energy, that is pollution free and inexhaustible and also plays significant role in providing the clear and clean energy. The usage of solar energy is acceptable for electricity in domestic, industrial, commercial and agricultural projects without creating any pollution or negative impact on the environment. The solar energy should be implemented in agricultural projects for operation of farms to control the environmental agriculture (Xue, 2017). Environmental knowledge is such an important factor in determining the consumer behavior that influence the usage of renewable energy resources. The people or the firms having environmental concerns and knowledge expected to act more environmentally friendly and adopt ecological behavior (Chan et al., 2014). It has been occurred in the literature that environmental knowledge positively related to the intention to purchase energy conservation products for production of agricultural products. It has been also found and reported that emission reduction behavior positively related to environmental knowledge (Chan et al., 2014; Ngo et al., 2009).

Similarly, the current study argues that perceived environmental knowledge has the tendency to influence the purchase decisions. The above literature and assumption of the study assist in devising the following hypothesis.

H4: Perceived environmental knowledge influences the purchase decision related to the agricultural sector of Indonesia

Moderating role of intention to use renewable energy

This study incorporates the important factor of intention to use renewable energy, the moderation effect of intention to use renewable energy is assessed in the study between exogenous and endogenous constructs. The innovative capability has the tendency to influence the purchase decisions and has the capacity to influence the relationship between various variables. The agriculture production is not vulnerable to climate changes but plays significant role in production of green house gas emission that drive climate shifts. The agricultural contributes to the greenhouse emissions, the agricultural sector reported to be emits up to 30% of greenhouse gas emissions worldwide due to equipment and inputs (Lombardi et al., 2017).

The utilization of renewable energy considered as an important initiative during farming and greening aspect reduce the greenhouse emissions and avoid alternative source of energy for agriculture through adoption and implementation of applications. There are number of barriers that have been highlighted for usage of alternative energy. The literature has expressed the intention as third layer and it has been reported as lack of community acceptance for adoption of alternate source of energy. The willingness of an individual for specific action considered as intention and intention to use renewable energy sources for effective purchase decisions (Huijts et al., 2012). There are number of influential variables that affect the intention by positive effect, negative effect, perceived cost, perceived benefits and perceived risk (Bozorgparvar et al., 2018).

The intention to use renewable resources brings the newly emerging ideas that are related to organizational activities that develop the new process, product or services. The prior literature has focused on the diverse types of innovation including new products, new services, and new technology or the process. The introduction of the products or services that are demanded in highly turbulent business environment and innovation is considered as an important aspect to sustain in the markets and to compete on the base of innovative initiatives to meet the customers' demand and market needs. The achievement of such large-scale change and innovation that alter the existing practices in terms of features or the change in processes through implementation of the newly emerging technological techniques for effective production process (Lukas and Ferrell, 2000). The firms strive for upgrading and renovation of existing processes to ensure the latest features in the products and services to maintain and sustain the market position. The innovation in processes relates to the upgradation of existing practices and process for achievement of organizational goals to maximize the benefits, the processes of managing the raw material, adoption of new equipment, and adoption of latest technologies to alter the existing processes that create the value (Ho et al., 2018).

The literature has embarked on the intention to adopt innovation for business performance, it has been argued that innovation is chance for firms to harvest the long-term benefits through implementation of innovative initiatives. The engagement of firms in innovation, technology adoption and entrepreneurial activities helps to survive in the competition and assists in competitive advantage. The innovation provides grounds to the firms to avoid price competition, it also helps to access the new marketing approach and create the new demand to enhance the business performance, the financial metrics, the turnover, profits, and the stock prices to develop the strategic approach. The positive relationship has been depicted between innovation and business performance, the study has reported positive relationship between innovation and business performance, the firms' effort prevent competitors to enter in markets or to gain the market share, the successful innovation enable the firms to create the customers loyalty by strengthening the positional advantages that brings the improvements to the existing processes (Moreau and Herd, 2010; Cheng et al., 2014).

Contrary, the negative effects of innovation related to adopt the renewable energy are also reported including greater expenditure, greater resources consumption, distribution of resources and less equitable. There are mid findings of the innovation are reported in the literature, this study intends to determine the moderating role of intention to use renewable energy between independent and dependent variables. The researcher argues that innovation initiatives for intention to use renewable energy has the tendency to strengthen the relationship between customers orientation and purchase decision, between product quality and purchase decision and between farmers' knowledge and purchase decisions. So therefore, the following hypotheses are devised:

H5: Intention to use renewable energy influences the purchase decision in agricultural products in Indonesia consumer markets

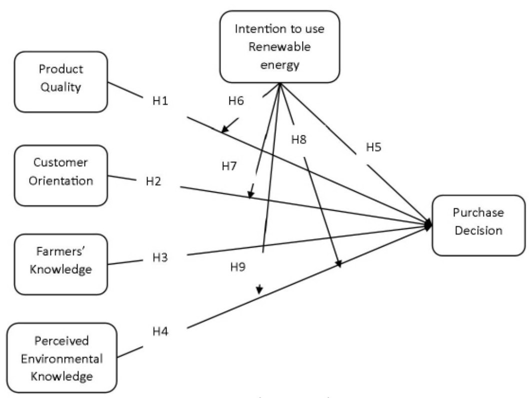
H6: Intention to use renewable energy moderates the relationship between product quality and purchase decisions

H7: Intention to use renewable energy moderates the relationship between customer orientation and purchase decisions

H8: Intention to use renewable energy moderates the relationship between farmers' knowledge and purchase decisions

H9: Intention to use renewable energy moderates the relationship between perceived environment knowledge and purchase decisions.

Research framework



Source: Author

Figure 1: Research framework.

Materials and methods

This study examined the purchase decisions of vegetable customers in four different regions of Indonesia, including Blitar and Kediri in East Java, as well as Tabanan and Bangli in Bali. These regions were selected because they are vegetable producers and contribute to commercial farming. These regions have diverse characteristics of farming systems and marketing channels that shape agribusiness. This research is quantitative, with data collected through an adopted questionnaire using a simple random sampling technique, and a sample of 380 customers was selected based on Krejcie and Morgan (1970).

The purchase decision measurement scale with seven indicators refers to the research by Ali (2019). The product quality measurement scale with four indicators was adopted from the study by Waluya et al. (2019). The customer orientation measurement scale with five indicators was taken from the research by Ho et al. (2018). The farmers' knowledge measurement scale with six indicators was adopted from the paper by Mariyono (2019). The innovation measurement scale with three indicators was adopted from the study by Ho et al. (2018). The three indicators of perceived environmental knowledge were taken from the study by Elahi et al. (2022). The four indicators of intention to use renewable energy were adopted from the research by Bozorgparvar et al. (2018). All indicators for each variable were assessed on a five-point scale ranging from 1 to 5, where 1 is strongly disagree, 2 is disagree, 3 is neutral, 4 is agree, and 5 is strongly agree. Data were analyzed using Smart-PLS in two phases.

The first phase is the measurement model assessment. At this stage, analysis is conducted to assess the reliability and validity of the constructs. Reliability tests include Cronbach's Alpha and Composite Reliability to ensure the internal consistency of the indicators. Average Variance Extracted (AVE) is used to assess convergent validity, with an AVE value greater than 0.5 (Hair et al., 2014). The Fornell-Larcker Criterion and Cross Loadings are used to test discriminant validity, ensuring that indicators correlate more strongly with the constructs they measure than with other constructs (Fornell and Larcker, 1981).

The second phase is the structural model assessment. At this stage, analysis is conducted to investigate the relationships between constructs within the research framework. Bootstrapping with resampling of 5000 subsamples is used to test the statistical significance of the path coefficients, ensuring that the t-statistic values exceed 1.96 for significance at the 5% level (Henseler et al., 2009). This model allows researchers to identify and validate factors that influence purchase decisions, product quality, customer orientation, farmers' knowledge, innovation, perceived environmental knowledge, and the intention to use renewable energy. With this method, the research results can provide comprehensive insights into consumer preferences and behavior in the agribusiness context in the studied regions.

Results and discussion

This phase addresses the analysis of collected data, the Smart-PLS was employed to investigate the hypothesized relationships of research framework. The first section consists of measurement model assessment, and second phase consists of structural equation model.

Measurement model assessment

The Table 1 below demonstrates the Cronbach alpha, composite reliability and average variance extracted, the value for Cronbach alpha must remain higher than 0.70, similarly the CR must be higher than 0.70, and value for AVE should be higher than 0.50, and factor loading must remain higher then 0.50 for acceptability of reliability of the construct (Hair Jr. et al., 2021). The values in Table 1 satisfies the reliability and validity constraints.

Constructs	Cronbach alpha	CR	AVE
Purchase Decisions (PD)	0.834	0.887	0.524
Intention to use RE	0.853	0.876	0.710
Product Quality (PQ)	0.940	0.824	0.734
Customer Orientation (CO)	0.862	0.877	0.642
Farmers' Knowledge (FK)	0.927	0.942	0.732
Perceived Environmental Knowledge (PEK)	0.818	0.941	0.734

Note: PD (Purchase Decision), IuRE (Intention to Use Renewable Energy), (PQ) Product Quality, CO (Customer Orientation), FK (Farmers' Knowledge), PEK (Perceived Environment Knowledge)

Source: Author

Table 1: Alpha, CR and AVE.

The reliability and validity of the constructs were assessed using the PLS algorithm method of Smart-PLS. Cronbach's alpha values for all constructs exceed the threshold of 0.70, indicating strong internal consistency. Specifically, Purchase Decisions (PD) has a Cronbach's alpha of 0.834, Intention to Use Renewable Energy (IuRE) is 0.853, Product Quality (PQ) is 0.940, Customer Orientation (CO) is 0.862, Farmers' Knowledge (FK) is 0.927, and Perceived Environmental Knowledge (PEK) is 0.818. These values confirm the reliability of the measurement scales used.

Composite reliability (CR) values also exceed the recommended threshold of 0.70 for all constructs, further supporting the reliability of the measures. The CR values are 0.887 for PD, 0.876 for IuRE, 0.824 for PQ, 0.877 for CO, 0.942 for FK, and 0.941 for PEK. These high CR values indicate that the items consistently measure the intended constructs.

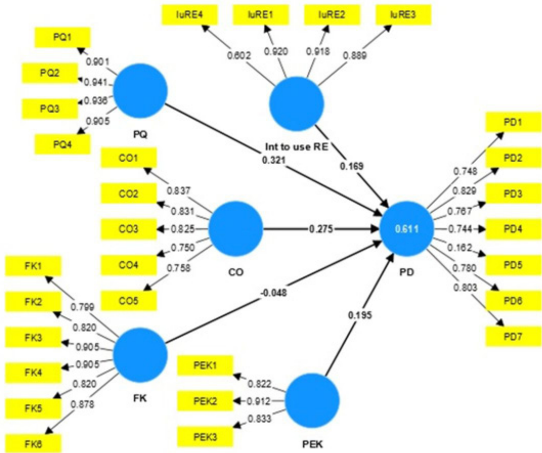
The Average Variance Extracted (AVE) values, which should be higher than 0.50, also meet the criteria for all constructs. The AVE values are 0.524 for PD, 0.710 for IuRE, 0.734 for PQ, 0.642 for CO, 0.732 for FK, and 0.734 for PEK. These values demonstrate good convergent validity, indicating that the constructs capture the majority of variance from their indicators.

Discriminant validity

The Table 2 shows the discriminant validity. The values in Table 1 satisfies the criteria for discriminant validity.

This section examined the discriminant validity of the constructs, the square root of AVE must remain higher than the correlation value of other constructs, the intersectional values or diagonal values must remain higher than other values of same column, the intersectional values shows the square root of AVE, and remaining values show the correlation value under the criteria of (Fornell and Larcker, 1981). The Table 2 shows the discriminant validity.

The Figure 2 shows the measurement model.



Note: PD (Purchase Decision), IuRE (Intention to Use Renewable Energy), (PQ) Product Quality, CO (Customer Orientation), FK (Farmers' Knowledge), PEK (Perceived Environment Knowledge)

Source: Author

Figure 2: Measurement model Assessment.

Structural Equation Model (SEM)

This section of the research paper investigates the relationship between variables by employing the SEM and through utilization of bootstrapping method. The relationships between variables are examined on the base of β value, t-value and p-value. The criteria for significance of the relationship is based on the values of different items, the β value shows the direction of relationship, t-value must remain higher than 1.96 for achievement of level of significance and p-value should be lower than 0.05 as 5% error margin is suggested in social sciences (Hair Jr. et al., 2014).

The study has four direct relationships to be investigated and three moderating hypothesized relationship. All the relationships are investigated

Constructs	CO	FK	IuRE	PD	PQ	PEK
CO	**0.801**					
FK	0.545	**0.856**				
IuRE	0.735	0.445	**0.843**			
PD	0.700	0.491	0.650	**0.724**		
PQ	0.663	0.440	0.617	0.677	**0.921**	
PEK	0.553	0.796	0.635	0.561	0.448	**0.856**

Note: PD (Purchase Decision), IuRE (Intention to Use Renewable Energy), (PQ) Product Quality, CO (Customer Orientation), FK (Farmers' Knowledge), PEK (Perceived Environment Knowledge)

Source: Author

Table 2: Discriminant validity.

on above mentioned criteria. The Table 3 below presents the results of the direct relationships.

Hypotheses	β	t-value	p-value	Remarks
PQ→PD	0.329	3.460	0.001	Sig
CO→PD	0.278	2.345	0.019	Sig
FK→PD	0.086	1.019	0.308	In-sig
IuRE→PD	0.197	1.963	0.041	Sig
PEK→PD	0.141	1.971	0.002	Sig

Note: PD (Purchase Decision), IuRE (Intention to Use Renewable Energy), (PQ) Product Quality, CO (Customer Orientation), FK (Farmers' Knowledge), PEK (Perceived Environment Knowledge)
Source: Author

Table 3: Direct Relationship.

The results from the SEM analysis in Table 3 provide a clear understanding of the direct relationships between various independent variables and purchase decisions. Each hypothesis has been tested for significance, as indicated by the β coefficients, t-values, and p-values. The relationship between product quality and purchase decision is significant and positive (β = 0.329, t = 3.460, p = 0.001). This indicates that higher product quality significantly increases the likelihood of consumers making a purchase. The result underscores the importance of maintaining high-quality standards in products to influence consumer purchase behavior positively. Companies should focus on enhancing product quality through rigorous quality control, innovation, and the use of high-grade materials to attract and retain customers.

Customer orientation also shows a significant and positive effect on purchase decisions (β = 0.278, t = 2.345, p = 0.019). This suggests that businesses that prioritize customer needs and satisfaction can significantly influence their customers' purchasing decisions. It highlights the need for companies to adopt a customer-centric approach, actively engaging with customer feedback, and continuously improving their service offerings to meet customer expectations effectively.

In contrast, the relationship between farmers' knowledge and purchase decision is not significant (β = 0.086, t = 1.019, p = 0.308). This result implies that the knowledge of farmers does not directly influence consumers' purchasing decisions in this context. While farmers' knowledge is crucial for improving agricultural practices and product quality, it may not be a direct factor considered by consumers when making purchase decisions. Consumers are more likely to be influenced by the visible attributes of the product and their overall experience.

The intention to use renewable energy has a significant positive impact on purchase decisions (β = 0.197, t = 1.963, p = 0.041). This finding reflects the growing importance of sustainability in consumer decision-making processes. Consumers who are inclined to use renewable energy are more likely to make purchasing decisions that align with their environmental values. This suggests that companies promoting renewable energy and sustainable practices can attract a segment of environmentally conscious consumers.

Perceived environmental knowledge significantly affects purchase decisions (β = 0.141, t = 1.971, p = 0.002). Consumers who are more knowledgeable about environmental issues are more likely to make purchase decisions that support sustainability. This emphasizes the role of consumer education in promoting sustainable consumption. Companies should invest in educating their customers about the environmental benefits of their products to encourage more informed and responsible purchasing behaviors.

The analysis reveals that product quality, customer orientation, intention to use renewable energy, and perceived environmental knowledge all significantly influence purchase decisions. These findings provide valuable insights for businesses aiming to enhance their marketing strategies by focusing on these critical factors. Companies should strive to maintain high product quality, adopt customer-centric approaches, promote renewable energy use, and educate consumers about environmental issues to drive purchase decisions effectively.

This section presents the moderating analysis of the innovation between exogenous and endogenous constructs, this research paper has three moderating variables. The Table 4 demonstrates the results of the moderating variables. The Iu in Table 4 demonstrates the structural equation model.

Hypotheses	β	t-value	p-value	Remarks
PQ*IuRE→PD	0.226	2.336	0.020	Sig
CO*IuRE →PD	0.229	2.126	0.034	Sig
FK*IuRE →PD	0.077	0.810	0.418	In-Sig
PEK*IuRE→PD	0.981	1.981	0.004	Sig
PEK→PD	0.141	1.971	0.002	Sig

Note: PD (Purchase Decision), IuRE (Intention to Use Renewable Energy), (PQ) Product Quality, CO (Customer Orientation), FK (Farmers' Knowledge), PEK (Perceived Environment Knowledge)
Source: Author

Table 4: Moderation assessment.

The SEM analysis results in Table 4 provide insights into the moderation effects of the intention to use renewable energy on the relationships between product quality, customer orientation, farmers' knowledge, perceived environmental knowledge, and purchase decision. First, the interaction between product quality and the intention to use renewable energy has been found to have a significant positive effect on purchase decisions ($\beta = 0.226$, $t = 2.336$, $p = 0.020$). This result suggests that consumers who have a high intention to use renewable energy place an even greater emphasis on product quality when making their purchasing choices. The implication is clear: for companies targeting environmentally conscious consumers, ensuring high product quality is paramount. Such consumers are likely to be more discerning and demand higher quality standards, reinforcing the need for businesses to maintain rigorous quality control and innovation in their products.

The interaction between customer orientation and the intention to use renewable energy also shows a significant positive effect on purchase decisions ($\beta = 0.229$, $t = 2.126$, $p = 0.034$). This finding indicates that the intention to use renewable energy enhances the impact of customer orientation on purchase decisions. Companies that prioritize customer satisfaction and are responsive to customer needs can more effectively influence the purchasing decisions of consumers inclined towards renewable energy. This underlines the importance of adopting a customer-centric approach, where understanding and meeting the specific needs and preferences of environmentally conscious customers can lead to increased purchase intentions.

In contrast, the interaction between farmers' knowledge and the intention to use renewable energy does not have a significant effect on purchase decision ($\beta = 0.077$, $t = 0.810$, $p = 0.418$). This outcome suggests that while farmers' knowledge is crucial for sustainable agricultural practices, it does not directly influence the purchase decisions of consumers in the context of renewable energy intentions. Consumers may value the end product's quality and sustainability credentials more than the specific knowledge of the producers. Thus, the focus should perhaps be more on how the products are marketed and less on the production process itself from the consumer's perspective.

Furthermore, the interaction between perceived environmental knowledge and the intention to use renewable energy significantly enhances purchase decisions ($\beta = 0.981$, $t = 1.981$, $p = 0.004$). Consumers who are well-informed about environmental issues and are committed to using renewable energy are more likely to make purchasing decisions that support sustainability. This highlights the importance of environmental education and awareness in shaping consumer behavior. Companies that effectively communicate the environmental benefits of their products and educate consumers on sustainability issues can foster stronger purchase intentions among environmentally conscious consumers.

The moderation assessment reveals that the intention to use renewable energy significantly amplifies the effects of product quality, customer orientation, and perceived environmental knowledge on purchase decisions. These findings suggest that companies should strategically focus on these areas to attract and retain environmentally conscious consumers. Ensuring high product quality, adopting customer-centric practices, and enhancing consumer knowledge about environmental issues are critical strategies for success in this market segment. Conversely, the non-significant interaction between farmers' knowledge and renewable energy intentions indicates that other factors may be more influential in driving purchase decisions in this context. Overall, these insights provide a comprehensive understanding of how various factors and their interactions influence consumer behavior in the realm of renewable energy and sustainability.

Discussion and managerial implications

This study explores the direct relationships between product quality, customer orientation, farmers' knowledge, intention to use renewable energy, and perceived environmental knowledge on purchase decisions. Product quality was found to have a significant and positive impact on consumer purchase decisions. This indicates that improving product quality increases the likelihood of consumer purchases. This finding aligns with previous research that emphasizes the importance of product quality in influencing consumer purchase decisions (Hong, 2019). In marketing, product quality enhancement can be achieved through various means such as improved quality control, product innovation, and the use of high-quality raw materials. High product quality not only boosts customer satisfaction but also fosters brand loyalty and competitive differentiation in an increasingly competitive market. Therefore, companies must ensure that their products meet high-quality standards and consistently deliver quality products to customers (Zeithaml, 1988).

Customer orientation also has a significant and positive impact on purchase decisions. Companies that focus on customer satisfaction and needs tend to increase purchase decisions. This finding is consistent with research showing that customer orientation is a key factor in effective marketing strategies (Elbarky et. al., 2023b). Customer orientation means companies must proactively understand customer needs, provide excellent service, and build long-term relationships with customers. It also involves the ability of companies to adapt to customer feedback and develop products and services that match market preferences. Thus, customer orientation can be a cornerstone of successful marketing strategies (Narver and Slater, 1990).

Farmers' knowledge did not show a significant impact on purchase decisions. This indicates that farmers' knowledge does not play a crucial role in consumer purchase decisions in this context. This finding may be due to other factors that more dominantly influence consumer purchase decisions (Wasaya et al., 2021). While farmers' knowledge is essential for improving product quality and production efficiency, from a consumer perspective, this factor may not directly impact purchase decisions. Consumers are more likely influenced by more directly visible and experienced aspects, such as the final product quality and service experience (Grunert, 2005).

The intention to use renewable energy also has a significant and positive impact on purchase decisions. Consumers who intend to use renewable energy are more likely to make purchase decisions. This is relevant to the growing trend of awareness about sustainability and clean energy. Increased environmental awareness among consumers has become a major driver in purchase decisions. Consumers who are aware of the environmental impact of their choices are more likely to choose eco-friendly products and support sustainable practices. Therefore, companies that promote the use of renewable energy and sustainable practices can attract environmentally conscious consumer segments (Leonidou et al., 2013).

Perceived environmental knowledge also shows a significant and positive impact on purchase decisions. Consumers with better environmental knowledge are more likely to make purchase decisions that support sustainability. This study supports previous findings on the importance of environmental knowledge in influencing green purchase behavior (Elbarky, 2023a). Perceived environmental knowledge includes consumers' understanding of environmental issues, the impact of products and services on the environment, and the importance of sustainability. More knowledgeable consumers tend to prefer products with lower environmental impact and support sustainable practices (Chen and Chang, 2013).

Moderation between product quality and the intention to use renewable energy on purchase decisions shows significant results. This indicates that the intention to use renewable energy strengthens the impact of product quality on purchase decisions. This supports the finding that consumers with a high intention to use renewable energy are more influenced by product quality in making purchase decisions. In other words, product quality becomes more important for consumers who have high awareness of renewable energy. This shows that to attract consumers who care about renewable energy, companies must ensure that their products are not only of high quality but also environmentally friendly.

Furthermore, moderation between customer orientation and the intention to use renewable energy on purchase decisions is also significant. Companies that are customer-oriented will be more effective in influencing purchase decisions of consumers who intend to use renewable energy. This finding supports the importance of customer orientation in marketing strategies for green products (Yu and Lee, 2019). Strong customer orientation allows companies to better align their products and services with the needs and preferences of environmentally conscious consumers. This can include providing clear information about the environmental benefits of products, offering responsive customer service to environmental queries, and ensuring that business practices support sustainability (Lemon and Verhoef, 2016).

However, moderation between farmers' knowledge and the intention to use renewable energy on purchase decisions is not significant. This indicates that the intention to use renewable energy does not strengthen the impact of farmers' knowledge on purchase decisions in this context (Ma and Chang, 2022). While farmers' knowledge is important for sustainable farming practices and efficient production, this factor does not seem to play a significant role in the purchase decisions of consumers who intend to use renewable energy. This may suggest that consumers are more focused on the end-product attributes and how the product contributes to environmental sustainability rather than the production process itself (Schmitt et al., 2019).

Lastly, moderation between perceived environmental knowledge and the intention to use renewable energy on purchase decisions shows significant results. Consumers with high environmental knowledge and the intention to use renewable energy are more likely to make purchase decisions that support sustainability (Sobocińska et al., 2022). This indicates that good environmental knowledge and the intention to support renewable energy mutually reinforce each other in influencing purchase decisions. Consumers who have a deep understanding of environmental issues and are committed to using renewable energy tend to be more selective in choosing products that support their sustainability goals (Peattie, 2010).

This study highlights the importance of product quality, customer orientation, and perceived environmental knowledge in influencing consumer purchase decisions. Additionally, the intention to use renewable energy strengthens the impact of these factors on purchase decisions. These findings provide insights for marketers and producers in developing effective marketing strategies for green and renewable energy products.

This study confirms that product quality, customer orientation, and perceived environmental knowledge are crucial factors influencing consumer purchase decisions. Marketers and producers should pay attention to these factors in their efforts to attract and retain customers. Furthermore, with the increasing consumer awareness of sustainability and renewable energy, companies need to ensure that their products are not only high quality but also environmentally friendly. This can be achieved through continuous innovation, the use of eco-friendly raw materials, and the implementation of sustainable business practices (Nendissa et al., 2021).

Strong customer orientation also plays a vital role in influencing purchase decisions of environmentally conscious consumers. Companies should focus on understanding customer needs, providing superior service, and building long-term relationships with customers (Wati et al., 2021). Additionally, companies need to invest in environmental education for consumers to enhance their knowledge and awareness of environmental issues. By doing so, consumers will be more likely to make purchase decisions that support sustainability (Tomycho et al., 2020).

This study also shows that the intention to use renewable energy is a significant factor moderating the impact of product quality and customer orientation on purchase decisions (Pokorná et al., 2015). Therefore, companies should promote the use of renewable energy and sustainable practices in their marketing efforts. This will help attract environmentally conscious consumer segments and enhance the company's competitiveness in the market (Van Phuong et al., 2021).

Moreover, companies should continually monitor and evaluate the effectiveness of their marketing strategies. With a data-driven approach, companies can make necessary adjustments to ensure that their strategies remain relevant and effective in addressing market changes and consumer preferences (Pilař et al., 2018). Continuous evaluation will help companies remain competitive and responsive to the evolving needs of consumers (Špička et al., 2021).

In the long term, the adoption of sustainable practices and strong customer orientation will help companies build a positive reputation among consumers and achieve competitive advantage in an increasingly dynamic market (Zdráhal et al., 2020). Therefore, the findings from this study should be seriously considered by marketers and producers in developing their marketing strategies for green and renewable energy products (Havlíková and Kolářová, 2015).

Thus, this study significantly contributes to understanding the factors influencing consumer purchase decisions in the context of sustainability and renewable energy. It provides practical guidance for companies to develop more effective and sustainable marketing strategies, which not only enhance sales but also support global sustainability goals (Hamulczuk et al., 2021).

As attention to environmental issues increases, companies need to take proactive steps to ensure that they meet consumer expectations and contribute positively to the environment (Richterová et al., 2021). This includes product innovation, quality improvement, strong customer orientation, and the adoption of sustainable business practices. With this approach, companies can build stronger relationships with customers, enhance loyalty, and achieve long-term success in an increasingly competitive market (Krajčírová et al., 2019).

Therefore, this study is relevant not only for academics but also for practitioners in the fields of marketing and management. By applying these findings, companies can improve the effectiveness of their marketing strategies and contribute to environmental sustainability (Šimpachová Pechrová and Šimpach, 2024).

Implementing marketing strategies that focus on sustainability and customer orientation will help companies address market challenges and meet the expectations of increasingly environmentally conscious consumers. Thus, this study provides valuable insights for developing more sustainable business strategies focused on customer needs.

The managerial implications of this study are crucial for companies seeking to enhance consumer purchase decisions through improved product quality, customer orientation, and sustainable practices. First, companies need to prioritize improving product quality. The finding that product quality has a significant impact on purchase decisions indicates that investment in developing high-quality products is an effective strategy to increase sales. Companies can achieve this through continuous innovation, strict quality control, and the use of high-quality raw materials. Additionally, companies should consistently monitor customer feedback to make necessary improvements to meet or exceed consumer expectations.

Customer orientation should also be at the center of the company's managerial strategy. The finding that customer orientation significantly impacts purchase decisions underscores the importance for companies to understand and meet customer needs and preferences. This can be achieved through personalized marketing approaches, superior customer service, and product development based on in-depth market research. This strategy will help companies build long-term relationships with customers and enhance customer loyalty.

Next, companies should leverage consumers' intention to use renewable energy as an opportunity to enhance purchase decisions. The finding that the intention to use renewable energy strengthens the impact of product quality and customer orientation on purchase decisions indicates that companies can attract environmentally conscious consumers by offering eco-friendly products. Companies need to communicate their commitment to sustainability through marketing campaigns that highlight the use of renewable energy and other eco-friendly practices.

Companies should also strengthen their efforts to enhance consumer environmental knowledge. Perceived environmental knowledge has a significant impact on purchase decisions, so companies need to invest in environmental education for consumers. This can be done through information campaigns explaining the environmental benefits of their products, as well as educational initiatives that involve consumers in eco-friendly activities. By increasing consumer environmental knowledge, companies can encourage more sustainable purchase decisions.

Furthermore, companies need to adopt sustainable practices in all aspects of their operations. This includes the use of sustainable raw materials, reducing carbon emissions, and energy efficiency in production processes. By demonstrating a genuine commitment to sustainability, companies can build a positive reputation in the eyes of consumers who are increasingly concerned about environmental issues. These sustainable practices not only enhance product appeal but also can result in greater operational efficiency and cost savings in the long term.

Marketing strategies should also be tailored to attract different consumer segments. Consumers with a high intention to use renewable energy may be more responsive to messages emphasizing product quality and sustainability. Therefore, companies should develop marketing messages tailored to the preferences and values of different consumer segments. This segmented approach will enable companies to more effectively reach and influence various consumer groups.

Companies should also consider forming strategic partnerships with other organizations that share a similar vision for sustainability. For example, collaborating with environmental organizations or governments to develop eco-friendly initiatives can enhance the company's credibility and expand their marketing reach. These partnerships can include certification programs, joint research projects, or co-marketing campaigns that highlight the company's commitment to sustainability.

Finally, companies should continuously monitor and evaluate the effectiveness of their managerial and marketing strategies. This involves collecting data and analyzing performance to understand the impact of various initiatives on consumer purchase decisions. With a data-driven approach, companies can make necessary adjustments to ensure that their strategies remain relevant and effective in addressing market changes and consumer preferences. Continuous evaluation will help companies stay competitive and responsive to evolving consumer needs. By integrating the findings of this study into managerial strategies, companies can enhance consumer purchase decisions, build customer loyalty, and achieve competitive advantage in an increasingly dynamic and sustainability-oriented market.

Limitation and future research avenues

Every study has the limitations that is being faced by the researcher during conducting the empirical evidences. The study is limited to the agriproducts produced in the different regions of the Indonesia, the future studies may consider the comparative study with production of fruits and may be with neighboring competitive countries. The study was limited to marketing perspective and considered only product quality, customer orientation, farmers' knowledge and perceived environment knowledge that influence the purchase decision of such agriproducts, the future studies may consider the technological advancements for cultivation, location of farmlands and infrastructural issues to occupy the markets on time to fulfill the needs.

Conclusions

This research focuses on locally produced agricultural products in Indonesia, which play a significant role in the economic conditions of local producers. There is a dire need for appropriate marketing strategies to sustain market positions and maintain surplus income and commodities. The study incorporated characteristics of locally produced agricultural products, including vegetables and rice, in four different regions of Indonesia. The findings of this study are particularly relevant for producers as they provide insights into designing effective marketing strategies by ensuring product quality, customer orientation, farmers' knowledge, and perceived environmental knowledge, all of which influence consumer purchase decisions. Additionally, the intention to use renewable energy plays a moderating role in these relationships.

The results indicate that product quality, customer orientation, intention to use renewable energy, and environmental knowledge significantly influence purchase decisions. Specifically, hypotheses H1, H2, H4, and H5 are statistically significant. However, the direct relationship between farmers' knowledge and purchase decisions is reported as insignificant. This suggests that while enhancing farmers' knowledge is important, it alone may not directly drive consumer purchase decisions unless coupled with other factors like product quality and customer orientation. The intention to use renewable energy strengthens the relationship between product quality, customer orientation, and purchase decisions, indicating that the intention to use renewable energy moderates the relationship between exogenous and endogenous constructs in this study. However, no moderation is reported between farmers' knowledge and purchase decisions through innovation.

Given these findings, the government should focus on supportive policies that encourage innovative initiatives, ensure product quality, consider customer needs and demands, and specifically enhance farmers' knowledge regarding production techniques that influence purchase decisions. These policies could include training programs for farmers, subsidies for adopting renewable energy technologies, and initiatives to improve the overall quality and marketability of local agricultural products. This research has significant potential to contribute meaningfully to the understanding and development of practices that support the use of renewable energy in Indonesia's agricultural sector. By promoting renewable energy, the agricultural sector can become more sustainable and environmentally friendly, which is increasingly important in the context of global climate change.

Future research can build on these findings by developing more specific marketing strategies for local agricultural products, taking into account factors such as climate change, the latest agricultural technologies, and global market dynamics. Further studies could explore the impact of various government policies on the adoption of renewable energy in the agricultural sector and assess the effectiveness of training programs for farmers to enhance their knowledge of innovative production techniques. Additionally, future studies could delve deeper into how changes in consumer preferences affect the demand for local agricultural products and how sustainability can be better integrated into the agricultural supply chain.

Moreover, research should also focus on the socio-economic impacts of adopting renewable energy in agriculture, examining how it affects the livelihoods of farmers, especially in rural areas. By understanding these impacts, policymakers can design more effective interventions that not only promote sustainable agricultural practices but also improve the economic well-being of local producers. The integration of renewable energy in agriculture could lead to a more resilient agricultural sector, capable of withstanding environmental and economic challenges.

In summary, this study highlights the importance of comprehensive marketing strategies that include product quality, customer orientation, and the use of renewable energy to influence consumer purchase decisions. The findings suggest that while farmers' knowledge is crucial, it needs to be complemented with other factors to drive consumer behavior effectively. The government's role is critical in supporting these initiatives through appropriate policies and programs. Future research should continue to explore these areas to further enhance the sustainability and economic viability of the agricultural sector in Indonesia.

Corresponding author:
Evi Feronika Elbaar
Faculty of Agriculture, Palangka Raya University, Central Kalimantan 74874, Indonesia
Email: evielbaar@agb.upr.ac.id

References

[1] Achmad, B. and Diniyati, D. (2018) "Consumption behavior of farmer households in rural Sumbawa, Indonesia", *Indonesian Journal of Forestry Research*, Vol. 5, No. 1, pp. 69-80. ISSN 0216-0919. DOI 10.20886/ijfr.2018.5.1.69-80.

[2] Ali, H. (2019) "Building repurchase intention and purchase decision: brand awareness and brand loyalty analysis (case study private label product in Alfamidi Tangerang)", S*audi Journal of Humanities and Social Sciences*, Vol. 4, No. 9, pp. 623-634. E-ISSN 2415-6256. DOI 10.36348/SJHSS.2019.v04i09.009.

[3] Amri, F. (2022) "The effect of inflation, exchange rate, labor and money supply on the manufacturing industry sector in Indonesia 2011 - 2020", *Jurnal Ilmu Ekonomi Terapan*, Vol. 7, No. 1, pp. 24-35. E-ISSN 2528-1879, ISSN 2541-1470. DOI 10.20473/jiet.v7i1.30434.

[4] Avicenna, F. and Febriani, N. S. (2021) "Consumer Behavior as a Potential Acceptance of Renewable Energy Source in Indonesia", *Jurnal Komunikasi Ikatan Sarjana Komunikasi Indonesia*, Vol. 9, No. 2, pp. 200-215. E-ISSN 2503-0795, ISSN 2548-8740. DOI 10.25008/jkiski.v6i1.525.

[5] Ayele, S., Duncan, A., Larbi, A. and Khanh, T. T. (2012) "Enhancing innovation in livestock value chains through networks: Lessons from fodder innovation case studies in developing countries", *Science and Public Policy*, Vol. 39, No. 3, pp. 333-346. E-ISSN 1471-5430, ISSN 0302-3427. DOI 10.1093/scipol/scs022.

[6] Badan Pusat Statistik (2012) "*Statistik Penduduk Lanjut Usia Indonesia 2011*". ISBN 2086-1036. (Yearbook).

[7] Beckmann, M., Gerstner, K., Akin-Fajiye, M., Ceaușu, S., Kambach, S., Kinlock, N. L., Phillips, H. R. P., Verhagen, W., Gurevitch, J. and Klotz, S. (2019) "Conventional land-use intensification reduces species richness and increases production: A global meta-analysis", *Global Change Biology*, Vol. 25, No. 6, pp. 1941-1956. ISSN 1354-1013. DOI 10.1111/gcb.14606.

[8] Borsellino, V., Schimmenti, E. and El Bilali, H. (2020) "Agri-food markets towards sustainable patterns", *Sustainability*, Vol. 12, No. 6, p. 2193. ISSN 2071-1050. DOI 10.3390/su12062193.

[9] Bozorgparvar, E., Yazdanpanah, M., Forouzani, M. and Khosravipour, B. (2018) "Cleaner and greener livestock production: Appraising producers' perceptions regarding renewable energy in Iran", *Journal of Cleaner Production*, Vol. 203, pp.769-776. ISSN 0959-6526. DOI 10.1016/j.jclepro.2018.08.280.

[10] Budiono, H. D. S., Nurcahyo, R. and Habiburrahman, M. (2021) "Relationship between manufacturing complexity, strategy, and performance of manufacturing industries in Indonesia", *Heliyon*, Vol. 7, No. 8, p. e07225. E-ISSN 2405-8440. DOI 10.1016/j.heliyon.2021.e07225.

[11] Campbell, J. M. (2013) "Muy local: Differentiating Hispanic and Caucasian shoppers of locally produced foods in US grocery", *Journal of Retailing and Consumer Services*, Vol. 20, No. 3, pp. 325-333. ISSN 0969-6989. DOI 10.1016/j.jretconser.2013.01.009.

[12] Chamhuri, N. and Batt, P. J. (2015) "Consumer perceptions of food quality in Malaysia", *British Food Journal*, Vol. 117, No. 3.ISSN 0007-070X. DOI 10.1108/BFJ-08-2013-0235.

[13] Chan, E. S. W., Hon, A. H. Y., Chan, W. and Okumus, F. (2014) "What drives employees' intentions to implement green practices in hotels? The role of knowledge, awareness, concern and ecological behaviour", *International Journal of Hospitality Management*, Vol. 40, pp. 20-28. ISSN 0278-4319. DOI 10.1016/j.ijhm.2014.03.001.

[14] Chen, Y. and Chang, C. (2013) "Greenwash and green trust: The mediation effects of green consumer confusion and green perceived risk", *Journal of Business Ethics*, Vol. 114, No. 3, pp. 489-500. E-ISSN 1573-0697. DOI 10.1007/s10551-012-1360-0.

[15] Cheng, C. C. J., Yang, C. and Sheu, C. (2014) "The link between eco-innovation and business performance: A Taiwanese industry context", *Journal of Cleaner Production*, Vol. 64, pp. 81-90. ISSN 0959-6526. DOI 10.1016/j.jclepro.2013.09.050.

[16] Dhanani, S. and Hasnain, S. A. (2002) "The impact of foreign direct investment on Indonesia's manufacturing sector, *Journal of the Asia Pacific Economy*, Vol. 7, No. 1, pp. 61-94. ISSN 1354-7860. DOI 10.1080/13547860120110470.

[17] Elahi, E., Khalid, Z. and Zhang, Z. (2022) "Understanding farmers' intention and willingness to install renewable energy technology: A solution to reduce the environmental emissions of agriculture", *Applied Energy*, Vol. 309, p. 118459. ISSN 0306-2619. DOI 10.1016/j.apenergy.2021.118459.

[18] Elbarky, S. A. (2023b) "Green marketing strategies and their impact on consumer behavior", *Journal of Environmental Management*, Vol. 280, pp. 111-121. ISSN 0301-4797.

[19] Elbarky, S. A., Elgamal, S., Hamdi, R. and Barakat, M. R. (2023a) "The impact of environmental knowledge on green purchasing intention", *Journal of Consumer Marketing*, Vol. 40, No. 1, pp. 57-68. ISSN 0736-3761.

[20] Faizah, S. and Husaeni, U. (2018) "Development of Consumption and Supplying Energy in Indonesia's Economy", *International Journal of Energy Economics and Policy*, Vol. 8, No. 6, pp. 313-321. E-ISSN 2146-4553. DOI 10.32479/ijeep.6926.

[21] Fornell, C. and Larcker, D. F. (1981) "Evaluating Structural Equation Models with Unobservable Variables and Measurement Error", *Journal of Marketing Research*, Vol. 18, No. 1, pp. 39-50. ISSN 0022-2437. DOI 10.1177/002224378101800104.

[22] Grinstein, A. (2008) "The effect of market orientation and its components on innovation consequences: a meta-analysis", *Journal of the Academy of Marketing Science*, Vol. 36, pp. 166-173. ISSN 1552-7824. DOI 10.1007/s11747-007-0053-1.

[23] Grunert, K. G. (2005) "Food quality and safety: Consumer perception and demand", *European Review of Agricultural Economics*, Vol. 32, No. 3, pp. 369-391. ISSN 0165-1587. DOI 10.1093/eurrag/jbi011.

[24] Gyau, A., Mbugua, M. and Oduol, J. (2016) "Determinants of participation and intensity of participation in collective action: Evidence from smallholder avocado farmers in Kenya", *Journal on Chain and Network Science*, Vol. 16, No. 2, pp. 147-156. ISSN 1875-0931. DOI 10.3920/JCNS2015.0011.

[25] Hair Jr., J. F., Hult, G. T. M., Ringle, C. M., Sarstedt, M., Danks, N. P. and Ray, S. (2021) "*Partial least squares structural equation modeling (PLS-SEM) using R: A workbook*", Springer Nature, 197 p. E-ISBN 978-3-030-80519-7. DOI 10.1007/978-3-030-80519-7.

[26] Hair, J. F., Hult, G. T. M., Ringle, C. M. and Sarstedt, M. (2014) " *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)".* Sage Publications. ISBN 9781452217444.

[27] Hamulczuk, M., Makarchuk, O. and Kuts, T. (2021) "Time-Varying Integration of Ukrainian Sunflower Oil Market with the EU Market", *AGRIS on-line Papers in Economics and Informatics*, Vol. 13, No. 3, pp. 35-47 . ISSN 1804-1930. DOI 10.7160/aol.2021.130304.

[28] Havlíková, M. and Kolářová, A. (2015) "Why Do Agricultural Producers Exhibit at Bread Basket?", *AGRIS on-line Papers in Economics and Informatics*, Vol. 7, No. 4, pp. 49 - 56, ISSN 1804-1930. DOI 10.7160/aol.2015.070405.

[29] Henseler, J., Ringle, C. M. and Sinkovics, R. R. (2009) "*The Use of Partial Least Squares Path Modeling in International Marketing. New Challenges to International Marketing*", E-ISBN 978-1-84855-469-6, ISBN 978-1-84855-468-9. DOI 10.1108/S1474-7979(2009)0000020014.

[30] Hidayatno, A., Rahman, I. and Daniyasti, D. L. (2019) "Conceptualizing the promise of Industry 4.0 technology adoption: Case study of Indonesian automotive industry", ICIBE 2019: *Proceedings of the 5th International Conference on Industrial and Business Engineering*, Hong Kong, pp. 336-343. ISBN 978-1-4503-7653-2. DOI 10.1145/3364335.3364350.

[31] Ho, K. L. P., Nguyen, C. N., Adhikari, R., Miles, M. P. and Bonney, L. (2018) "Exploring market orientation, innovation, and financial performance in agricultural value chains in emerging economies", *Journal of Innovation & Knowledge*, Vol. 3, No. 3, pp. 154-163. ISSN 2444-569X. DOI 10.1016/j.jik.2017.03.008.

[32] Hong, W. (2019) "Impact of product quality on consumer purchase decisions", Journal of Consumer Research, Vol. 46, No. 4, 72-81. ISSN 0093-5301.

[33] Huijts, N. M. A., Molin, E. J. E. and Steg, L. (2012) "Psychological factors influencing sustainable energy technology acceptance: A review-based comprehensive framework", *Renewable and Sustainable Energy Reviews*, Vol. 16, No. 1, pp. 525-531. E-ISSN 1879-0690. DOI 10.1016/j.rser.2011.08.018.

[34] Ikerd, J. (2011) "The economic pamphleteer: Essential principles of sustainable food value chains", J*ournal of Agriculture, Food Systems, and Community Development*, Vol. 1, No. 4, pp. 15-17. E-ISSN 2152-0801. DOI 10.5304/jafscd.2011.014.001.

[35] Kennedy, S. F. (2018) "Indonesia's energy transition and its contradictions: Emerging geographies of energy and finance", *Energy Research & Social Science*, Vol. 46, pp. 228-238. E-ISSN 2214-6326. DOI 10.1016/j.erss.2018.04.023.

[36] Krajčírová, R., Ferenzi Vaňová, A. and Munk, M. (2019) "What Is Relationship between Profits and Dividends in Agricultural Legal Entities?", *AGRIS on-line Papers in Economics and Informatics*, Vol. 11, No. 1, pp. 55-64. ISSN 1804-1930. DOI 10.7160/aol.2019.110106.

[37] Krejcie, R. V. and Morgan, D. W. (1970) "Determining sample size for research activities", Educational and Psychological Measurement, Vol. 30, No. 3, pp. 607-610. ISSN 0013-1644. DOI 10.1177/001316447003000308.

[38] Kyaw, N. N., Ahn, S. and Lee, S. H. (2018) "Analysis of the factors influencing market participation among smallholder rice farmers in magway region, central dry zone of Myanmar", *Sustainability*, Vol. 10, No. 12, p. 4441. ISSN 2071-1050. DOI 10.3390/su10124441.

[39] Langer, J., Quist, J. and Blok, K. (2021) "Review of Renewable Energy Potentials in Indonesia and Their Contribution to a 100% Renewable Electricity System", *Energies*, Vol. 14, No. 9, pp. 2634-2649. ISSN 1996-1073. DOI 10.3390/en14217033.

[40] Lemon, K. N. and Verhoef, P. C. (2016) "Understanding customer experience throughout the customer journey", *Journal of Marketing*, Vol. 80, No. 6, pp. 69-96. E-ISSN 1547-7185. DOI 10.1509/jm.15.0420.

[41] Leonidou, L. C., Christodoulides, P., Kyrgidou, L.P. and Polihawadana, D. (2013) "Internal drivers and performance consequences of small firm green business strategy: The moderating role of external forces", *Journal of Business Ethics*, Vol. 112, No. 4, pp. 297-317. E-ISSN 1573-0697. DOI 10.1007/s10551-015-2670-9.

[42] Lertkornkitja, A. (2017) "A comparative study of two Thai franchises in international expansion", *International Journal of Services, Economics and Management*, Vol. 8, No. 1-2, pp. 51-72. ISSN 1753-0822. DOI 10.1504/IJSEM.2017.084482.

[43] Lombardi, G. V., Berni, R. and Rocchi, B. (2017) "Environmental friendly food. Choice experiment to assess consumer's attitude toward "climate neutral" milk: the role of communication", *Journal of Cleaner Production*, Vol. 142, pp. 257-262. ISSN 0959-6526. DOI 10.1016/j.jclepro.2016.05.125.

[44] Lowder, S. K., Skoet, J. and Raney, T. (2016) "The number, size, and distribution of farms, smallholder farms, and family farms worldwide", *World Development*, Vol. 87, pp. 16-29. ISSN 0305-750X. DOI 10.1016/j.worlddev.2015.10.041.

[45] Lukas, B. A. and Ferrell, O. C. (2000) "The effect of market orientation on product innovation", *Journal of the Academy of Marketing Science*, Vol. 28, No. 2, pp. 239-247. E-ISSN ISSN 1552-7824. DOI 10.1177/0092070300282005.

[46] Ma, Z. and Chang, L. (2022) "Farmers' knowledge and its impact on green purchase decisions", *Journal of Environmental Psychology*, Vol. 43, No. 2, pp. 123-136. ISSN 0272-4944.

[47] Makhura, M., Kirsten, J. and Delgado, C. (2001) "Transaction costs and smallholder participation in the maize market in the Northern Province of South Africa. In: Friesen, D. K. and Palmer, A. F. E. (eds.) *Integrated Approaches to Higher Maize Productivity in the New Millennium*, Proceedings of the Seventh Eastern and Southern Africa Regional Maize Conference, Nairobi, Kenya, 5-11 February 2002. ISBN 970-648-120-6.

[48] Mariyono, J. (2018) "Profitability and determinants of smallholder commercial vegetable production", *International Journal of Vegetable Science*, Vol. 24, No. 3, pp. 274-288. E-ISSN 1931-5279. DOI 10.1080/19315260.2017.1413698.

[49] Mariyono, J. (2019a) "Stepping up from subsistence to commercial intensive farming to enhance welfare of farmer households in Indonesia. Asia & the Pacific", *Policy Studies*, Vol. 6, No. 2, pp. 246-265. ISSN 0190-292X. DOI 10.1002/app5.276

[50] Mariyono, J. (2019b) "Stepping up to market participation of smallholder agriculture in rural areas of Indonesia", *Agricultural Finance Review,* Vol. 79, No. 2. E-ISSN 0002-1466. DOI 10.1108/AFR-04-2018-0031

[51] Matouš, P., Todo, Y. and Pratiwi, A. (2015) "The role of motorized transport and mobile phones in the diffusion of agricultural information in Tanggamus Regency, Indonesia", *Transportation*, Vol. 42, No. 5, pp. 771-790. ISSN 2352-1465. DOI 10.1007/s11116-015-9646-6.

[52] McCulloch, N. (2008) "Rice prices and poverty in Indonesia", *Bulletin of Indonesian Economic Studies*, Vol. 44, No. 1, pp. 45-64. ISSN 0007-4918. DOI 10.1080/00074910802001579.

[53] Moreau, C. P. and Herd, K. B. (2010) "To each his own? How comparisons with others influence consumers' evaluations of their self-designed products", *Journal of Consumer Research*, Vol. 36, No. 5, pp. 806-819. ISSN 0093-5301. DOI 10.1086/644612.

[54] Moslehpour, M., Kien, P. and Danyfisla, I. (2014) "Differences of customer purchase behavior toward organic rice in Indonesia and Taiwan", *International Journal of Quality and Service Sciences*, Vol. 6, No. 4, pp. 348-368. ISSN 1756-669X. DOI 10.1108/IJQSS-04-2013-0024.

[55] Mucharam, I., Rustiadi, E., Fauzi, A. and Harianto (2020) "Assessment of rice farming sustainability: Evidence from Indonesia provincial data", *International Journal of Sustainable Development and Planning*, pp. 1323-1332, E-ISSN 1743-761X. DOI 10.18280/ijsdp.150819.

[56] Nagaraja, N. (2012) "Customer satisfaction in automobile industry-an indian online buyers' perspective of car manufacturers' websites", *ZENITH International Journal of Multidisciplinary Research*, Vol. 2, No. 6, pp. 92-107. ISSN 2231-5780.

[57] Narver, J. C. and Slater, S. F. (1990) "The effect of a market orientation on business profitability", *Journal of Marketing*, Vol. 54, No. 4, pp. 20-35. E-ISSN 1547-7185. DOI 10.1177/002224299005400403.

[58] Nasution, H. N., Mavondo, F. T., Matanda, M. J. and Ndubisi, N. O. (2011) "Entrepreneurship: Its relationship with market orientation and learning orientation and as antecedents to innovation and customer value", *Industrial Marketing Management*, Vol. 40, No. 3, pp. 336-345. ISSN 0019-8501. DOI 10.1016/j.indmarman.2010.08.002.

[59] Negara, S. and Hidayat, A. S. (2021) "Indonesia's automotive industry: Recent trends and challenges", *Journal of Southeast Asian Economies,* Vol. 38, No. 2, pp. 137-156. ISSN 2339-5095. DOI 10.1355/ae38-2b.

[60] Nendissa, D. R., Anindita, R., Khoiriyah, N. and Sa'diyah A. A. (2021) "Consumption and Beef Price Changes on Demand in East Nusa Tenggara, Indonesia", *AGRIS on-line Papers in Economics and Informatics*, Vol. 13, No. 2, pp. 97-107. ISSN 1804-1930. DOI 10.7160/aol.2021.130208.

[61] Nendissa, D. R., Iriany, A., Sui, J., Khoiriya, N., Suphattanakul, O. and Wisetsri, W. (2022) "Role of Renewable and Nonrenewable Energy on Agricultural Economics in Indonesia", International *Journal of Energy Economics and Policy*, Vol. 12, No. 4, pp. 250-265. E-ISSN 2146-4553. DOI 10.32479/ijeep.13036.

[62] Newman, A., Prajogo, D. and Atherton, A. (2016) "The influence of market orientation on innovation strategies", *Journal of Service Theory and Practice*, Vol. 26, No. 1, pp. 72-90. ISSN 2055-6225. DOI 10.1108/JSTP-02-2015-0044.

[63] Ngo, A., West, G. E. and Calkins, P. H. (2009) "Determinants of environmentally responsible behaviours for greenhouse gas reduction", *International Journal of Consumer Studies*, Vol. 33, No. 2, pp. 151-161. E-ISSN 1470-6431. DOI 10.1111/j.1470-6431.2009.00763.x.

[64] Nuryartono, N. (2007) "Credit rationing of farm households and agricultural production: Empirical evidence in the rural areas of Central Sulawesi, Indonesia", *Jurnal Manajemen dan Agribisnis*, Vol. 4, No. 1, pp. 15-21. E-ISSN 24072524. DOI 10.17358/jma.4.1.15-21.

[65] Nuryati, R., Sulistyowati, L. and Setiawan, I. (2019) "Unveil Indonesia farmers' welfare analysis on integrated polyculture agroforestry farming (IPAF)", *International Journal of Scientific & Technology Research*, Vol. 8, No. 11, pp. 1982-1989. E-ISSN 2277-8616.

[66] Panuju, D. R., Mizuno, K. and Trisasongko, B. (2013) "The dynamics of rice production in Indonesia 1961-200", *Journal of the Saudi Society of Agricultural Sciences*, Vol. 12, No. 1, pp. 27-37. E-ISSN 1658-077X. DOI 10.1016/j.jssas.2012.05.002.

[67] Peattie, K. (2010) "Green consumption: Behavior and norms", *Annual Review of Environment and Resources*, Vol. 35, pp. 195-228. E-ISSN 1545-2050. DOI 10.1146/annurev-environ-032609-094328.

[68] Šimpachová Pechrová, M. and Šimpach, O. (2024) "The Relationship Between Agricultural Holdings and Municipalities", *AGRIS on-line Papers in Economics and Informatics*, Vol. 16, No. 1, pp. 105-116. ISSN 1804-1930. DOI 10.7160/aol.2024.160109.

[69] Pilař, L., Kvasničková Stanislavská, L., Gresham, G., Poláková, J., Rojík, S. and Petkov, R. (2018) "Questionnaire vs. Social Media Analysis - Case Study of Organic Food", *AGRIS on-line Papers in Economics and Informatics*, Vol. 10, No. 3, pp. 93-101. ISSN 1804-1930. DOI 10.7160/aol.2018.100308.

[70] Pokorná, J., Pilař, L., T. Balcarová, T. and Sergeeva, I. (2015) "Value Proposition Canvas: Identification of Pains, Gains and Customer Jobs at Farmers' Markets", *AGRIS on-line Papers in Economics and Informatics*, Vol. 7, No. 4, pp. 123 - 130, ISSN 1804-1930.

[71] Poole, N. (2017) "*Smallholder agriculture and market participation*", Food and Agriculture Organization of the United Nations (FAO) ISBN 978-1-78044-941-8. DOI 10.3362/9781780449401.

[72] Rahayu, B. I. and Riyanto, R. (2020) "The role of mobile phone and internet use in the performance of rural non-farm enterprises: An analysis of Indonesian rural households", *Buletin Pos dan Telekomunikasi*, Vol. 18, No. 1, pp. 29-46. E-ISSN 2443-1524. DOI 10.17933/bpostel.2020.180103.

[73] Raihan, A. (2023) "An overview of the energy segment of Indonesia: present situation, prospects, and forthcoming advancements in renewable energy technology", *Journal of Technology Innovations and Energy*, Vol. 15, No. 3, pp. 100-115. ISSN 2957-8809. DOI 10.56556/jtie.v2i3.599.

[74] Reschiwati, R., Budiantini, A. and Gusmiarni, G. (2021) "Examining the effect of firm-specific factors on the automotive industry in Indonesia", *International Journal of Research in Business and Social Science*, Vol. 10, No. 3, pp. 36-45. E-ISSN 2147-4478. DOI 10.20525/ijrbs.v10i3.1092.

[75] Richterová, E., Richter, M and Palkovič, J. (2021) "World´s 24 Biggest Agricultural Producers` Eco-Efficiency Considering Undesirable Outputs", *AGRIS on-line Papers in Economics and Informatics,* Vol. 13, No. 3, pp. 89-100. ISSN 1804-1930. DOI 10.7160/aol.2021.130309.

[76] Rissman, J., Bataille, C., Masanet, E., Aden, N., Morrow III, W. R., Zhou, N., Elliott, N., Dell, R., Heeren, N. and Huckestein, B. (2020) "Technologies and policies to decarbonize global industry: Review and assessment of mitigation drivers through 2070", *Applied Energy*, Vol. 266, p. 114848. ISSN 0306-2619. DOI 10.1016/j.apenergy.2020.114848.

[77] Sambodo, M., Yuliana, C. I., Hidayat, S., Novandra, R., Handoyo, F., Farandy, A. R., Inayah, I. and Yuniarti, P. I. (2022) "Breaking barriers to low-carbon development in Indonesia: Deployment of renewable energy", *Heliyon*, Vol. 8, No. 7, p. e09989. E-ISSN 2405-8440. DOI 10.1016/j.heliyon.2022.e09304.

[78] Sarjono, H., Trisnianto, M. M. and Handoko, B. (2021) "Machine maintenance planning with reliability centered maintenance to increase product quality reliability in The Indonesian automotive industry", *EBEE '21: Proceedings of the 2021 3rd International Conference on E-Business and E-commerce Engineering*, pp. 291 - 297. ISBN 978-1-4503-8739-2. DOI 10.1145/3510249.3510300.

[79] Sarstedt, M., Ringle, Ch. M., Smith, D., Reams, R., and Hair, J. F. (2014) "Partial least squares structural equation modeling (PLS-SEM): A useful tool for family business researchers", *Journal of Family Business Strategy*, Vol. 5, No. 1, pp. 105-115. E-ISSN 1877-8593, ISSN 1877-8585. DOI 10.1016/j.jfbs.2014.01.002.

[80] Scheffran, J., Felkers, M. and Froese, R. (2020) "Economic growth and the global energy demand", In: Vertes, A. A., Qureshi, N., Blaschek, H. P. and Yukawa, H. (eds) *Green Energy to Sustainability: Strategies for Global Industries*, pp. 1-44. ISBN 9781119152026. DOI 10.1002/9781119152057.ch1.

[81] Schiermeier, Q. (2019) "Eat less meat: UN climate-change report calls for change to human diet", *Nature*, Vol. 572, pp. 291-293. E-ISSN 1476-468.7. DOI 10.1038/d41586-019-02409-7.

[82] Seppelt, R., Beckmann, M., Ceauşu, S., Cord, A. F., Gerstner, K., Gurevitch, J., Kambach, S., Klotz, S., Mendenhall, C. and Phillips, H. R. P. (2016) "Harmonizing biodiversity conservation and productivity in the context of increasing demands on landscapes", *BioScience*, Vol. 66, No. 10, p. 890-896. E-ISSN 1525-3244. DOI 10.1093/biosci/biw004.

[83] Silalahi, D., Blakers, A., Stocks, M., Lu, B., Cheng, C. and Hayes, L. (2021) "Indonesia's Vast Solar Energy Potential", *Energies*, Vol. 14, No. 7, pp. 1456-1470. ISSN 1996-1073. DOI 10.3390/en14175424.

[84] Simatupang, P. and Timmer, C. P. (2008) "Indonesian rice production: Policies and realities", *Bulletin of Indonesian Economic Studies*, Vol. 44, No. 1, pp. 65-80. ISSN 0007-4918. DOI 10.1080/00074910802001587.

[85] Skoufias, E. and Olivieri, S. (2013) "Sources of spatial welfare disparities in Indonesia: Household endowments or returns?", *Journal of Asian Economics*, Vol. 29, pp. 62-79. ISSN 1049-0078. DOI 10.1016/j.asieco.2013.08.004.

[86] Sobocińska, M. (2022) "The moderating role of renewable energy intention on green purchase behavior", *Journal of Cleaner Production*, Vol. 253, pp. 119-130. ISSN 0959-6526.

[87] Špička, J., Eastham, J. and Arltová, M. (2021) "How the Income Elasticity of Meat Consumption differs between social groups? A case of the UK and the Czech Republic", *AGRIS on-line Papers in Economics and Informatics*, Vol. 13, No. 4, pp. 101-117. ISSN 1804-1930. DOI 10.7160/aol.2021.130409.

[88] Susilo, D. (2018) "Macro environment analysis of automotive industry in Indonesia", *BISE Journal*, Vol. 4, No. 2, pp. 65-73. E-ISSN 2548-7175. ISSN 2548-8961.

[89] Syamni, G., Wardhiah, Zulkifli, M. A. and Siregar, Y. (2021) "The relationship between renewable energy and sustainable development in Indonesia", *IOP Conference Series: Earth and Environmental Science*, Vol. 922, p. 012034. ISSN 1755-1307. DOI 10.1088/1755-1315/922/1/012034.

[90] Tang, R. Y. W. (1990) "The auto makers and their related party transactions in Indonesia", *Asia Pacific Journal of Management*, Vol. 7, No. 1, pp. 59-78. ISSN 0217-4561. DOI 10.1007/BF01731423.

[91] Tiawon, H. and Miar, M. (2023) "The Role of Renewable Energy Production, Energy Efficiency and Green Finance in Achieving Sustainable Economic Development: Evidence from Indonesia", *International Journal of Energy Economics and Policy*, Vol. 13, No. 1, pp. 120-135. ISSN 2146-4553. DOI 10.32479/ijeep.13915.

[92] Timmer, C. (1974) "A model of rice marketing margins in Indonesia", *Food Research Institute Studies*, Vol. 13, pp. 145-167. ISSN 0193-9025.

[93] Tomycho, O., Roy, N. D. and Nikmatul, K. (2020) "Shallot spatial market integration between surplus and deficit areas", *Russian Journal of Agricultural and Socio-Economic Sciences*, Vol. 105, No. 9, pp. 163-175. E-ISSN 2226-1184. DOI 10.18551/rjoas.2020-09.18.

[94] Udin, U. (2020) "Renewable Energy and Human Resource Development: Challenges and Opportunities in Indonesia", *International Journal of Energy Economics and Policy*, Vol. 10, No. 1, pp. 233-237. ISSN 2146-4553. DOI 10.32479/ijeep.8782.

[95] Van Phuong, N., Mai, N. T. N., Mergenthaler, M. Cuc, L. T. and Quynh, P. N. H. (2024) "The role of Social Media on Green Food Consumption Intention in Hanoi, Vietnam", *AGRIS on-line Papers in Economics and Informatics*, Vol. 16, No. 2, pp. 107-120. ISSN 1804-1930. DOI 10.7160/aol.2024.160208.

[96] Wahyudi, A., Kuwornu, J. K. M., Gunawan, E., Datta, A. and Nguyen, L. T. (2019) "Factors influencing the frequency of consumers' purchases of locally-produced rice in Indonesia: A Poisson regression analysis", *Agriculture*, Vol. 9, No. 6, pp. 117. ISSN 2077-0472. DOI 10.3390/agriculture9060117.

[97] Waluya, A. I., Iqbal, M. A. and Indradewa, R. (2019) "How product quality, brand image, and customer satisfaction affect the purchase decisions of Indonesian automotive customers", *International Journal of Services, Economics and Management*, Vol. 10, No. 2, pp. 177-193. E-ISSN 1753-0830. DOI 10.1504/IJSEM.2019.100944.

[98] Wati, S., Nendissa, D. R., Olviana, T. and Retang, E. U. K. (2021) "The Shallot Market Cointegration Between Markets in Province West Southeast and East Nusa Tenggara", *International Journal of Business, Technology and Organizational Behavior (IJBTOB)*, Vol. 1, No. 3, pp. 176-188. ISSN 2775-4936. DOI 10.52218/ijbtob.v1i3.92.

[99] Wibowo, S. (2015) "Credit constraints, risk sharing, and household welfare: The case of Indonesia", *Bulletin of Indonesian Economic Studies*, Vol. 51, No. 2, pp. 307-308. ISSN 0007-4918. DOI 10.1080/00074918.2015.1061918.

[100] Wicaksono, P., Hikmah, Y. and Ilmiawani, R. N. (2023) "Productivity and global value chains: A tale from the Indonesian automobile sector", *Economies*, Vol. 11, No. 10, p. 262. E-ISSN 2227-7099. DOI 10.3390/economies11100262.

[101] Xue, J. (2017) "Photovoltaic agriculture-New opportunity for photovoltaic applications in China", *Renewable and Sustainable Energy Reviews*, Vol. 73, pp. 1-9. E-ISSN 1879-0690. DOI 10.1016/j.rser.2017.01.098.

[102] Yu, J. and Lee, J. (2019) "Customer orientation and green product innovation", *Journal of Business Research*, Vol. 95, pp. 218-227. ISSN 0148-2963.

[103] Zafeiriou, E., Mallidis, I., Galanopoulos, K. and Arabatzis, G. (2018) "Greenhouse gas emissions and economic performance in EU agriculture: An empirical study in a non-linear framework", *Sustainability*, Vol. 10, No. 11, p. 3837. E-ISSN 2071-1050. DOI 10.3390/su10113837.

[104] Zdráhal, I., Verter, N. and Lategan, F. (2020) 'Products Mapping' of South Africa's Agri-food trade with the EU28 and Africa, *AGRIS on-line Papers in Economics and Informatics*, Vol. 12, No. 4, pp. 133-149. ISSN 1804-1930. DOI 10.7160/aol.2020.120410.

[105] Zeithaml, V. A. (1988) "Consumer perceptions of price, quality, and value: A means-end model and synthesis of evidence, *Journal of Marketing*, Vol. 52, No. 3, pp. 2-22. E-ISSN 1547-7185, ISSN 0022-2429. DOI 10.1177/002224298805200302.

[106] Zulkifli, M., Tohyama, R., Tohyama, T. and Maeda, K. (2019) "Renewable Energy Developments in Indonesia", *EPI International Journal of Engineering*, Vol. 7, No. 3, pp. 314-326. ISSN 2615-5109. DOI 10.25042/epi-ije.022019.15.

Volume XVI Number 4, 2024

Does Monetary Policy Stabilise Food Inflation in Hungary?

Imre Fertő[1,2,3], Tibor Bareith[1]

[1] Centre for Economic and Regional Studies, Budapest, Hungary

[2] Department of Agricultural Economics and Rural Development, Faculty of Business Administration, Corvinus University of Budapest, Hungary

[3] Department of Economics, Faculty of Economics and Management, Czech University of Life Sciences, Prague, Czech Republic

Abstract

This study examines the relationship between monetary policy and food price inflation in Hungary from January 2007 to December 2023 using the Nonlinear Autoregressive Distributed Lag (NARDL) model. Our analysis reveals that although the short-term impact of monetary policy on food prices is minimal, there is a notable long-term effect where implementing tighter monetary measures increases food price inflation over time. Policymakers must take a nuanced approach when dealing with food price shocks, considering both monetary and fiscal interventions. Our research highlights the significance of combining monetary policy actions with specific fiscal strategies and structural changes in the agriculture to reduce the negative effects of food inflation and protect the well-being of vulnerable populations.

Keywords

Food prices, inflation, monetary policy, Nonlinear ARDL, asymmetry.

JEL code: E31, E52, Q11, Q18

Fertő, I. and Bareith, T. (2024) "Does Monetary Policy Stabilise Food Inflation in Hungary?", *AGRIS on-line Papers in Economics and Informatics*, Vol. 16, No. 4, pp. 69-77. ISSN 1804-1930. DOI 10.7160/aol.2024.160405.

Introduction

The efficacy of monetary policy in stabilising food prices has been called into question by policymakers in light of the recent high and volatile food inflation in developed and developing countries. The recent increase in both the unpredictability and scale of food price inflation in developed and developing countries has raised doubts about the efficacy of monetary policy in controlling food prices. A theoretical framework for determining the most effective monetary policy to affect food inflation may be found in the literature (Pourroy et al., 2016; Anand et al., 2015; Catao and Chang, 2015; Soto, 2003; and Aoki, 2001). There has been an extensive amount of study on the link between monetary policy and inflation, but less on food inflation.

Policymakers are struggling to address the challenge of reducing food price shocks, as there are concerns that conventional monetary tools may not be sufficient for this task. While monetary restrictions may not have a direct impact on food inflation, they can significantly affect non-food prices and the overall economic output. Policymakers are considering how monetary policy affects food shocks, especially with increased uncertainty and inflation expectations due to spikes in food inflation. In impoverished nations, food insecurity contributes to an increase in infant and child mortality as well as malnutrition (de Brauw, 2011; Kidane and Woldemichael, 2020). The rapid and uncontrolled acceleration of inflation has been one of the biggest challenges for farmers in the commodity, energy and food markets (Belinska et al., 2023). The need to understand the connection between monetary policy and food prices is becoming more urgent as rising food prices disproportionately affect lower-income households. Elucidating this connection not only enhances our comprehension of economic mechanisms but also enhances public policy discussions, directing actions aimed at reducing the negative impacts of food inflation.

Hungary serves as a case study because within the European Union, food prices in Hungary are also particularly high. For comparison, in June 2023, average inflation in the European Union was 5.5%, food price growth was 11.6%, while the Hungarian data for the same period for the general price level was 19.9%, and food price growth was 29.3% annualised. The current situation is not a temporary shock, with food price growth consistently above 10% since January 2022, and above 20% since June 2022, exceeding 40% for six months. Such a price increase will affect lower-income households much more severely than those on higher incomes (Figure 1).

This study aims to examine the effectiveness of monetary policy in stabilising food price inflation, with a specific focus on Hungary. We use the Nonlinear Autoregressive Distributed Lag (NARDL) model to analyse the intricate connection between monetary policy shocks and food inflation from January 2007 to December 2023. We aim to use thorough empirical analysis to gain insights into the factors influencing food price changes and provide useful guidance for policymakers dealing with the challenge of reducing the negative effects of rising food prices.

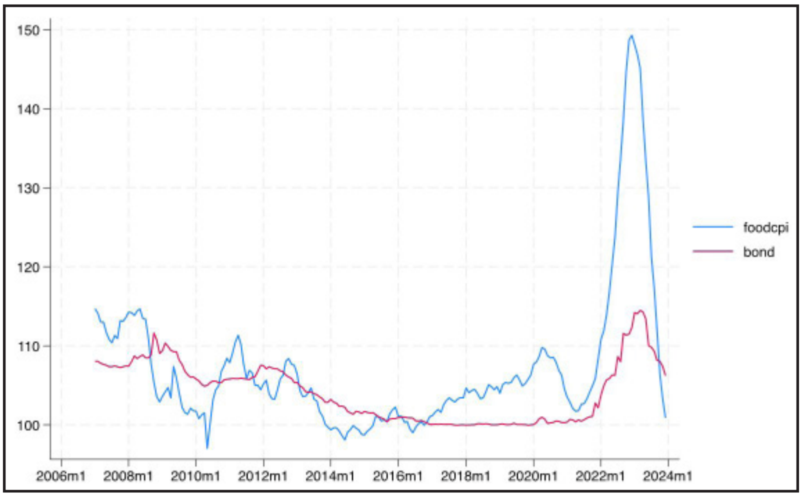
Review of related literature

Empirical studies on the impact of monetary policy on food inflation reveal a complex relationship, reflecting diverse outcomes across different countries and economic contexts. In India, research has directly examined the impact of monetary policy on food inflation. Anand et al. (2014) found that restrictive monetary policy effectively lowers food inflation. Kumar and Dash (2020) observed that monetary policy reduces inflation more in the industrial sector than in agriculture, and that tightening monetary policy promotes disaggregated food inflation. Höltemoller and Mallick (2016) reported that increasing interest rates reduces food price inflation in India, whereas Samal and Goyari (2022) indicated that monetary policy stabilizes food inflation. The transmission of monetary policy through exchange rate and asset price channels raises food inflation across all quantiles, while bank credit and interest rate channels reduce it at lower inflation rates in the lower and middle quantiles. Samal et al. (2022) found that per capita income, money supply, global food prices, and agricultural wages are positively and significantly impacted food price inflation in both the short and long-run.

Ali et al. (2022) investegated the impact of monetary policy on food inflation in Pakistan. They found that monetary policy and transportation prices remain highly significant across all quantiles, exhibiting a positive impact on food inflation. Thus restrictive monetary policy leads to higher flood inflation in the country. Their related paper found that monetary policy has limited short-term impact on food inflation in Pakistan due to inelastic food demand and supply constraints. However, in the long run, changes in money supply and interest rates significantly influence food prices (Ali et al., 2023).

In African context Iddrisu and Alagidede (2020) examined South African food prices, revealing that restrictive monetary policy increases food price uncertainty. Iddrisu and Alagidede (2021) found similar results for Ghana, where monetary policy tightening heightened food price uncertainty.

Bhattacharya and Jain (2020) expanded the scope to 16 advanced and emerging economies from 2006 to 2016, finding that unexpected monetary tightening increases food inflation via the cost of production channel.



Source: Hungarian Central Statistical Office and Hungarian National Bank

Figure 1: Evolution of food price inflation and 3-month bond rate.

In sum, empirical studies suggest that while tighter monetary policy generally reduces aggregate commodity prices, its effect on food inflation is more varied and context-dependent. Factors such as country-specific economic structures, the responsiveness of agricultural versus industrial prices, and the channels through which monetary policy operates (such as exchange rates, interest rates, and production costs) all play crucial roles in shaping the outcomes. Notice that there is no canonical theoretical background in the empirical literature, and studies using different empirical approaches including VAR (Vector Autoregressive models), quantile regression and NARDL models.

Materials and methods

The variables for empirical analysis are based on recent literature (Bhattacharya and Jain, 2020; Iddrisu and Alagidede, 2020, 2021; Samal et al., 2022). In studies examining the relationship between food inflation and monetary policy, economic output is frequently utilized as a key variable, with Gross Domestic Product (GDP) (e.g., Iddrisu and Alagidede, 2020; Kumar and Dash, 2020). Economic output levels serve as key indicators of a nation's economic health. In an economy, rising disposable incomes often spur increased inflation, including food inflation, as consumer demand grows. For a small, open economy such as Hungary, the strength of the national currency is an important macroeconomic variable. Hungary's external food trade is predominantly conducted with EU Member States and neighboring European nations, with transactions largely denominated in euros. Consequently, the Hungarian forint/euro exchange rate significantly influences imported food prices. Empirical models frequently incorporate foreign currency prices as variables (e.g., Holtemöller and Mallick, 2016; Umar and Umar, 2022; Ismaya and Anugrah, 2018). In many studies, the monetary policy variable is represented by the three-month government bond rate, which reflects changes in monetary policy (Bhattacharya and Jain, 2020; Iddrisu and Alagidede, 2020; Samal and Goyari, 2022).

We use monthly data from the Hungarian Central Statistical Office and the Hungarian National Bank for the period January 2007 to December 2023. The main variables are the Hungarian food inflation (CPIfood), the Hungarian economic output (GDP), the Hungarian forint/euro exchange rate (Euro), and the monetary policy variable (Policy), which is the three-month Hungarian government bond yield. All variables in the empirical analysis are included in the natural logarithm. Descriptive statistics of variables are shown in Table 1. lnPolicy exhibits the least variability, implying stable monetary policy. lnCPIfood also shows low variability, suggesting stable food inflation. In contrast, lnGDP has the highest standard deviation, indicating greater variability in economic output. lnGDP has the widest range, reflecting significant fluctuations in economic output. lnEuro shows moderate range and variability, pointing to exchange rate volatility. lnCPIfood and lnPolicy have narrower ranges, indicating relative stability in food inflation and bond yields, respectively (Table 1).

Variable	Obs	Mean	Std. dev.	Min	Max
lnCPIfood	204	4.672	0.082	4.575	5.006
lnGDP	204	15.997	0.308	15.487	16.823
lnEuro	204	5.732	0.128	5.447	6.037
lnPolicy	204	4.645	0.036	4.605	4.740

Source: own calculation

Table 1: Descriptive statistics.

Unit root tests are the first step in the NARDL analysis process. Financial and macroeconomic variables frequently show non-stationarity or trending behaviour in the mean. Unit root tests are statistically used to test the variables used in this study for (non)stationarity. We employ three unit root tests: Elliott-Rothenberg-Stock (1996), Phillips-Perron (1988) test and Zivot-Andrews (2002) unit root test with structural breaks. The optimal lag structure of the Elliott-Rothenberg-Stock test is chosen based on the Akaike Information Criterion. The optimal lag structure of the Phillips–Perron test is chosen based on the Newey–West bandwidth with Bartlett weights. The optimal lag structure of the Zivot and Andrews (2002) test was selected based on the Akaike information criterion. As can be seen from Figure 1, taking into account the breaks in the time series improves the estimation accuracy.

The analysis used a NARDL (Nonlinear AutoRegressive Distributed Lag) model to examine the research problem. The NARDL is a statistical model used to analyse the relationship between time series data when the relationship between variables is non-linear and asymmetric. To check for non-linearity, we employ the BDS (Brock-Dechert-Scheinkman) test. The BDS test tests the time series for deviations from the assumptions of independence and identity of distribution (IID).

The NARDL model includes both autoregressive (AR) and moving average (MA) terms. The NARDL model can be used to separate positive and negative effects on the dependent variable in both the short and long run. The NARDL model is assuming stationarity, which has been verified by unit root tests. The most common application of NARDL is to understand the relationships between different macroeconomic time series. Examining the asymmetric effect between variables provides a way to measure how the dependent variable changes as each variable decreases and increases. When relationships are not symmetric, economic and monetary policy makers need to take this effect into account. The asymmetric long-run equilibrium can be defined as follows:

$$y_t = ß^+ x_t^+ + ß^- x_t^- + \varepsilon_t \quad (1)$$

where y_t is the dependent variable, x_t^+ and x_t^- are the partial cumulative sum processes of positive and negative changes in the dependent variables (x_t), β^+ and β^- represent the asymmetric long-run parameter, ε_t is the random error term. The NARDL model can be posed as follows when we combine model (1) with the unconstrained linear ARDL (p, q) specification:

$$\Delta y_t = \alpha_0 + r y_{t-1} + \theta^+ x_{t-1}^+ + \theta^- x_{t-1}^- + + \sum_{j=1}^{p-1} \tau_j \Delta y_{t-j} + \sum_{j=0}^{q-1} (\pi_j^+ \Delta x_{t-j}^+ + \pi_j^- \Delta x_{t-j}^-) + \varepsilon_t \quad (2)$$

where y_t is the dependent variable (lnCPIfood), x_t represents the independent variables (lnGDP, lnEuro, lnPolicy), and the superscripts + and - denote positive and negative partial sum processes, respectively. The lag lengths p and q are chosen based on the Akaike Information Criterion (AIC).

where $\sum_{j=0}^{q-1} \pi_j^+$ and $\sum_{j=0}^{q-1} \pi_j^-$ represent the short-run asymmetry of Δx_t, and the parameterizations of the long-run asymmetry are as follows:

$$ß^+ = -\frac{\theta^+}{r} \; and \; ß^- = -\frac{\theta^-}{r} \quad (3)$$

Diagnostic tests for heteroskedasticity, autocorrelation, and model stability are performed to ensure the robustness of the estimates. The natural logarithms of all variables were used in the modelling, as shown in the descriptive statistics (Table 1).

The statistical method chosen has several advantages over OLS estimation: (1) First, the relationship between most macroeconomic variables is non-linear; (2) Second, heteroskedasticity is better handled, and therefore the estimation is more reliable; (3) Last but not least, autocorrelation is better handled than the traditional OLS model. The estimation were done with STATA MP 17.

Results and discussion

The various unit root test results for the variables utilised in the analysis, both at the level and at first difference, are shown in Table 2. The Elliott-Rothenberg-Stock unit root test is based on the Akaike information criterion lag. Results show that, the first difference of all variables can be considered as stationary, which is important for NARDL modelling.

Table 3 shows the results of the Zivot-Andrews unit root test with structural break (intercept and trend). The results of the Zivot-Andrews unit root test are the same as the results of the Elliott-Rothenberg-Stock and Phillips-Perron tests in Table 2, i.e. the first difference of the variables is stationary. Hereafter, the first differences are used in the models. The results of the structural break test (break date) can be used for modelling. A dummy variable can be created, denoted by 1 from the time series break date, to measure the effect of the time series break and to separate it.

After testing for unit root tests, we estimated the linear model and employed BDS independence test Broock et al. (1996) on residuals to check non-linearity. The results confirm that of the series is not identically and independently distributed which confirms the presence of asymmetries (Table 4). Therefore, it is necessary to the employ dynamic asymmetric framework for the analysis of the nonlinear relationship between food inflation and macroeconomic variables in Hungary.

	Elliott-Rothenberg-Stock (AIC)				Phillips-Perron			
	intercept		intercept, trend		intercept		intercept, trend	
	Level	First diff.	Level	First diff.	Level	First diff.	Level	First diff.
lnCPIfood	-1.258	-3.508***	-1.322	-3.800***	-2.312	-6.680 ***	-2.427	-6.658***
lnGDP	2.718	-1.578*	-0.353	-3.146 **	0.020	-5.644***	-4.012 ***	-5.648***
lnEuro	2.145	-4.196***	-1.912	-6.116***	-1.077	-11.417***	-3.950 ***	-11.388***
lnPolicy	-1.140	-3.958***	-1.605	3.457***	-1.497	-13.178***	-1.207	-13.225***

Note: *** p<0.01; ** p<0.05; * p<0.1
Source: own calculation

Table 2: Unit-root tests.

	Level		First diff.	
	min. t-statistics	break date	min. t-statistics	break date
lnfoodcpi	-5.256***	2013m7	-5.106***	2021m6
lnGDP	-6.729***	2012m1	-7.378***	2020m9
lneuro	-5.292**	2016m8	-11.538**	2011m12
lnPolicy	-3.180	2018m6	-5.039***	2021m6

Note: Critical values: 1%: -5.57; 5%: -5.08; 10%: -4.82
*** $p<0.01$; ** $p<0.05$; * $p<0.1$
Source: own calculation

Table 3: Zivot-Andrews unit root test with structural break (intercept and trend).

	BDS statistic at different dinemsions				
	2	3	4	5	6
lnCPIfood	23.968***	25.192***	26.773***	29.108***	32.339***
lnGDP	53.919***	56.341***	59.551***	64.592***	71.669***
lnEuro	39.435***	41.637***	44.498***	48.779***	54.625***
lnPolicy	48.287***	51.389***	55.215***	60.761***	68.280***

Source: own calculation

Table 4: BDS tests.

The results of the unit root tests show that the first difference of all variables can be considered stationary, the BDS tests show that asymmetry is present in the data, therefore, we can thoroughly estimate the NARDL model.

The NARDL short-run coefficients of the inflation equation are presented in Table 5, while the computed long-run coefficients and asymmetric tests are presented in Table 6. The Bounds-test for Nonlinear Cointegration rejects the null hypothesis of no cointegration. In the long run, food prices show a downward trend ($lncpifood_{t-1}$), while in the short run, the stickiness of inflation is typical, with positive coefficients ($Dlncpifood_{t-1}$; $Dlncpifood_{t-3}$) The fall in GDP in period t-1 ($lnGDP_{t-1}^{-}$; $lnGDP_{t-1}^{+}$) also reduces food prices. In the short run, GDP growth ($DlnGDP^{+}$) decreases food prices. In the case of the HUFEUR exchange rate ($DlnEuro_{t-2}^{-}$), a fall in the exchange rate (strengthening of the forint) increases food prices, an effect that is the same in the short and long run. An increase in the monetary policy variable ($lnPolicy_{t-1}^{+}$) increases food prices in the long run, indicating inefficiency of monetary policy, as prices do not fall during the monetary policy tightening period. The effects of monetary policy tightening in African countries contrast with the trends observed in Hungary and globally (e.g., Iddrisu and Alagidede, 2020; 2021). Despite efforts to manage monetary policy, both food prices and overall price levels have escalated. This phenomenon can be attributed to several factors, including rising costs on the supply side and inflation expectations, which undermine the efficacy of monetary policy.

A significant factor influencing this dynamic is Hungary's role in foreign trade. As a net exporter of basic food commodities like wheat and maize, Hungary imports a substantial amount of processed food products. This trade structure affects the domestic food inflation response to monetary policy changes.

Contrary to common findings in similar studies, monetary policy in Hungary appears to have a neutral impact on food inflation in the short run. Most research typically finds that tightening monetary policy suppresses price increases (e.g., Kumar and Dash, 2020; Anand et al., 2014). Several reasons may explain this neutrality. First, as a small and open economy, Hungary's capacity to counteract international trends is limited. The economies examined in the literature where restrictive monetary policy successfully curbs food inflation are generally more powerful than Hungary's. Moreover, the inelastic demand for food and the higher proportion of food in Hungarian household consumption compared to the EU average further diminish the impact of monetary policy on food inflation.

We also estimated the model incorporating structural break identified by the Zivot-Andrews unit root test as dummy variable. We find that the structural break dummy variables were not significant, and the model did not show cointegration within the NARDL framework. The insignificance of the structural break dummy variables and the lack of cointegration within the NARDL framework suggest that structural breaks do not meaningfully impact the relationship between the variables in our model. This indicates that the observed dynamics are stable over time, and the effects of monetary policy on food inflation are not influenced by these structural changes.

	Coefficient
lncpifood t-1	-0.133***
$lnGDP^+$ t-1	-0.036**
$lnGDP^-$ t-1	-0.077**
$lnEuro^+$ t-1	-0.009
$lnEuro^-$ t-1	0.067
$lnPolicy^+$ t-1	0.168**
$lnPolicy^-$ t-1	0.137
Dlncpifood t-1	0.375***
Dlncpifood t-2	0.129
Dlncpifood t-3	0.304***
$DlnGDP^+$	-0.202**
$DlnGDP^+$ t-1	0.212
$DlnGDP^+$ t-2	-0.168
$DlnGDP^+$ t-3	0.017
$DlnGDP^-$	-0.039
$DlnGDP^-$ t-1	0.179
$DlnGDP^-$ t-2	-0.046
$DlnGDP^-$ t-3	0.087
$DlnEuro^+$	0.046
$DlnEuro^+$ t-1	-0.086
$DlnEuro^+$ t-2	-0.071
$DlnEuro^+$ t-3	-0.028
$DlnEuro^-$	-0.117
$DlnEuro^-$ t-1	0.122
$DlnEuro^-$ t-2	0.335***
$DlnEuro^-$ t-3	0.125
$DlnPolicy^+$	0.266
$DlnPolicy^+$ t-1	0.399
$DlnPolicy^+$ t-2	0.451*
$DlnPolicy^+$ t-3	0.32
$dlnPolicy^-$	0.065
$dlnPolicy^-$ t-1	0.412
$dlnPolicy^-$ t-2	-0.33
$dlnPolicy^-$ t-3	0.114
constant	0.630***
N	200
R^2	0.6408
Bound test	Value
F- statistics	-4.5976***
t-statistics	5.5643***

Note: *** p<0.01; ** p<0.05; * p<0.1
Source: own calculation

Table 5: Results of NARDL model.

Table 6 displays the outcomes of the short- and long-term asymmetry tests as well as the long-term impacts of the positive and negative shocks. The proxy variable for monetary policy (lnPolicy) is positive and significant for the long-run positive shocks, meaning that tightening monetary policy over time raises food prices which is in line with Samal et al. (2022). Negative shocks do not significantly have the same effect. On the other hand, for the long-run negative shocks, at 95% confidence level, food inflation rises with a decline in GDP, at 90% confidence level, food inflation decreases with an increase in GDP in the long run. The results show that there is no statistically proven relationship between food prices and the EUR exchange rate. Results on asymmetry imply that over the long term, asymmetry affects GDP and exchane rate; for example, the direction of a shock affects how food prices respond to it. This effect is only seen for exchange rate (lnEUR) in the short run.

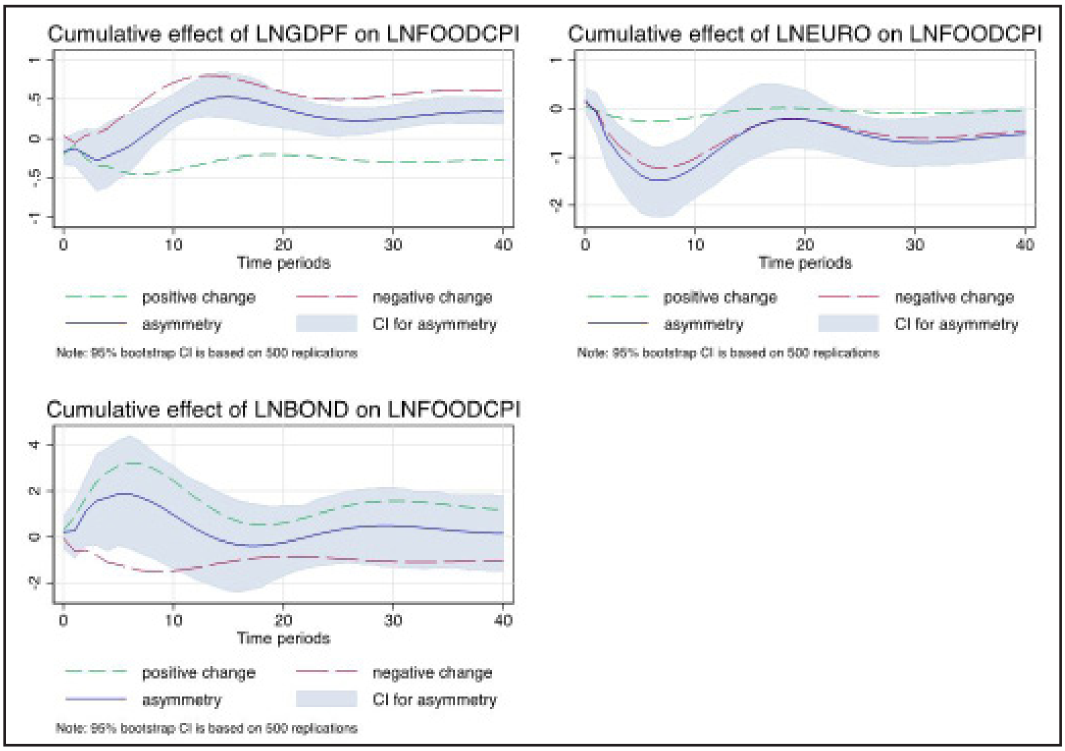
The monetary policy variable was found to be symmetric, while the variable was significant only for long-run positive shocks, i.e. positive shocks (tightening) increase food prices in the long run. In a high or rising inflation environment, monetary policy tightening is found to have the opposite effect on food prices. With rising food prices, lower income households are at risk. High general inflation causes the real value of wages to fall while food prices rise due to tightening monetary policy. The situation is not improved by the asymmetric effect, the results suggest that monetary policy easing does not reduce food prices in the long run.

The results in Table 6 demonstrate that the asymmetry persists over an extended period of time, as shown the graphs in Figure 2. The asymmetric effect for GDP shows a decline in the very short run (3-4 months), then increases steadily until months 13-14 and stabilises around months 17-18 with low volatility. That is, in the long run, GDP growth increases food prices more than GDP decline reduces them. The exchange rate asymmetry is negative throughout the period. Up to months 8-9, asymmetry increases, the negative shock reduces food prices, but this trend reverses and at month 18 asymmetry is at its lowest, but still negative. Thereafter, asymmetry settles to a broadly stable level. Monetary policy asymmetry (LNBOND on LNFOODCPI) increases in the short run, peaks around months 6-7 and then steadily decreases and staticizes around 0, i.e. there is no asymmetry in the long run.

	Long-run effect [+]			Long-run effect [-]		
	coef.	F-stat	P value	coef.	F-stat	P value
lnGDP	-0.271	3.646	0.058	0.583	6.624	0.011
lnEuro	-0.065	.07426	0.786	-0.501	2.063	0.153
lnPolicy	1.270	9.713	0.002	-1.030	1.212	0.273
		Long-run asymmetry			Short-run asymmetry	
		F-stat	P value		F-stat	P value
lnGDP		11.26	0.001		2.696	0.103
lnEuro		3.818	0.052		3.519	0.062
lnPolicy		0.065	0.8		1.85	0.176

Note: *** p<0.01; ** p<0.05; * p<0.1
Source: own calculation

Table 6: Results of asymmetric effects.



Source: own calculation

Figure 2: Cumulative effects on food price index.

Conclusion

Our study using the NARDL model provides detailed insights into the complex connection between monetary policy and food price inflation, offering important guidance for policymakers dealing with the task of managing food price fluctuations. Our main findings are following. Estimations indicate that monetary policy exerts a positive and significant impact on long-run positive shocks, suggesting that tightening monetary policy elevates food prices, corroborating prior research. Conversely, negative shocks do not yield the same effect. In the long run, food inflation rises with GDP declines and decreases with the strengthening of the Hungarian forint against the euro, although the relationship between food prices and the EUR exchange rate is not statistically significant.

The monetary policy variable demonstrates symmetry, with asymmetric effects only observed for long-run positive shocks. In environments characterized by high or rising inflation, monetary policy tightening paradoxically increases food prices. This asymmetric effect persists over an extended period, with GDP growth driving food prices up more than GDP declines bring them down. The exchange rate asymmetry remains negative throughout the period, increasing until months 8-9 and decreasing by month 18, while the exchange rate shows no long-run asymmetry.

Our results offers some policy implications. These findings suggest that policymakers should exercise caution when tightening monetary policy to control food price inflation, as it may inadvertently elevate food prices, particularly in the long term. This counterintuitive response emphasizes the need for a balanced approach to avoid exacerbating food inflation. Effective management of food price inflation necessitates an integrated strategy combining monetary and fiscal policy measures. Given the substantial share of disposable income that Hungarian households allocate to food, targeted fiscal interventions are essential to mitigate the adverse effects of food inflation. Addressing structural issues within the agricultural sector, enhancing productivity, and building resilience against external disruptions are imperative. Investments in agricultural infrastructure, research and development, and social safety nets are crucial for bolstering food security and reducing household vulnerability to food price volatility. he impact of monetary policy on food inflation is influenced by global economic conditions, exchange rate fluctuations, and supply chain interruptions. Thus, policy responses must be adaptable to these external factors.

Finally, future research directions could include examining inter-country food trade and incorporating additional variables to measure the robustness of monetary policy effects. Comparing Hungary's outcomes with those of similarly sized countries could yield further valuable insights into managing food price inflation.

Acknowledgements

This work has been funded by the Hungarian Scientific Research Fund (OTKA: otka.hu) grant No. PD146385.

Corresponding author:
Tibor Bareith, Ph.D.
Centre for Economic and Regional Studies
Tóth Kálmán u. 4., 1097 Budapest, Hungary
Phone: +36 30 282 3511, Email: bareith.tibor@krtk.hun-ren.hu

References

[1] Ali, C. I., Ullah, S., Ahmed, U. I., Baig, I. A., Iqbal, M. A. and Masood, A. (2022) "Can Food Inflation Be Stabilized By Monetary Policy? A Quantile Regression Approach", *Journal of Economic Impact*, Vol. 4, No. 3, pp. 205-212. ISSN 2664-9764. DOI 10.52223/jei4032207.

[2] Ali, C. I., Ullah, S., Ahmed, U. I., Rehman, A. U., Mehmood, H. Z., Yasin, M. and Raza, M. (2023) "Short and Long Run Effects of Monetary Policy on Food Inflation: A Study of Pakistan", *Journal of Economic Impact*, Vol. 5, No. 2, pp. 146-154. ISSN 2664-9764. DOI 0.52223/j.econimpact.2023.5203.

[3] Anand, R., Ding, D. and Tulin, M. V. (2014) "Food inflation in India: The role for monetary policy", IMF Working Paper WP/14/178, International Monetary Fund.

[4] Aoki, K., (2001) "Optimal monetary policy responses to relative-price changes", *Journal of Monetary Economics,* Vol. 48, No. 1, pp. 55-80. E-1873-1295, ISSN 0304-3932. DOI /10.1016/S0304-3932(01)00069-1.

[5] Belinska, S., Bielik, P. and Belinska, Y. (2023) "The Impact of the Price Factor on Farmers' Incomes in Turbulent Conditions", *AGRIS online Papers in Economics and Informatics*, Vol. 15, No. 3, pp. 15-24. ISSN 1804-1930. DOI 10.7160/aol.2023.150302.

[6] Bhattacharya, R. and Jain, R. (2020) "Can monetary policy stabilise food inflation? Evidence from advanced and emerging economies", *Economic Modelling*, Vol. 89, pp. 122-141. ISSN 0264-9993. DOI 10.1016/j.econmod.2019.10.005

[7] Catão, L. A. V. and Chang, R., (2015) "World food prices and monetary policy", *Journal of Monetary Economics,* Vol. 75, No. 1, pp. 69-88. E-1873-1295, ISSN 0304-3932. DOI 10.1016/j.jmoneco.2014.12.010.

[8] De Brauw, A. (2011) "Migration and child development during the food price crisis in El Salvador", *Food Policy*, Vol. 36, No. 1, pp. 28-40. ISSN 0306-9192. DOI 10.1016/j.foodpol.2010.11.002.

[9] Elliott, G., Rothenberg, T. J. and Stock, J. H. (1996) "Efficient tests for an autoregressive unit root", *Econometrica*, Vol. 64, pp. 813-836. E-ISSN 1468-0262. ISSN 0012-9682. DOI 10.2307/2171846.

[10] Holtemöller, O. and Mallick, S. (2016) "Global food prices and monetary policy in an emerging market economy: The case of India", *Journal of Asian Economics*, Vol. 46, pp. 56-70. ISSN 1049-0078. DOI 10.1016/j.asieco.2016.08.005.

[11] Iddrisu, A. A. and Alagidede, I. P. (2020) "Monetary policy and food inflation in South Africa: A quantile regression analysis", *Food Policy*, Vol. 91, p. 101816. ISSN 0306-9192. DOI 10.1016/j.foodpol.2019.101816.

[12] Iddrisu, A. A. and Alagidede, I. P. (2021) "Asymmetry in food price responses to monetary policy: a quantile regression approach", *SN Business & Economics*, Vol. 1, No. 3, pp. 1-25. E-ISSN 2662-9399. DOI 10.1007/s43546-021-00056-7.

[13] Ismaya, B. I. and Anugrah, D. F. (2018) "Determinant of food inflation", *Bulletin of Monetary Economics and Banking*, Vol. 21, No. 1, pp. 81-94. ISSN 14108046. DOI 10.21098/bemp.v21i1.926.

[14] Kidane, D. and Woldemichael, A. (2020) "Does inflation kill? Exposure to food inflation and child mortality", *Food Policy*, Vol. 92, p. 101838. ISSN 0306-9192. DOI 10.1016/j.foodpol.2020.101838.

[15] Kumar, A. and Dash, P. (2020) "Changing transmission of monetary policy on disaggregate inflation in India", *Economic Modelling*, Vol. 92, pp. 109-125. ISSN 0264-9993. DOI 10.1016/j.econmod.2020.07.016

[16] Phillips, P. C. and Perron, P. (1988) "Testing for a unit root in time series regression", *Biometrika,* Vol. 75, pp. 335-346. E-ISSN 1464-3510, ISSN 0006-3444. DOI 10.1093/biomet/75.2.335.

[17] Pourroy, M., Carton, B. and Coulibaly, D. (2016) "Food prices and inflation targeting in emerging economies", *International Economics*, Vol. 146, pp. 108-140. E-ISSN 2542-6869, ISSN 2110-7017. DOI 10.1016/j.inteco.2015.12.001.

[18] Samal, A. and Goyari, P. (2022) "Does Monetary Policy Stabilise Food Inflation in India? Evidence From Quantile Regression Analysis", *Australian Economic Review*, Vol. 55, No. 3, pp. 361-372. ISSN 1467-8462, ISSN 0004-9018. DOI 10.1111/1467-8462.12474.

[19] Samal, A., Ummalla, M. and Goyari, P. (2022) "The impact of macroeconomic factors on food price inflation: an evidence from India", *Future Business Journal*, Vol. 8, No. 1, pp. 1-14. E-ISSN 2314-7210. DOI 10.1186/s43093-022-00127-7.

[20] Soto, C. (2003) "Non-traded Goods and Monetary Policy Trade-Offs in a Small Open Economy", Working Paper 214. Central Bank of Chile.

[21] Umar, U. A. and Umar, A. (2022) "Effects of exchange rate on food inflation in Nigeria: A non-linear ARDL approach", *Gusau International Journal of Management and Social Sciences*, Vol. 5, No. 1, pp. 195-209. E-ISSN 2787-0383, ISSN 2735-9026.

[22] Broock, W. A., Scheinkman, J. A., Dechert, W. D. and LeBaron, B. (1996) "A test for independence based on the correlation dimension", *Econometric Reviews*, Vol. 15, No. 3, pp. 197-235. E-ISSN 1532-4168, ISSN 0747-4938. DOI 10.1080/07474939608800353.

[23] Zivot, E. and Andrews, D. W. K. (2002) "Further evidence on the great crash, the oil-price shock, and the unit-root hypothesis". *Journal of Business & Economic Statistics,* Vol. 20, pp. 25-44. E-1537-2707, ISSN 0735-0015. DOI 10.1198/073500102753410372.

Volume XVI Number 4, 2024

Application of Quality Management System in the Research Process: A Case Study for Plant Phenotyping Research

Alexander Galba, Eva Kánská, Vojtěch Mikeš, Jiří Vaněk, Jan Jarolímek

Department of Information Technologies, Faculty of Economics and Management, Czech University of Life Science Prague, Czech Republic

Abstract

Phenomics research, driven by advancements in imaging and image processing, enables high-throughput measurements of plant traits, providing insights into growth, tissue development, and biochemical states. However, data accuracy is critical to reliable outcomes, especially in complex methods like 3D reconstruction and hyperspectral imaging. This study demonstrates the role of Quality Management Systems (QMS) in enhancing the research process in plant phenotyping. The study emphasizes the importance of a robust data quality assurance pipeline, focusing on error identification and improving data labeling processes through semi-automation. Root Cause Analysis (RCA) was employed to address discrepancies in annotated datasets and identify critical issues, such as misalignment in experimental protocols and operational errors, including the misplacement of irrigation hoses during data collection. Corrective actions, such as photo documentation and procedural revisions, significantly improved data quality. Additionally, algorithmic support streamlined the annotation process, increasing efficiency and data reliability. This integrated approach underscores the necessity of quality control in research, especially for geographically distributed teams working under variable conditions, and highlights the broader applicability of QMS in optimizing research outputs.

Keywords

Quality management system, data quality, plant phenotyping, research process, root cause analysis, data labeling process.

Galba, A., Kánská, E., Mikeš, V., Vaněk, J. and Jarolímek, J. (2024) "Application of Quality Management System in the Research Process: A Case Study for Plant Phenotyping Research", *AGRIS on-line Papers in Economics and Informatics*, Vol. 16, No. 4, pp. 79-86. ISSN 1804-1930. DOI 10.7160/aol.2024.160406.

Introduction

Phenomics research has benefited from the methods and devices allowing the high throughput measurements of plant traits at different levels, including growth-related traits, cells and tissue development, and biochemical and physiological states. Imaging and image processing developments enable capturing how these traits vary over time. Advancements in parallel and automated image acquisition allow for processing images of large plant populations under specific growth conditions. Image-processing capabilities enable 3D reconstruction of image data and automated quantification of biological features. (Simek et al., 2015) These advancements allow modeling at the systems level (Dhondt et al., 2013; Fiorani and Schurr, 2013; Kartal et al., 2021; Paulus, 2019; Pongpiyapaiboon et al., 2023; Sozzani et al., 2014; Vadez et al., 2015).

The goal of using digital methods is to achieve the best possible accuracy in identifying the biological parameters of the observed plants. A prerequisite for such accuracy is a high-quality database. Errors in data are the basis for poor-quality outputs or erroneous research conclusions. To achieve the best possible research results, it is necessary to pay attention to the quality of the entire research process (Ronanki et al., 2022).

The application of Quality Management Systems (QMS) in plant phenotyping research plays a pivotal role in ensuring data accuracy and consistency, especially with the increasing complexity of hyperspectral imaging and sensor-based techniques. For instance, a quality assurance pipeline developed for hyperspectral imaging systems ensures that spatial and spectral quality parameters are accurately maintained, enabling reliable detection of plant diseases such as Cercospora Leaf Spot through convolutional neural network (CNN)-supported data analysis. This quality-assured approach is crucial for evaluating and refining imaging systems in real-time plant health monitoring (Detring et al., 2024). Another critical aspect of QMS in plant phenotyping is data management, essential for handling the vast amounts of digital data generated by automated sensing systems. Ensuring that data-sharing practices align with FAIR (Findability, Accessibility, Interoperability, and Reusability) principles can enhance the reproducibility and efficiency of research processes. (Ugochukwu and Phillips, 2022) The integration of advanced phenotyping methods, such as 3D reconstruction and leaf surface estimation, further highlights the need for robust data collection and analysis quality control to optimize workflows and reduce processing times (Daiki and Noshita, 2024).

The application of Quality Management Systems in the research process ensures consistent standards, minimizes errors, and enhances the reliability of outcomes. In clinical and public health research, QMS is essential to maintain protocol integrity, prevent deviations, and uphold the credibility of research findings. By implementing systematic procedures, research teams can ensure rigorous data quality and operational efficiency (Isere and Omorogbe, 2024). Additionally, in biomedical laboratories, QMS helps address quality issues, such as result stability and replication crises, by optimizing research processes and increasing effectiveness and efficiency. Despite initial resistance due to resource allocation and bureaucracy concerns, QMS offers significant advantages in process control and reliability.(Brünschwitz and Kleymann-Hilmes, 2024) Furthermore, operations research methods integrated with QMS in engineering and industrial contexts enable continuous improvement through mathematical modeling and optimization techniques, ensuring product and service quality across all phases (Parker, 2024). The application of QMS in research laboratories, such as in the petroleum industry, improves client satisfaction, reduces failure rates, and fosters industry-academia collaboration, providing a robust framework for process optimization and innovation (Vianna et al., 2022).

This article's main objective is to apply the quality management system in the research process to increase the quality of outputs.

Material and methods

Our research in the field of plant phenotyping is conducted by an international team located worldwide in various places and time zones. Researchers are located in the Czech Republic (The Czech University of Life Sciences), the Netherlands (Phenospex), India (ICRISAT - The International Crops Research Institute for the Semi-Arid Tropics), and Turkey (Cukurova University)

The research aims to estimate plant traits from 3D scans of plants acquired by the high-throughput phenotyping platform LeasyScan (built using Phenospex PlantEye F600 sensor). Subsequently, individual plant detection, organs, and other analyses are performed mainly using 3D computer vision methods. Obtaining 3D models outdoors brings efficiency to the entire research process. It does not require excessive manipulation with plants. Part of the process involves manually annotating datasets to train the artificial neural network models. The general scheme of the entire research is depicted in Figure 1.

The research commenced following the task assignment. Time sessions were set up for regular meetings where interim results were reviewed, schedules were discussed, and next steps were suggested. Control mechanisms were also part of the regular consultations. The method of selecting and checking a sample of data was chosen for control. The conclusions from the data control were regularly consulted, and measures were taken to correct the identified deficiencies.

The following procedure was chosen for the data flow: Data acquisition -> Data preprocessing -> Data Annotation. Data acquisition was performed in India using the LeasyScan platform. The source data was then stored and managed by Phenospex's Hortcontrol system, which is also available using BrAPI. Validated algorithms were used for

Source: Author

Figure 1: The general scheme of the entire research.

data preprocessing. The preprocessing consists of several steps, i.e., rotation, merging, voxelization, smoothing, and soil segmentation. The subsequent data annotation step was performed using the Segments.ai environment. All procedures were rechecked and verified (*Multi-Sensor Data Labeling Platform for Robotics and AV | Segments. Ai, n.d.; Phenospex - Smart Plant Analysis and Phenotyping Systems, n.d.*).

Over time, it became clear that the set rules needed to be revised to ensure the overall quality of the research process. Weaknesses in the quality of the data, rather than in the quality of the steps used, were identified. Regular online meetings of all groups and information sharing, including the control mechanisms, are still needed to eliminate the deficiencies.

The primary source of deficiencies was identified in the data annotation process for generating test and control datasets using artificial neural networks. The number of annotated plants for the ground-truth did not match the predictions. The first step to correcting this situation was to increase the qualification of persons designated for data labeling through regular training and more detailed checks. It turned out that this procedure only solved the consequences and not the source of the error. It was evident that it was necessary to revise the entire research process and find the source of the inaccuracies.

The control mechanisms, consisting of the selection of samples and their control, needed to be revised, and it was decided that it was necessary to find a way to check all the acquired data. At the same time, it was essential to check all steps to exclude the possibility of multiple sources of errors. To avoid further problems in the future, the methodological procedure expressed in Figure 2 Plan to improve the research process was chosen.

Source: Author

Figure 2: Plan to improve research process.

It was important for the whole process to choose a method to identify the bottleneck. During the discussion, it became clear that the methods used are mainly focused on the commercial area or processes in the public sector. Their application in research is only partially obvious. Most methods focus on streamlining the process regarding time, costs, or risk analysis. Some methods are extensive, and their application would require longer (ISO). A common attribute of these methods is creating a detailed procedure diagram in various formats. This procedure is then supplemented with tools and procedures to detect deficiencies and thereby increase the quality of the entire process. The diagram expresses the sequence of causes and effects and the influence of the main actors. (Bali et al., 2021; *ISO 9001:2015 - Quality Management Systems - Requirements, n.d.*; Serrat, 2017; Shook, 2008; Starzyńska and Hamrol, 2013; Venkatasubramanian et al., 2003) The display allows a better understanding of the sequence of events and the identification of critical points. The methods then focus on these and increase quality by applying appropriate control mechanisms. It is a suitable tool to express the quality of the process in a measurable quantity. In practice, this may be time, the number of erroneous outputs, or a combination of similar values. Based on such a criterion, the success of the applied method can then be evaluated. An overview of the methods is shown in Figure 3 (Tarí and Sabater, 2004a).

The assessment of which method is appropriate depends on the perspective of the participants and the definition of the target parameters. Finally, the point of view of the greatest possible generality in use and applicability for scientific research was chosen. From this point of view, the root case analysis method was chosen. A Root Cause Analysis (RCA) is the process of identifying the most fundamental reason for the problem, which, if eliminated or corrected, would prevent the problem from reoccurring. Various techniques for analysis can be used for this method, and therefore, its application is suitable for multiple environments, including high-risk industries such as medicine or drug development (Andersen and Fagerhaug, 2000; Percarpio et al., 2008; Andersen, B. and Fagerhaug, T. (2006); Wilson et al., 1993; Yuniarto, 2012).

Creating a measurable parameter expressing the source data's quality and accuracy proved essential. In addition to the position in 3D space, the data from the device also contained information about the point's color. A method based on the height parameter of individual points (z-axis value) was chosen for the check. The points in each data sample were divided into 2 groups according to height. The division had the following assumptions:

The seven basic quality control tools	The seven management tools	Other tools	Techniques
Cause and effect diagram	Affinity diagram	Brainstorming	Benchmarking
Check sheet	Arrow diagram	Control plan	Departmental purpose
Control chart	Matrix diagram	Flow chart	analysis
Graphs	Matrix data analysis method	Force field analysis	Design of experiments
Histogram	Process decision	Questionnaire	Failure mode and effects analysis
Pareto diagram	Programme chart	Sampling	Fault tree analysis
Scatter diagram	Relations diagram		Poka yoke
	Systematic diagram		Problem solving methodology
			Quality costing
			Quality function deployment
			Quality improvement teams
			Statistical process control

Source: Tarí and Sabater, 2004b

Figure 3: Overview of the methods.

- Group 1 may contain points belonging to the color of soil and flower pots
- Group 2 may contain points in a color belonging only to plants

Subsequently, the color in individual groups was checked algorithmically for all samples. It turned out that in Group 2, there were points whose color did not correspond to the points of plants. This finding was supplemented by the knowledge from the manual labeling of samples, where some points and shapes could not be labeled as parts of plants. The number of points not corresponding to plants in group 2 was determined as a measurable data quality criterion. This finding focused the research team's attention on preparing and implementing experiments when obtaining source data. In addition to creating a quantifiable indicator expressing the quality of the data, we focused on the entire research process.

Results and discussion

To apply RCA in our research, we created a process diagram. Our problem was the quality of the source data. After the analysis, we identified 4 areas that impact the source data. These were the technologies used, the settings of individual experiments, the execution of separate experiments, and the data processing methods. In these areas, any shortcomings could affect the quality of the data. We set up control mechanisms to verify the correct functioning in all areas. Some control mechanisms are determined by the type of area. For technical equipment, this meant performing a setting check and calibration. To set up individual experiments, we conducted discussions with everyone involved in the settings. In the area of experiment execution, we conducted more detailed operator training. For processing methods, we prepared control outputs of the algorithms used to verify their functioning. However, we were unable to improve the quality of the data. After a detailed analysis of the experiment execution, it was found that the operators needed to adhere sufficiently to the established procedures. To rectify this situation, a requirement for photographic time documentation of each experiment was introduced. The documentation showed that the irrigation hoses (black color) were carelessly placed, causing their points to overlap with the source data (Figure 4).

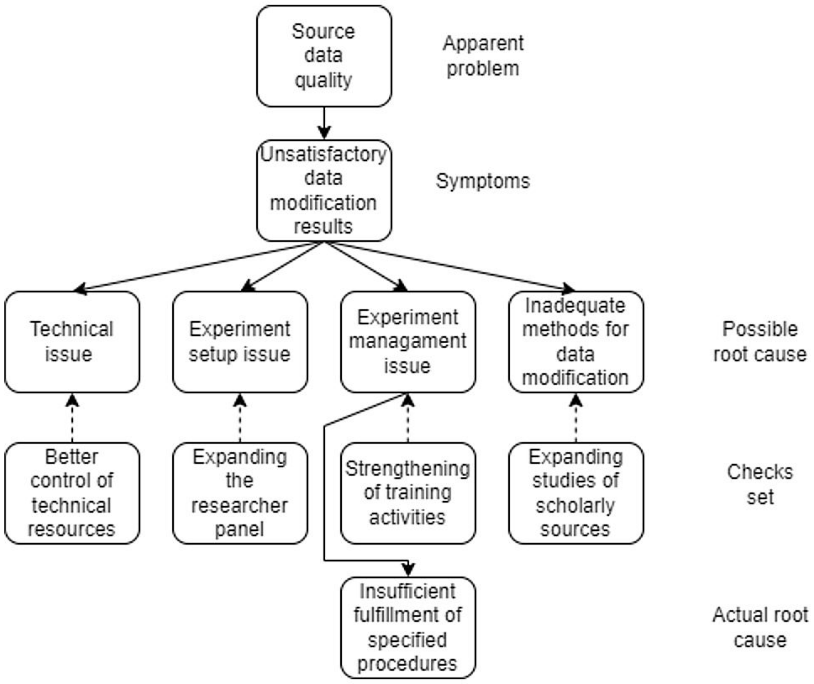
Source: Author

Figure 4: Irrigation hoses.

After correcting errors in the execution of experiments and implementing photo documentation control, the source data quality increased. After corrective actions, we selected and reviewed a new data set of acquired data. It no longer showed anomalies in the 2nd group of points. The entire RCA tree diagram is shown in Figure 5.

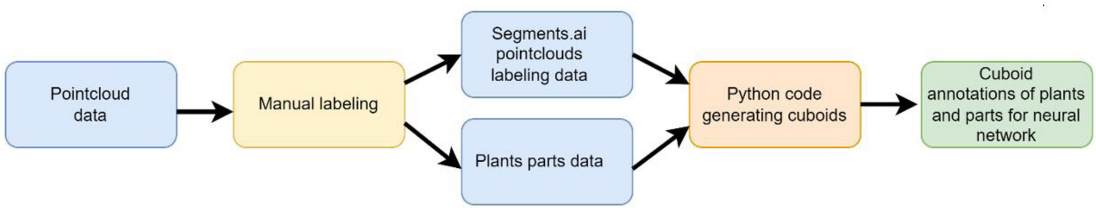
Taking photo documentation and storing it for each experiment brought success by revealing the cause of the insufficient data quality. After discussing why the entire process of conducting experiments needed to be set up from the beginning, including photo documentation, it turned out that the reason was technical complexity. It was necessary to install a photo device for the outdoor scanner and connect it to the data storage. This measure seemed expensive and unnecessary.

Finding the error also resulted in another discovery: unsatisfactory data labeling speed and labeling data quality. We discovered that trained operators still need help accurately labeling the designated class of objects. After an analysis, we changed the marking procedure so that the operators' duty was to mark only defined categories of plant organs (leaves, bay leaves, stems, and petiole) and to record the belonging of the parts to a specific plant in the form of recording identifiers in numerical terms. An algorithm was subsequently written to mark the whole plant, automatically generating this mark. Further streamlining of the labeling process was found in dropping the labeling of object detection points and replacing this process with an algorithm that produces this labeling automatically from labeled parts. These changes made it possible to include a larger group of operators in the labeling process, thereby speeding up the entire labeling process. The set procedure is shown in Figure 6.



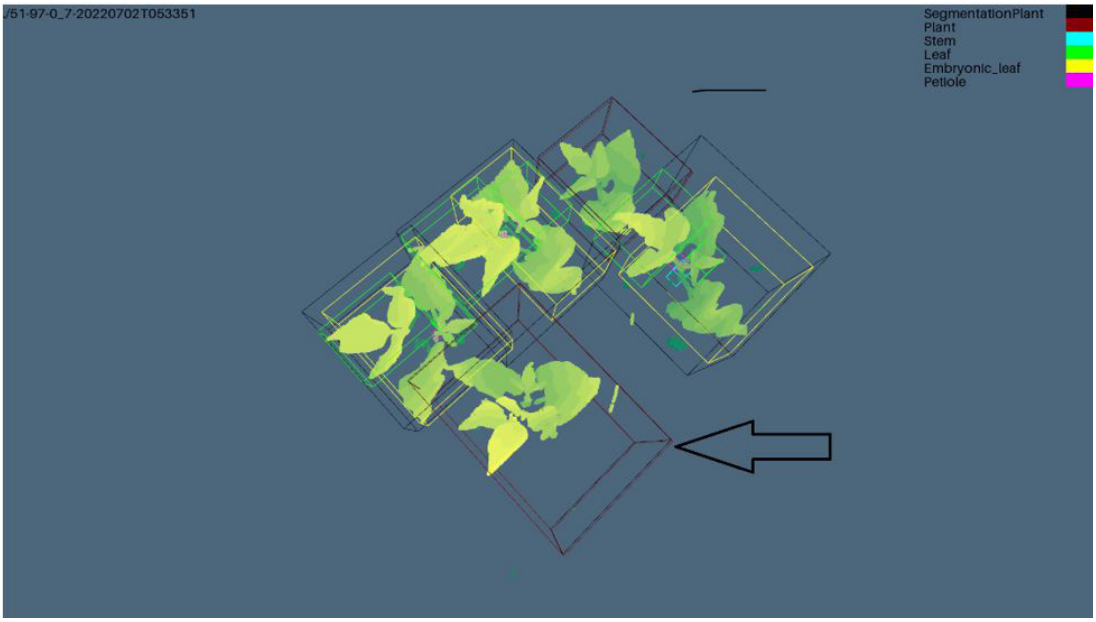
Source: Author

Figure 5: Root cause analysis tree diagram.



Source: Author

Figure 6: Semi-automated labeling process.



Source: Author

Figure 7: Visual control of labeling data.

Automatic cuboid generation also proved helpful in detecting incorrect labeling. The labeling process was supplemented with images of the generated cuboids, enabling more efficient control. Visual identification of suspicious samples was much more accessible. See Figure 7.

Conclusion

The mentioned research project is part of broader research in plant phenotyping using artificial intelligence. Our findings showed that using critical insight in the research process is very beneficial. The quality of research outputs directly depends on the data quality used. Our research takes place in an international team, geographically separated and in different time zones. The nature of the experiments performed does not allow their exact repetition. Cultivation of plants for experimental purposes in an outdoor environment cannot be repeated with identical conditions. All this makes it challenging to identify the sources of errors and inaccuracies. Creating a measurable parameter to express data quality was a guide to finding the source of errors. In the outdoor plant scanning environment, the acquired data is less rich than in the case of indoor scanning. Therefore, the highest possible quality of the source data was achieved important. The use of optimization methods for improving quality is mainly concentrated in the area of the process in the sphere of production, trade, and services. Their use in a research environment is more challenging. The hierarchy of research teams is not strictly defined, and the results often depend on individual abilities, ideas, and creativity. The fact that we were not satisfied with the original quality of the data and implemented procedures to increase the quality of the entire process moved us to a higher level. At the same time, we increased the efficiency of part of the process (labeling), and this shortened the time frame and expanded the database for generating higher-quality research outputs. An important factor was also the fact that we introduced measures in source data quality in the following areas.

Acknowledgements

The results and knowledge included herein have been obtained owing to support from the following institutional grant. Internal grant agency of the Faculty of Economics and Management, Czech University of Life Sciences Prague, grant no. IGA 2023A0017.

This work was supported by the EC's Horizon Europe funding in the project CODECS grant agreement No. 101060179.

This work was supported by the EC's Digital Europe Programme in the project AGRITECH EU grant agreement No. 101123258.

Corresponding author:
Doc. Ing. Pavel Šimek, Ph.D.
Department of Information Technologies, Faculty of Economics and Management
Czech University of Life Sciences Prague,
Kamýcká 129, 165 00 Prague - Suchdol, Czech Republic
E-mail: simek@pef.czu.cz

References

[1] Andersen, B. and Fagerhaug, T. (2000) "*Root cause analysis: simplified tools and techniques*", pp. 155. [Online]. Available: https://books.google.com/books/about/Root_Cause_Analysis.html?hl=csandid=i_EJAQAAMAAJ. [Accessed: Sept. 8, 2024]. ISBN 0873894669.

[2] Andersen, B. and Fagerhaug, T. (2006) "*Root Cause Analysis, Second Edition: Simplified Tools and Techniques*" , 240 p., Quality Oress. ISBN 9780873896924.

[3] Bali, P., Kutikuppala, L. V. S., Avti, P. and Medhi, B. (2021) "*Data Fraud and Essence of Data Verifiability, Quality Assurance Implementation in Research Labs*", pp. 137-159. ISBN 978-981-16-3074-3. DOI 10.1007/978-981-16-3074-3_9.

[4] Brünschwitz, S. and Kleymann-Hilmes, J. (2024) "Benefits and approaches of a quality management system in biomedical research laboratories", *Bundesgesundheitsblatt, Gesundheitsforschung, Gesundheitsschutz*, Vol. 67, No. 1, pp. 99-106. E.ISSN ISSN 1437-1588. DOI 10.1007/S00103-023-03797-Y.

[5] Daiki, S. and Noshita, K. (2024) "A comparative study of plant phenotyping workflows based on three-dimensional reconstruction from multi-view images", *BioRxiv*. DOI 10.1101/2024.03.21.586185.

[6] Detring, J., Barreto, A., Mahlein, A.-K. and Paulus, S. (2024) "*Quality Assurance of Hyperspectral Imaging Systems for Neural Network supported Plant Phenotyping*". DOI 10.21203/RS.3.RS-4648326/V1.

[7] Dhondt, S., Wuyts, N. and Inzé, D. (2013) "Cell to whole-plant phenotyping: the best is yet to come", *Trends in Plant Science*, Vol. 18, No. 8, pp. 428-439. ISSN 1360-1385. DOI 10.1016/J.TPLANTS.2013.04.008.

[8] Fiorani, F. and Schurr, U. (2013) "Future Scenarios for Plant Phenotyping", *Annual Review of Plant Biology*, Vol. 64, pp. 267-291. ISSN 1543-5008. DOI 10.1146/annurev-arplant-050312-120137.

[9] Isere, E. E. and Omorogbe, N. E. (2024) "Quality Management in Clinical and Public Health Research: A Panacea for Minimising and Eliminating Protocol Deviations in Research Operations", *Nigerian Medical Journal*, Vol. 65, No. 3, pp. 367-375. ISSN 0300-1652. DOI 10.60787/NMJ-V65I3-421.

[10] ISO 9001:2015 - Quality management systems - Requirements. (n.d.) [Online]. Available: https://webstore.ansi.org/standards/iso/iso90012015 [Nov. 15, 2023].

[11] Kartal, S., Choudhary, S., Masner, J., Kholova, J., Stoces, M., Gattu, P., Schwartz, S. and Kissel, E. (2021) "Machine Learning-Based Plant Detection Algorithms to Automate Counting Tasks Using 3D Canopy Scans", *Sensors,* Vol. 21, No. 23, pp. 8022. ISSN 1424-8220. DOI 10.3390/S21238022.

[12] Multi-sensor data labeling platform for robotics and AV | Segments.ai. (n.d.). [Online]. Available: https://segments.ai/. [April 28, 2024].

[13] Parker, J. (2024) "The application of operation research in the quality management engineering", *Advances in Operation Research and Production Management*, Vol. 1, No. 1, pp. 25-32. ISSN 1687-9155. DOI 10.54254/3006-1210/DIRECT/2532.

[14] Paulus, S. (2019) "Measuring crops in 3D: Using geometry for plant phenotyping", *Plant Methods,* Vol. 15, No. 1, pp. 1-13. ISSN 1746-4811. DOI 10.1186/S13007-019-0490-0/FIGURES/5.

[15] Percarpio, K. B., Watts, B. V. and Weeks, W. B. (2008) "The effectiveness of root cause analysis: what does the literature tell us?", *Joint Commission Journal on Quality and Patient Safety*, Vol. 34, No. 7, pp. 391-398. ISSN 1553-7250 . DOI 10.1016/S1553-7250(08)34049-5.

[16] Phenospex - Smart plant analysis and Phenotyping systems. (n.d.). [Online]. Available: https://phenospex.com/ [Nov. 15, 2023].

[17] Pongpiyapaiboon, S., Tanaka, H., Hashiguchi, M., Hashiguchi, T., Hayashi, A., Tanabata, T., Isobe, S. and Akashi, R. (2023) "Development of a digital phenotyping system using 3D model reconstruction for zoysiagrass", *The Plant Phenome Journal*, Vol. 6, No. 1, ISSN 2578-2703. DOI 10.1002/PPJ2.20076.

[18] Ronanki, S., Pavlík, J., Masner, J., Jarolímek, J., Stočes, M., Subhash, D., Talwar, H. S., Tonapi, V. A., Srikanth, M., Baddam, R. and Kholová, J. (2022). An APSIM-powered framework for post-rainy sorghum-system design in India, *Field Crops Research*, Vol. 277, p. 108422. ISSN 0378-4290. DOI 10.1016/J.FCR.2021.108422.

[19] Serrat, O. (2017) "The Five Whys Technique", In: *Knowledge Solutions*, pp. 307-310. Springer, Singapore. ISBN 978-981-10-0982-2. DOI 10.1007/978-981-10-0983-9_32.

[20] Shook, J. (2008) "Managing to Learn: Using the A3 Management Process to Solve Problems, *Gain Agreement, Mentor and Lead"*, pp. 10-11. ISBN 1934109207.

[21] Šimek, P., Stočes, M., Vaněk, J., and Masner, J. (2015) "Mobile accessibility of information sources in the areas of agriculture, forestry, water management, food industry and rural development", *Agrarian Perspectives XXIV: Global Agribusiness and the Rural Economy*, pp. 440-446. ISBN 978-80-213-2581-4.

[22] Sozzani, R., Busch, W., Spalding, E. P. and Benfey, P. N. (2014) "Advanced imaging techniques for the study of plant growth and development", *Trends in Plant Science*, Vol. 19, No. 5, pp. 304-310. ISSN 1878-4372. DOI 10.1016/J.TPLANTS.2013.12.003.

[23] Starzyńska, B. and Hamrol, A. (2013) "Excellence toolbox: Decision support system for quality tools and techniques selection and application", *Total Quality Management and Business Excellence*, Vol. 24, No. 5-6, pp. 577-595. ISSN 0954-4127. DOI 10.1080/14783363.2012.669557.

[24] Tarí, J. J. and Sabater, V. (2004a) "Quality tools and techniques: Are they necessary for quality management?", *International Journal of Production Economics*, Vol. 92, No. 3, pp. 267-280. ISSN 0925-5273. DOI 10.1016/J.IJPE.2003.10.018.

[25] Ugochukwu, A. I. and Phillips, P. W. B. (2022) "Data sharing in plant phenotyping research: Perceptions, practices, enablers, barriers and implications for science policy on data management", *Plant Phenome Journal*, Vol. 5, No. 1. ISSN 2578-2703. DOI 10.1002/PPJ2.20056.

[26] Vadez, V., Kholová, J., Hummel, G., Zhokhavets, U., Gupta, S. K. and Hash, C. T. (2015) "LeasyScan: a novel concept combining 3D imaging and lysimetry for high-throughput phenotyping of traits controlling plant water budget", *Journal of Experimental Botany*, Vol. 66, No.18, pp. 5581. ISSN 0022-0957. DOI 10.1093/JXB/ERV251.

[27] Venkatasubramanian, V., Rengaswamy, R., Yin, K. and Kavuri, S. N. (2003) "A review of process fault detection and diagnosis: Part I: Quantitative model-based methods", *Computers and Chemical Engineering*, Vol. 27, No. 3, pp. 293-311. ISSN 0098-1354. DOI 10.1016/S0098-1354(02)00160-6.

[28] Vianna, E. L. F., De Figueiredo, V. V., Da Silva, C. M. F., Bertolino, L. C. and Spinelli, L. (2022) "Impact of implementing quality control systems in laboratories associated with teaching and research institutions − The case study of the laboratory for macromolecules and colloids in the petroleum industry. International Journal of Metrology and Quality Engineering, Vol. 13, pp. 4. ISSN 2107-6847. DOI 10.1051/IJMQE/2022004.

[29] Wilson, P. F. ., Dell, L. D. and Anderson, G. F. (1993) "*Root cause analysis: a tool for total quality management*", pp. 216. ASQC Quality Press, 1993. ISBN 9780873891639.

[30] Yuniarto, H. A. (2012) "The Shortcomings of Existing Root Cause Analysis Tools", *Proceedings of the World Congress on Engineering 2012 Vol III,* WCE 2012, July 4 - 6, 2012, London, U.K. ISSN 2078-0958.

Volume XVI Number 4, 2024

Hybrid Approaches for Irrigation Optimization Based on Weather Forecast: a Study on Reference Evapotranspiration Prediction in Beni Mellal

Hamza Jdi[1], Khalid El Moutaouakil[1], Noureddine Falih[1], Karim Doumi[2]

[1] LIMATI Laboratory, Polydisciplinary Faculty, Sultan Moulay Slimane University, Beni Mellal, Morocco

[2] Alqualsadi Research Team, ENSIAS, Mohammed V University in Rabat, Rabat, Morocco

Abstract

Accurate prediction of Reference Evapotranspiration (ET0) is vital for optimizing irrigation, thereby facilitating efficient water management and agricultural planning. This study compares three distinct methods for predicting ET0 using the FAO Penman-Monteith (FAO-PM), leveraging daily weather data collected over a span of 38 years, from 1984 to 2022. The first approach involves predicting ET0 directly based on actual ET0 values, while the second hybrid approach uses Recurrent Neural Networks (RNN) to predict Net Radiation, Temperature, Wind speed, and Dew Point Temperature. These predicted values are then utilized in the FAO-PM equation to calculate ET0 (RNN-FAO-PM). The third approach is another hybrid method that combines RNN for predicting the weather parameters, followed by the application of a well-trained Random Forest (RF) model that uses the predicted weather parameters as features to predict ET0 (RNN-RF). The performance of each method is evaluated using various metrics, including Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and R-squared (R2) values for both training and testing datasets. The results of this study reveal that the hybrid approaches demonstrate comparable performance for long-term prediction of ET0 of the period Spanning from 2020 to 2022 (3 years). These hybrid approaches slightly outperform the RNN method when applied solely on the ET0 time series. This finding contributes to the research in the area of water resource management, specifically in the context of irrigation optimization. It provides valuable insights that can inform agricultural decision-making in the Beni Mellal region, enabling more efficient and effective use of water resources for irrigation purposes..

Keywords

Reference evapotranspiration forecast, irrigation optimization, deep learning, weather forecast.

Jdi, H., Moutaiuakil, K. E., Falih, N. and Doumi, K. (2024) "Hybrid Approaches for Irrigation Optimization Based on Weather Forecast: a Study on Reference Evapotranspiration Prediction in Beni Mellal", *AGRIS on-line Papers in Economics and Informatics*, Vol. 16, No. 4, pp. 87-97. ISSN 1804-1930. DOI 10.7160/aol.2024.160407.

Introduction

Optimizing irrigation is crucial in agriculture for enhancing crop yield, conserving water, and minimizing environmental impacts. Especially in the region of Beni Mellal, where agriculture is the main source of income, in addition to the region having unprecedented consecutive years of insufficient rainfall. This has significantly affected the water levels in the dams, making it crucial to have a clear vision of long-term variations and anticipate on daily basis the required water for proper irrigation. ET0 plays a central role in determining the appropriate water application and timing of irrigation sessions. ET0 holds paramount significance as it stands as a crucial input in various methods. Indeed, it is the central component and playing a vital role in optimizing irrigation management (Liu and Yang, 2021), ET0 serves as the foundation for calculating Crop Evapotranspiration (ETc), a key component in the soil water balance equation (Hou et al., 2022) (Mininnia et al. 2022), water budget (Das et al., 2023), a reference point for plant indicators (Livellara et al., 2011), and decision support systems (DSS) (Olberz et al., 2018) (Khatua and Pasupalak, 2018). Understanding and utilizing ET0 can improve water use efficiency, reduce waste, and enhance crop productivity. The importance of ET0 in irrigation management cannot be overstated, and it is essential for farmers and researchers to continue exploring new ways to utilize ET0 to improve irrigation practices. This study aims to compare three methods for predicting ET0 with the goal of identifying the most effective method. The methods under investigation are: Direct prediction of ET0 from actual ET0 values using RNN, Hybrid RNN-FAO-PM and Hybrid RNN-RF.

This following literature review highlights the significance of ET0 estimation and explores the potential of machine learning techniques in studying ET0 patterns. It discusses specific methods for different implementations, and the effectiveness of hybrid models and simplified determination approaches. In the following study (Yildirim et al., 2023), the authors employ machine learning methods, including the k-nearest neighbor algorithm, multigene genetic programming, and support vector regression (SVR), to predict daily ET0 in various regions, including Türkiye. In another study (Ling et al., 2023) the authors focus on rubber plantations and propose the "Kc-ET0" method, which demonstrates good performance and acceptable precision, particularly in the dry season. The authors of a separate study (Zheng et al., 2023) suggest a strategy based on Multivariate Variational Mode Decomposition hybridized with Soft Feature Filter and Gated Recurrent Unit (GRU) to predict one-day daily ET0. This strategy outperforms other models such as Long Short-Term Memory (LSTM), BiLSTM, RNN, BiRNN, and BiGRU, proving to be the most accurate for predicting one-day ahead ET0. In the realm of sustainable agricultural development, the authors (Bashir et al., 2023) highlight the importance of ET0 for the preservation of irrigation water. They suggest machine learning approaches to simplify ET0 determination with limited parameters, achieving high precision and correlation with the FAO-56 Penman-Monteith (FAO-56 PM) method. The precision of ET0 estimated by reanalysis products, such as CLDAS and ERA5, is evaluated in another study (Yu et al., 2023). These products demonstrate acceptable precision in China, with CLDAS estimates showing higher spatial and temporal consistency with site observations. In Egypt, where climates range from arid to semi-arid and there are challenges related to a lack of meteorological data and future information on ET0. The authors (Elbeltagi et al., 2023) investigate the use of machine learning models such as linear regression (LR), random subspace (RSS), additive regression (AR), and reduced error pruning tree (REPTree) to precisely estimate ET0. Among these models, REPTree demonstrates the best performance. The authors of a different study (Saggi et al., 2023) explore various machine learning models, including Extreme Machine Learning (ELM), Multi-layer Perceptrons-Neural Network (MLP), and Support Vector Machine (SVM), for modeling daily ET0. An ensemble method with SVM demonstrates good precision in predicting the daily ET0. Addressing the challenges faced by irrigation district managers. The authors (González Perea et al., 2023) develop a hybrid model combining Fuzzy Logic (FL), Genetic Algorithm (GA), LSTM encoder-decoder, and dense or fully connected neural networks (DNN) for the one-week forecasting of irrigation water demand at the irrigation district scale. The potential of ET0 as a key variable for irrigation management, agricultural planning, and modeling different hydrological processes is emphasized in another study (Adnan et al., 2020), the authors validate temperature-based heuristic models such as group method of data handling neural network (GMDHNN), multivariate adaptive regression spline (MARS), and M5 model tree (M5Tree) for estimating monthly ET0. Among these models, the GMDHNN model provides the best accuracy. In regard of This research (Amirashayeri et al., 2023) it focus on accurately predicting ET0 using machine learning models and empirical equations. The study compares the performance of an artificial neural network (ANN) model and a tree model (MT) with two empirical equations. Additionally, a preprocessing algorithm called ensemble empirical mode decomposition (EEMD) is used to enhance the prediction accuracy of the MT model and eliminate time-series noises. The results show that the MT model outperforms the ANN model, and the incorporation of EEMD significantly improves the MT model's performance. Overall, this research highlights the potential of machine learning models and the EEMD algorithm in accurately predicting ET0, which has important implications for managing agricultural water needs and irrigation systems. Based on the analysis of various studies, including the one included in the literature review, it is evident that there is a lack of long-term prediction of ET0 with various combinations. In order to address this gap, we propose three methods. The first method utilizes a forecasting technique based on the temporal dependencies of the ET0 time series using RNN. By considering the historical patterns and trends in the ET0 data, the RNN model can make predictions for future time periods. The second method involves a hybrid model that combines the impractical equation FAO-PM method with RNN. By integrating this equation with RNN, which can capture the temporal dependencies, we can enhance the accuracy of long-term ET0 predictions. The third method combines RNN with RF, another machine learning algorithm known for its ability to handle complex datasets. By leveraging the strengths of both RNN and RF, we can further improve the accuracy and robustness of long-term ET0 predictions. These three methods aim to address the lack of long-term ET0 prediction by utilizing different approaches and models, considering temporal dependencies, integrating practical equations, and leveraging the power of machine learning algorithms to provide more accurate and reliable predictions for ET0 in various combinations.

Materials and methods

The FAO-PM method is widely recognized as the standard approach for estimating ET0 backed by the Food and Agriculture Organization of the United Nations as the sole method for determining ET0 (Allen et al. 2000; Allen, 1977). The ET0 formula refines the original Penman-Monteith equation, incorporating aerodynamic and surface resistance for accurate evapotranspiration estimation. The equation (1) is:

$$\mathrm{ET0} = \frac{0.408\Delta(R_n - G) + \gamma \frac{900}{T+273} u_2 (e_s - e_a)}{\Delta + \gamma(1 + 0.34u_2)} \quad (1)$$

Where:

ET0: Reference Evapotranspiration [mm day-1].

Rn: net radiation at the crop surface [MJ m-2 day-1].

G: soil heat flux density [MJ m-2 day-1].

T: air temperature at 2 m height [°C].

u2: wind speed at 2 m height [m s-1].

es: saturation vapour pressure [kPa].

ea: actual vapour pressure [kPa].

es-ea: saturation vapour pressure deficit [kPa].

Δ: slope vapour pressure curve [kPa °C-1].

γ: psychrometric constant [kPa °C-1], the psychrometric constant is rounded to 0.067 kPa/°C.

Because of it efficiency to approximate grass ET0 at various locations, in addition to accounting for various meteorological parameters, such as Net Radiation, Temperature, Wind speed, and Dew Point Temperature. in addition to various studies whom Backed-up it efficiency (Jayashree et al., 2023; Eliades et al., 2022). To estimate ET0 using the FAO-PM method, we utilized four weather parameters: all-sky surface shortwave upward irradiance and the all-sky surface shortwave downward irradiance [MJ m-2 day-1], mean Temperature at 2 meters above the ground [°C], Dew Point Temperature [°C], and Wind speed at 2 meters height [m s-1]. These parameters are obtained from Modern-Era Retrospective Analysis for Research and Applications, Version 2 (MERRA-2). The FAO-PM method requires several calculations, such as determining the slope of the saturation vapor pressure curve (Δ) and the actual vapor pressure (ea) and Mean saturation vapour pressure (es) using temperature-dependent equations. The actual vapor pressure is calculated based on the Dew Point Temperature. given by (Equation 2):

$$e_a = 0.6108\exp\left[\frac{17.27\, T_{dew}}{T_{dew} + 237.3}\right] \quad (2)$$

The saturation vapor pressure is intricately tied to the air temperature, and its calculation is elucidated by the following relationship (Equation 3):

$$e_s = 0.6108\exp\left[\frac{17.27\, T}{T + 237.3}\right] \quad (3)$$

In regard to the slope of saturation vapor pressure curve (Δ) is computed using Temperature data (Equation 4):

$$\Delta = \frac{4098\left[0.6108\exp\left(\frac{17.27\, T}{T + 237.3}\right)\right]}{(T + 237.3)^2} \quad (4)$$

Where

Δ: slope of saturation vapour pressure curve at air temperature T [kPa °C-1].

T: air temperature [°C].

exp[]: base of natural logarithm.

Net radiation is derived by subtracting the all-sky surface shortwave upward irradiance from the all-sky surface shortwave downward irradiance. For daily ET0 calculations, the soil heat flux is considered zero, as its impact on the daily ET0 is negligible compared to Net Radiation and other energy fluxes.

We develop predictive RNNs models using historical daily values from January 1, 1984 to November 30, 2022 in total 14213 records this time series is split as the following sets: 12792 records for training (90%), 1421 records for testing (10%) in addiction to conserving 10% of the training set to make a validation set. The data is further prepared for the LSTM model using the look-back period of 8. Upon performing a grid search to determine optimal parameters the LSTM and GRU models were implemented with identical parameter settings due to their similar response patterns to any changes in parameters, resulting in either improvement or deterioration of the models. The RNN model is then created using the Sequential API. The RNN model consists of either a GRU or LSTM layer with 256 units, followed by a Dense layer with 64 units, and finally a Dense layer with a single unit. The activation function used is ReLU. The model is compiled using the Adam optimizer with a learning rate of 0.001 was utilized in conjunction with the learning rate scheduler. Moreover, the loss function is MSE. The model is then trained using a batch size of 64 and a validation split of 0.1. The training is performed for 20000 epochs, with the model checkpoint as a callback. A model checkpoint is created to save the model after each epoch, the 20000 models are saved then base on the validation loss values the best model is applied on the time series. The meteorological parameters are namely Net Radiation, Temperature, Dew point, Wind speed collected from MERRA-2, And the daily-calculated ET0 values are based on the FAO-PM approach.

The first method, consist of directly predicting of ET0 from actual ET0 values, this method being the simplest and most straightforward. It involves around simply predicting ET0 directly from actual ET0 values. This is done using two RNN namely GRU and LSTM. We shall compare the result using three metric namely MAE, RMSE and R2.

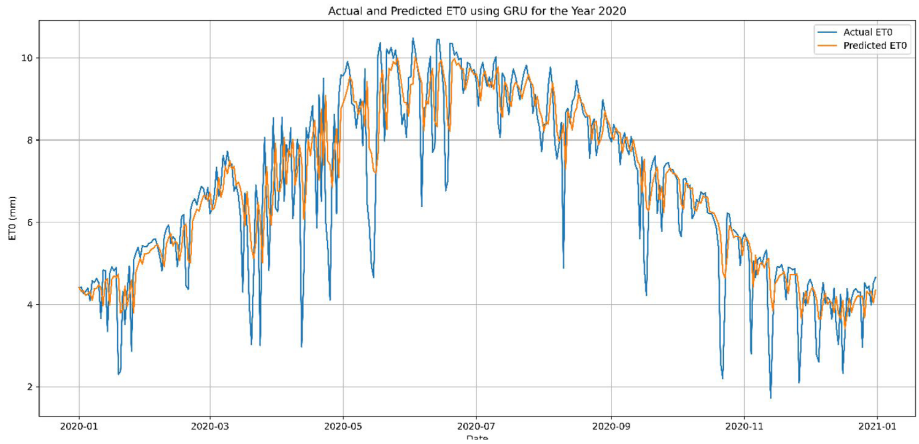
The second method, the hybrid RNN- FAO-PM method, this method first involves predicting individual weather parameters required for the FAO-PM method using both GRU and LSTM models. The weather parameters to be predicted include Net Radiation, air temperature, dew point temperature, and wind speed. Based on the performance metrics of MAE, RMSE, and R2, the best prediction model between GRU and LSTM is selected for each weather parameter. After choosing the best RNN algorithm from the two, the predicted weather parameters are then used to calculate ET0 using the FAO-PM method.

The third method, we employed a RF regression model to predict ET0 using the predicted four weather parameters as features namely Net Radiation, Temperature, Wind speed, and Dew Point Temperature. To evaluate the RF model's performance during training and estimate its ability to generalize to new data, we used Time Series Cross-Validation with 5 folds. In this approach, the training set is divided into 5 contiguous blocks, and the model is trained and evaluated 5 times, with each block being used for testing and validation. The average MAE across all five iterations is used to assess the model's performance during training. After the RF model proved it efficacy, we supplemented it with the predicted weather parameters from RNN. This combined RNN-RF approach aimed to leverage the strengths of combined models, with the RNN capturing complex temporal patterns in the weather data and the RF model providing ET0 predictions based on the predicted weather parameters acting as features

Results and discussion

Weather forecasting using deep learning algorithms

The first method is the most straight forward, two deep learning algorithms GRU and LSTM, were employed to predict ET0. The performance of these models is evaluated using three metrics: MAE, RMSE, and R2. Table 1 presents a comparison based on the values obtained from the best parameters found during a three-year prediction period spanning from 2020 to 2022. Comparing the performance of the two RNNs models, The GRU model appears to be more effective in predicting the component of the water cycle ET0 compared to the LSTM model, as evidenced by the lower MAE and RMSE for both the training and testing datasets and higher R2 values. The Figure 1 illustrates the comparison between the actual and predicted ET0 values for the entire year of 2020. The x-axis represents the ET0 values in millimeters per day, while the y-axis represents the time period, ranging from January to December. The overall trend of the predicted values closely follows the actual ET0 values, it is clear that the predicted values do not demonstrate a similar level of decrease during periods characterized by sudden drops in ET0.



Source: Author's illustration

Figure 1: Comparison of actual and predicted ET0 values for the year 2020 using GRU.

Component of the water cycle	Deep learning algorithm	Number of epochs	MAE		RMSE		R2	
			Training	Testing	Training	Testing	Training	Testing
ET0	GRU	24	0.7247	0.6937	1.0953	1.0403	0.7536	0.7649
	LSTM	29	0.7254	0.6958	1.1030	1.0532	0.7501	0.7609

Source: Authors

Table 1: Evaluation of GRU and LSTM models for ET0 prediction period spanning from 2021 to 2022.

Hybrid approaches

Weather Forecasting Using Deep Learning Algorithms

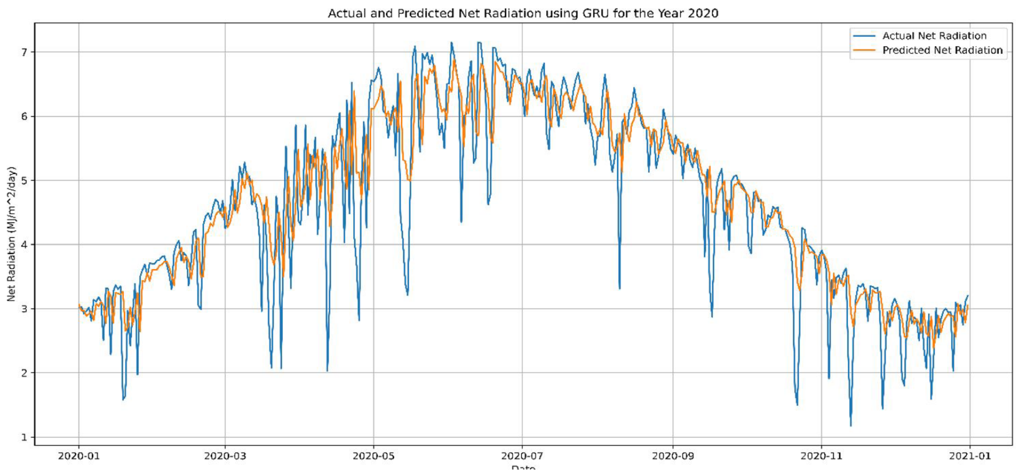
In the pursuit of accurate ET0 prediction, two hybrid approaches were developed. The RNN-FAO-PM, is designed to forecast the weather parameters then calculation ET0 using the FAO-PM method. The RNN-RF employs a RF model to predict ET0, utilizing as features the following Net Radiation, Temperature, Wind speed, and Dew Point Temperature. To provide reliable input for these approaches, weather parameters are predicted using two deep learning algorithms: GRU and LSTM. The performance of these models is evaluated using MAE, RMSE, R2 values for both training and testing datasets the results are shared in Table 2.

The analysis of the predicted four weather using deep learning algorithms GRU and LSTM, reveals several key insights. The prediction of Net Radiation, as depicted in Figure 2, is quite satisfactory. The overall trend of the predicted values closely mirrors the actual values, demonstrating the model's ability to capture the general patterns of Net Radiation. However, during periods of sudden drops in Net Radiation, the predicted values do not exhibit the same magnitude of decrease as the actual values. This discrepancy suggests that the model may struggle to accurately capture extreme fluctuations in Net Radiation, a limitation that warrants further investigation. The prediction of Temperature, on the other hand, is exceptional. Both GRU and LSTM algorithms yield low MAE and RMSE values for both training and testing, indicating a high degree of accuracy in predicting Temperature. Figure 3, which illustrates the Temperature predictions, further corroborates this observation by showing a close alignment between the predicted and actual values. The prediction of Wind speed, as shown in Figure 4, is generally good as it follows the main patterns. However, the model's performance diminishes when it comes to accurately predicting extreme highs and lows in Wind speed. This is evident from the higher MAE and RMSE values for Wind speed compared to Temperature, indicating a higher degree of error in these predictions. The prediction of Dew Point Temperature, represented in Figure 5, is also good, albeit not as accurate as Temperature. The MAE and RMSE values for Dew Point Temperature are slightly higher compared to Temperature, indicating that the models had slightly higher errors in predicting Dew Point Temperature. However, the models still exhibited relatively low errors, suggesting that they were able to capture the overall patterns and variations in Dew Point Temperature.

Weather parameter	Deep learning algorithm	Number of epochs	MAE		RMSE		R2	
			Training	Testing	Training	Testing	Training	Testing
Net Radiation	GRU	29	0.4948	**0.4710**	0.7547	**0.7134**	0.7469	**0.7625**
	LSTM	30	0.4934	0.4722	0.7528	0.7165	0.7481	0.7605
Temperature	GRU	70	1.2296	**1.2639**	1.6065	**1.6440**	0.9559	**0.9533**
	LSTM	67	1.2341	1.2695	1.6053	1.6473	0.9559	0.9531
Wind speed	GRU	61	0.2648	**0.2511**	0.3919	**0.3533**	0.3426	**0.3594**
	LSTM	32	0.2671	**0.2511**	0.3979	0.3555	0.3225	0.3516
Dew Point Temperature	GRU	81	1.6368	**1.5913**	2.1243	**2.1097**	0.7362	**0.7610**
	LSTM	55	1.6357	1.5935	2.1271	2.1123	0.7355	0.7604

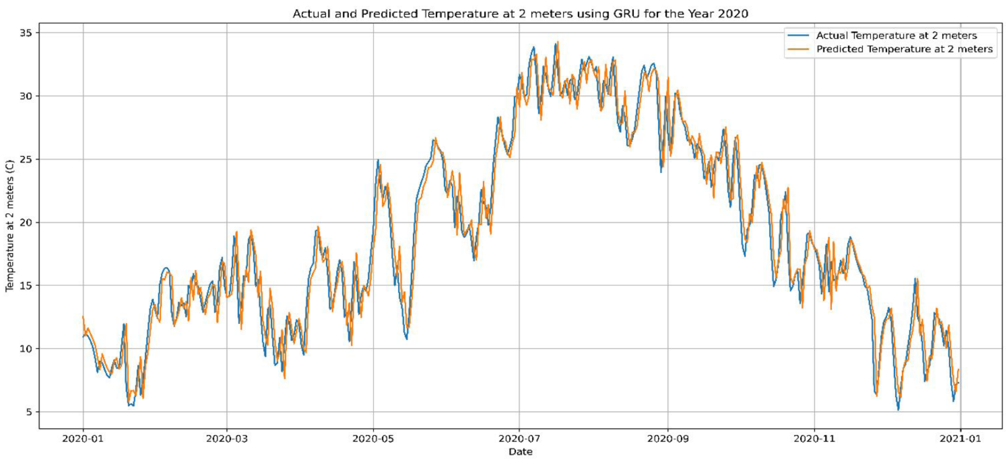
Source: Authors

Table 2: Performance evaluation of GRU and LSTM models for weather parameter prediction in the period spanning from 2021 to 2022.



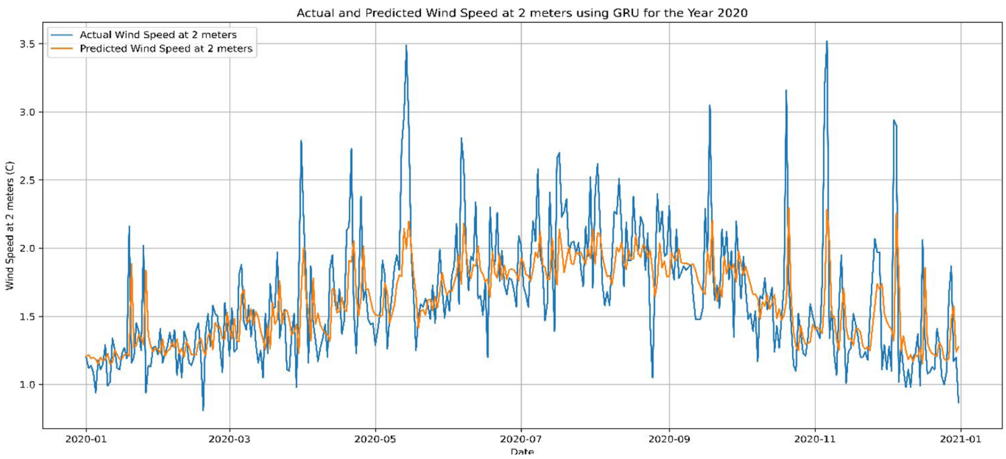
Source: Author's illustration

Figure 2: Comparison of actual and predicted net radiation values for the year 2020 using GRU.



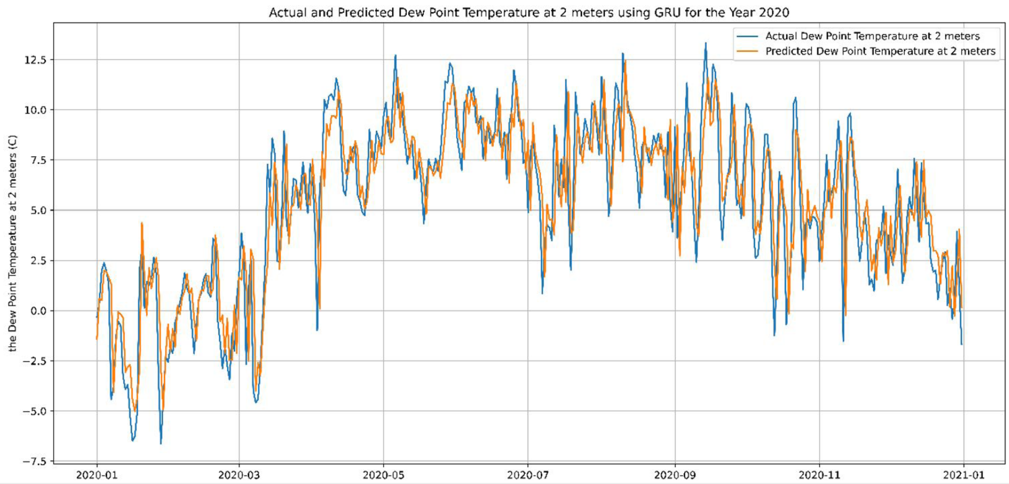
Source: Author's illustration

Figure 3: Comparison of actual and predicted temperature values for the year 2020 using GRU.



Source: Author's illustration

Figure 4: Comparison of actual and predicted wind speed values for the year 2020 using GRU.



Source: Author's illustration

Figure 5: Comparison of actual and predicted dew point temperature values for the year 2020 using GRU.

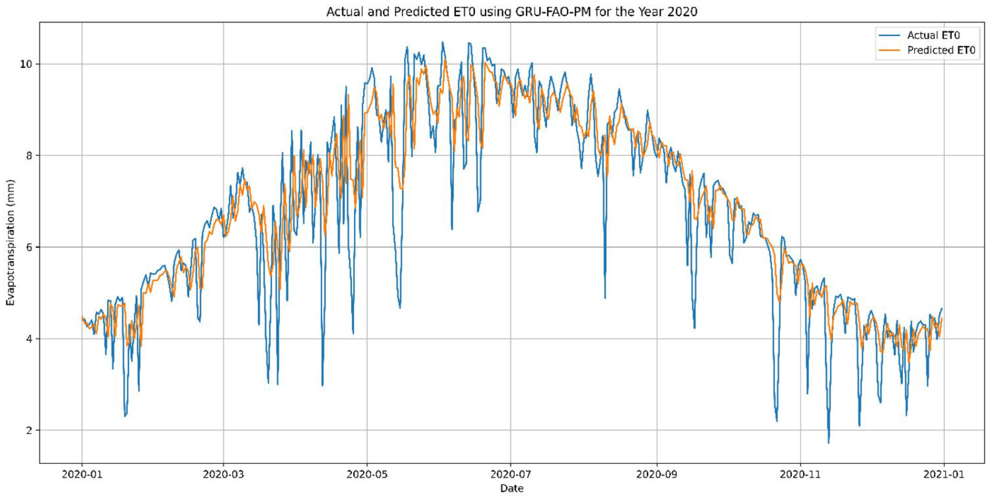
The hybrid model: using Deep Learning-based prediction of weather parameters to calculate ET0 using the FAO-PM method (GRU-FAO-PM)

After choosing the best RNN algorithm for each individual weather parameter, the predicted weather parameters were used as input to calculate ET0 using the FAO-PM method. The MAE and RMSE, R2 values indicated in Table 3 obtained when comparing actual ET0 vs predicted ET0 for the Period Spanning from 2020 to 2022. The MAE of 0.6873 and RMSE of 1.0422 demonstrate a reasonably accurate prediction of ET0 and the same remark persists the ET0 values are not well predicted in cases of sudden drops. Refer to Figure 6 for a comparison of actual and predicted ET0 using GRU-FAO-PM.

	Model	MAE	RMSE	R2
ET0 (in mm)	GRU-FAO--PM	0.6873	1.0422	0.7640

Source: Authors

Table 3: Performance metrics of a Hybrid Deep Learning-Based Approach for ET0 prediction using the FAO-PM method for the period spanning from 2020 to 2022.



Source: Author's illustration

Figure 6. Comparison of actual and predicted ET0 values for the year 2020 using GRU-FAO-PM.

The Hybrid model: RF based prediction of ET0 from predicted weather parameters using GRU (GRU-RF)

A two-step approach is employed to predict ET0 using weather parameters. First, the RNN models is used to predict weather parameters: Net Radiation, Temperature, Wind speed, and Dew Point Temperature using GRU. These predicted weather parameters were then used as input features for a RF regression model to predict ET0. The model's performance on both the testing and validation sets is consistently strong across all metrics as shown in Table 4, which is a good indication that it is not overfitting and can generalize well to new data. Additionally, the use of Time Series Cross-Validation with 5 folds during training helps to ensure that the model is robust and can handle different time periods in the data.

The performance of the combined GRU-RF model in predicting ET0 is assessed using various metrics indicated in The Table 5. With a MAE of 0.6873, the model's predictions, on average, deviate from the actual ET0 values by a relatively small margin. This highlights the overall accuracy of the model. Furthermore, the R2 value of 0.7642 indicates that the model can explain approximately 76.42% of the variance in the actual ET0 data, suggesting a reasonably good fit to the data and the model's ability to capture a significant portion of the underlying patterns in ET0. These results show that the model is effective in predicting ET0 and has potential for further optimization and improvement. Refer to Figure 7 for a comparison of actual and predicted ET0 using GRU-RF.

Features	Label	MAE		RMSE		R2	
		Tes-ting	Vali-dation	Tes-ting	Vali-dation	Tes-ting	Vali-dation
Net Radiation, Temperature, Wind speed, Temperature	ET0	0.0069	0.0063	0.0114	0.0093	0.9999	0.9999

Source: Authors

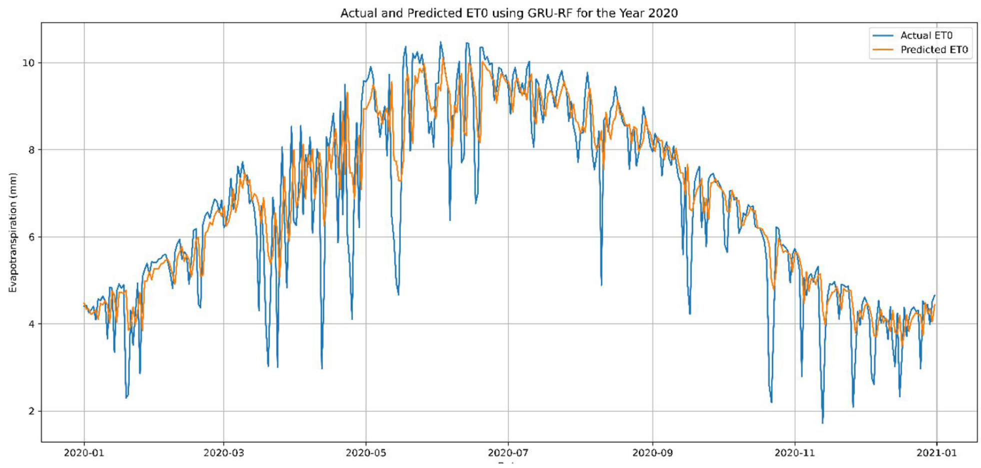
Table 4: Performance metrics of RF regression Mmdel for ET0 prediction using predicted RNN model as features for the period spanning from 2020 to 2022.

	Model	MAE	RMSE	R2
ET0 (in mm)	GRU-RF	0.6873	1.0418	0.7642

Source: Authors

Table 5. Performance metrics of hybrid random RF-based prediction of ET0 from predicted weather parameters using GRU.

Having the same MAE, RMSE, and R2 values indicates that both hybrid approaches are equally effective in predicting ET0. This suggests that the use of RNN for predicting weather parameters, followed by either the FAO-PM equation or a RF model, yields comparable results. There are several reasons why both approaches yielded similar MAE, RMSE, and R2 values. Firstly, the RNN used for weather prediction proved to be effective, providing reliable inputs for subsequent steps. The RNN's architecture and training process allowed it to accurately model the sequential nature of weather data. Secondly, both the FAO-PM equation and the RF model are well-established and robust methods for estimating ET0 when provided with relevant input parameters. The accurate weather predictions from the RNN



Source: Author's illustration

Figure 7: Comparison of actual and predicted ET0 values for the year 2020 using GRU-RF.

served as valuable inputs for leveraging the strengths of these models. Thirdly, the datasets used for training and evaluation contained sufficient and representative data, enabling both approaches to learn the underlying patterns and relationships effectively. This facilitated good generalization to unseen data. Lastly, its important to keep in mind while the evaluation metrics (MAE, RMSE, R2) provide an overall assessment of model performance, they may not capture subtle differences in prediction distributions or localized errors and biases.

Conclusion

This paper explore three methods for predicting ET0 over a period of three years. The methods included using a GRU model, a hybrid model combining RF with GRU (GRU-RF), and another hybrid model combining deep learning-based weather parameter prediction with the FAO-PM method (GRU-FAO-PM). The results of the study indicated that the GRU model performed well in predicting net radiation, although it struggled in cases of sudden drops in values. On the other hand, temperature and Dew Point Temperature predictions were found to be accurate. Wind Speed prediction, while relatively good, was identified as the weakest. In terms of predicting ET0, all three methods showed good overall performance. However, similar to Net Radiation, they faced challenges in accurately predicting values during sudden drops. Notably, the hybrid approaches GRU-RF and GRU-FAO-PM demonstrated better performance compared to the standalone GRU model, with similar MAE and RMSE values. In future work, we will explore several avenues in order to further improve the prediction accuracy of ET0 and address the challenges associated with predicting sudden drops in values, particularly for Net Radiation. One potential direction is to investigate alternative algorithms that may offer better performance in capturing these fluctuations such the Transformer-based models that leverages self-attention to capture the complex temporal dynamics in the time series through using Temporal Fusion Transformer mode

Corresponding author:
Hamza Jdi
Polydisciplinary Faculty, Sultan Moulay Slimane University
Beni Mellal 592, Morocco
Phone: +212 640 83 96 59, E-mail: hamzajdi@gmail.com

References

[1] Adnan, R. M., Salim, H., Zaher, M. Y., Shamsuddin S., Ozgur, K. and Binquan, L. (2020) "Prediction of Potential Evapotranspiration Using, Temperature-Based Heuristic Approaches", *Sustainability,* Vol. 13, No. 1, pp. 297. E-ISSN 2071-1050. DOI 10.3390/su13010297.

[2] Allen, R. G. (1977) "*FAO Irrigation and Drainage Paper*", FAO. ISBN 9789251011867.

[3] Allen, R. G, Smith, M., Pereira,L. S., Raes, D. and Wright, J. L. (2000) "Revised FAO Procedures for Calculating Evapotranspiration: Irrigation and Drainage Paper No. 56 with Testing in Idaho", *conference proceedings Watershed Management and Operations Management 2000*, pp. 1-10. DOI 10.1061/40499(2000)125.

[4] Amirashayeri, A., Behmanesh, J., Rezaverdinejad, V. and Attar, N. F. (2023) "Evapotranspiration Estimation Using Hybrid and Intelligent Methods", *Soft Computing,* Vol. 27, No. 14, pp. 9801-9821. ISSN 1433-7479. DOI 10.1007/s00500-023-07822-9.

[5] Bashir, R. N., Khan, F. A., Khan, A. A., Tausif,M., Abbas, M. Z., Shahid, M. M. A. and Khan, N. (2023) "Intelligent Optimization of Reference Evapotranspiration (ETo) for Precision Irrigation", *Journal of Computational Science,* Vol. 69, No. May, p. 102025. ISSN 1877-7503. DOI 10.1016/j.jocs.2023.102025.

[6] Das, S., Baweja, S. K., Raheja, A., Gill, K. K. and Sharda, R. (2023) "Development of Machine Learning-Based Reference Evapotranspiration Model for the Semi-Arid Region of Punjab, India", *Journal of Agriculture and Food Research,* Vol. 13, No. September, p.100640. ISSN 2666-1543. DOI 10.1016/j.jafr.2023.100640.

[7] Elbeltagi, A., Srivastava, A., Al-Saeedi, A. H., Raza, A., Abd-Elaty, I. and El-Rawy, M. (2023) "Forecasting Long-Series Daily Reference Evapotranspiration Based on Best Subset Regression and Machine Learning in Egypt", *Water*, Vol. 15, No. 6, pp. 1149. E-ISSN 2073-4441. DOI 10.3390/w15061149.

[8] Eliades, M., Bruggeman, A., Djuma, H., Christofi, C. and Kuells, C. (2022) "Quantifying Evapotranspiration and Drainage Losses in a Semi-Arid Nectarine (Prunus Persica Var. Nucipersica) Field with a Dynamic Crop Coefficient (Kc) Derived from Leaf Area Index Measurements", *Water,* Vol. 14, No. 5, pp. 734. E-ISSN 2073-4441. DOI 10.3390/w14050734.

[9] González Pérea, R., García, F. I., Poyato, C. E. and Díaz, J. A. R. (2023) "New Memory-Based Hybrid Model for Middle-Term Water Demand Forecasting in Irrigated Areas", *Agricultural Water Management,* Vol. 284, No. June, p. 108367. E-ISSN 1873-2283. DOI 10.1016/j.agwat.2023.108367.

[10] Hou, X., Fan, J. , Zhang, F., Hu, W., Yan, F., Xiao, C., Li, Y. and Cheng, H.(2022) "Determining Water Use and Crop Coefficients of Drip-Irrigated Cotton in South Xinjiang of China under Various Irrigation Amounts", *Industrial Crops and Products*, Vol. 176, No. Feb., p. 114376. ISSN 0926-6690. DOI 10.1016/j.indcrop.2021.114376.

[11] Jayashree, T. R., Reddy, N.V. S., Acharya, D. and Eslamian, S. (2023) "Prediction of Reference Crop Evapotranspiration: Empirical and Machine Learning Approaches", In: Eslamian, S. and Eslamian, F. (eds) "*Handbook of Hydroinformatics*", pp. 253-268. Elsevier. ISBN 9780128219614. DOI 10.1016/B978-0-12-821961-4.00007-5.

[12] Khatua, R. and Pasupalak, S. (2018) "Comparison of Methods for Estimation of Reference Evapotranspiration in North-Central Plateau Zone of Odisha", *Indian Journal of Agricultural Research*, Vol. 52, No. 2, pp. 187-190. ISSN 0367-8245. DOI 10.18805/IJARe.A-4702.

[13] Ling, Z., Shi, Z., Xia, T., Gu, S., Liang, J. and Xu, Ch.-Y. (2023) "Short-Term Evapotranspiration Forecasting of Rubber (Hevea Brasiliensis) Plantations in Xishuangbanna, Southwest China", *Agronomy*, Vol. 13, No. 4, p. 1013. E-ISSN 2073-4395. DOI 10.3390/agronomy13041013.

[14] Liu, X. and Yang, D. (2021) "Irrigation Schedule Analysis and Optimization under the Different Combination of P and ET0 Using a Spatially Distributed Crop Model", *Agricultural Water Management,* Vol. 256, No. Oct., p. 107084. E-ISSN 1873-2283. DOI 10.1016/j.agwat.2021.107084.

[15] Livellara, N., Saavedra, F. and Salgado, E. (2011) "Plant Based Indicators for Irrigation Scheduling in Young Cherry Trees", *Agricultural Water Management*, Vol. 98, No. 4, pp. 684-690. E-ISSN 1873-2283. DOI 10.1016/j.agwat.2010.11.005.

[16] Mininnia, A. N., Laterza, D., Tuzio, A. C., Di Biase, R. and Dichio, B. (2022) "Soil Water Content Monitoring as a Tool for Sustainable Irrigation Strategy in a Kiwifruit Orchard under Semi-Arid Conditions", *Acta Horticulturae*, Vol. 1332, pp.203-209. ISSN 0567-7572. DOI 10.17660/ActaHortic.2022.1332.27.

[17] Olberz, M., Kahlen, K. and J. Zinkernage, J. (2018) "Assessing the Impact of Reference Evapotranspiration Models on Decision Support Systems for Irrigation", *Horticulturae*, Vol. 4, No. 4. E-ISSN 2311-7524. DOI 10.3390/horticulturae4040049.

[18] Saggi, M. K., Jain, S., Bhatia, A. S. and Rakesh, R. (2023) "Proposition of New Ensemble Data-Intelligence Model for Evapotranspiration Process Simulation", *Journal of Ambient Intelligence and Humanized Computing,* Vol. 14, No.7, pp. 8881-8897. E-ISSN 1868-5145. DOI 10.1007/s12652-021-03636-5.

[19] Yildirim, D., Küçüktopcu, E., Cemek, B. and Simsek, H. (2023) "Comparison of Machine Learning Techniques and Spatial Distribution of Daily Reference Evapotranspiration in Türkiye", *Applied Water Science*, Vol. 13, No. 4, p. 107. E-ISSN 2190-5495. DOI 10.1007/s13201-023-01912-7.

[20] Yu, X., Qian, L., Wang, W., Huo, X., Hu, X. and Wang, Y. (2023) "Assessing and Comparing Reference Evapotranspiration across Different Climatic Regions of China Using Reanalysis Products", *Water*, Vol. 15, No. 11, p. 2027. E-ISSN 2073-4441. DOI 10.3390/w15112027.

[21] Zheng, Z., Ali, M., Jamei, M., Xiang, Y., Karbasi, M., Yaseen, Z. M. and Farooque, A. A. (2023) "Design Data Decomposition-Based Reference Evapotranspiration Forecasting Model: A Soft Feature Filter Based Deep Learning Driven Approach", *Engineering Applications of Artificial Intelligence*, Vol. 121, No. May, p. 105984. E-ISSN 1873-6769. ISSN 0952-1976. DOI 10.1016/j.engappai.2023.105984.

Volume XVI Number 4, 2024

Risk Optimality and, Subscription and Subscription Intensity of Weather Index Insurance: Application of T-MOTAD and Negative Binomial Double Hurdle Model

Augustine Koufie, Henry de-Graft Acquah, Samuel Kwesi Ndzebah Dadzie

Department of Agricultural Economics and Extension, University of Cape Coast, Ghana

Abstract

This study sought to analyze risk efficient income and examine its effect on subscription and subscription intensity of weather index insurance (WII). Data was obtained from food crop farmers who were randomly sampled from the Upper West Region; and further, the T-MOTAD and Negative binomial hurdle model were estimated to arrive at the study findings. The study fills methodological gap by estimating the negative binomial hurdle and Zero-inflated negative binomial models as advancement of the Poisson regression model. Further, AIC, BIC, Log-likelihood, rootogram as well as the Vuong test were employed to ascertain the empirical superiorities of the estimated models to the data set. Results show that the risk efficient plans' incomes of GHS9403.42 ($854.08) and GHS9835.10 ($893.29) are higher than that of the income of GHS7412.97 ($673.29) from the farmer's optimal plans. Also, about two-third of farmers have subscribed to the weather index insurance in the study area; for intensity of subscription, 0.39ha on average out of every hectare of land cultivated is covered with the weather index insurance. The negative binomial hurdle model showed empirical superiority for the fit of the data set. The farmer's decision to subscribe and their subscription intensity of the weather index insurance are significantly influence by age, sex, farm size, experience, education, insurance prompt payment, extension service, credit access and risk efficient income. It is recommended that farmers should adopt the risk efficient plan to earn higher income to be able to afford WII premium, as this will increase their subscription intensity.

Keywords

Risk optimality, Subscription intensity, weather index insurance, T-MOTAD, Negative binomial double hurdle model, food crops, Upper West region of Ghana.

Koufie, A., de-Graft Acquah, H. and Dadzie, S. K. N. (2024) "Risk Optimality and, Subscription and Subscription Intensity of Weather Index Insurance: Application of T-MOTAD and Negative Binomial Double Hurdle Model", *AGRIS on-line Papers in Economics and Informatics*, Vol. 16, No. 4, pp. 99-108. ISSN 1804-1930. DOI 10.7160/aol.2024.160408.

Introduction

In Ghana, the agricultural sector is dominated by smallholder farmers and is mostly rain-fed, characterized by production and climate risk (Abdul-Razak and Kruse, 2017). Traditionally, these smallholder farmers have informally managed both production and climatic risk in their own way, but this has always led to their incurring losses (Antwi, 2016). Ellis (2017) noted that the Government of Ghana and other stakeholders in the agricultural and insurance sector upon realizing this, piloted and implemented the weather index-based insurance in the Upper West Region. The weather index insurance policy covers food crops such as maize, millet, sorghum, soya bean and groundnut and uses climate indicators to predict losses to the farmer (Amponsah et al., 2018). This was done to give the farmers access to a market-based risk management policy that could cater for the risks that is beyond their control (GAIP, 2013). Despite the significance of the weather index insurance policy, its penetration level is still very low in the Upper West Region. The factors identified are lack of awareness, insurance prompt payment, lack of preferred attributes, and a key among them is the low income level of the farmers (Akinola, 2014; Fiala, 2017; Addey et al., 2020; Feng et al., 2021).

Udo et al. (2015) asserted that to increase the income level of farmers in the events of production risk, a risk optimum farm plan is required. A risk optimum farm plan can be an effective support policy for weather index insurance and serve as an effective channel for farm credit facilities and advisory services, as well as agricultural risk management intervention (Koufie, 2020; Dai et al., 2023). Therefore, this study bridges the literature gap by providing a rigorous empirical evidence to know the risk efficient income obtained from the risk optimum farm plan, subscription and subscription intensity of the weather index insurance and the interaction between the risk efficient income, subscription and subscription intensity of the weather index insurance. The study also bridges the methodological gap by making Poisson regression model as base model and compare it with advanced count models such as the negative binomial hurdle model, and the zero-inflated negative binomial model. The study went further to empirically test the three selected count models to see which one among them is the best fit model for the study, using Akaike Information Criteria (AIC), Bayesian Information Criteria (BIC), Log-like hood ratio test, Vuong statistical test and a rootogram.

Materials and methods

Study area, sampling procedure and sample size

The study was conducted in the Upper West region of Ghana, and a multi-stage sampling technique was used to select the food crop farmers for the study. The first stage was to purposively select the Wa Municipality and Wa West district. The second stage involved grouping all the twenty-six (26) major farming communities in the selected districts and randomly selecting sixteen (16) out of the twenty-six (26) communities using the lottery method. At stage three, proportionate sampling was used to select the 64 percent subscribers and 36 percent non-subscribers from the 16 selected farming communities. At the end of the sampling proceedure, 450 food crop farmers constituting 287 subscribers and 163 non-subscribers became the sample for the analysis.

Data collection and analysis

A face-to-face interview was conducted using a structured questionnaire to obtain cross-sectional data from the 450 food crop farmers who decided to be part of the survey. The Data was analysed using R statistical software version 4.04 and LiPS software.

Empirical estimation of Target MOTAD model for the study

In the context of this study, to formulate the actual Target-MOTAD problem, we first analyse the LP problem of the study without including risk constraint in the model. This was done by maximizing the expected gross margin E(GM) of the decision variables (x_j) subject to resource constraint. In this study, we defined the decision variables (x_j) as hectares of land to be allocated to the various crop enterprises. The various crop enterprises used in this study were maize, groundnut, soya bean and sorghum as these are the major food crop enterprises produced in the study area (Dembele, 2018). Therefore, the optimum income obtained from the LP model now becomes the Target Income for the Target-MOTAD model. The Target-MOTAD is analysed by including a risk constraint into the LP model and setting the Target income. Therefore, mathematically the Target-MOTAD for this study is given as:

$$\text{Maximize: } \mathrm{E(GM)} = c_1x_1 + c_2x_2 + c_3x_3 + c_4x_4 \quad (1)$$

Subject to: Resource constraint

$$a_{1,1}x_1 + a_{1,2}x_2 + a_{1,3}x_3 + a_{1,4}x_4 \leq b_1$$

(Land constraint) (2)

$$a_{2,1}x_1 + a_{2,2}x_2 + a_{2,3}x_3 + a_{2,4}x_4 \leq b_2$$

(Labour constraint) (3)

$$a_{3,1}x_1 + a_{3,2}x_2 + a_{3,3}x_3 + a_{3,4}x_4 \leq b_3$$

(Capital constraint) (4)

$$a_{4,1}x_1 + a_{4,2}x_2 + a_{4,3}x_3 + a_{4,4}x_4 \leq b_4$$

(Fertilizer Constraint) (5)

Risk constraint

$$\sum_{j=1}^{n} C_{rj}x_j + y_r \geq T \text{ ... where } r = 1\ldots m \quad (6)$$

$$\sum_{r=1}^{s} p_r y_r = \lambda \quad (7)$$

$$x_1, x_2, x_3, \ldots \geq 0. \text{ (Non –negativity constraint)} \quad (8)$$

Where gross margin E(GM) of the decision variables (x_j) represent the difference between the total revenue and the total variable cost (which comprised of labor cost and inputs cost during the production season). x_1 = maize, x_2 = groundnut, x_3 = soyabeans, x_4 = sorghum ($a_{1,1}$, $a_{1,2}$, $a_{1,3}$ and $a_{1,4}$) are the hectares of land apportion to maize, groundnut, soya bean and sorghum respectively. ($a_{2,1}$, $a_{2,2}$, $a_{2,3}$ and $a_{2,4}$) represent the labor days (man-days) apportion to maize, groundnut, soya bean and sorghum.($a_{3,1}$, $a_{3,2}$, $a_{3,3}$, and $a_{3,4}$) represent the amount of capital (GHS) apportioned to maize, groundnut, soya bean and sorghum respectively. ($a_{4,1}$, $a_{4,2}$, $a_{4,3}$ and $a_{4,4}$) represent kg/hectare of fertilizer apportioned to maize, groundnut, soya bean and sorghum. Also, b_1 represent the total hectares of land available to the farmer, b_2 represent the total labor days(man-days) available to the farmer, b_3 represent the total capital (GHS) available to the farmer for production activity and b_4 represent the total amount of fertilizer (kg) available to farmer. (c_1, c_2, c_3 and c_4) is the gross margin obtain by maize, groundnut, soya bean and sorghum enterprises. T = the optimum income obtained from the LP model without risk constraint (Target gross margin). s is the total number of time period considered. C_{rj} is the expected gross margin of the j^{th} enterprise in the r time period or farming season. y_r is the deviation below the target income (T) in time period r. λ is the maximum amount of short fall in the gross margin permitted. Therefore, the model solution was feasible and risk efficient plans (II and III) were obtained.

Empirical model estimation for the count regression model

The study employed the count regression model to analyse the risk-efficient income and risk aversion levels of farmers with regard to their subscription and subscription intensity of weather index insurance. The count model comprises two component modelling processes. The first is the binary stage, which employs the binary model, and the second is the truncated stage, which utilises the truncated model. In the initial stage, which is the binary stage, the respondent is presented with the option of subscribing to weather index insurance products or not. Given that the initial stage is the binary decision stage, the probit model was employed. With regard to the second stage, the study employed the zero-truncated negative binomial model to analyse the intensity of subscription. The empirical model for this study is specified as follows:

Binomial model with probit link function:

$$\begin{aligned}\textbf{Subscription}_{\mathbf{i}} = {} & \beta_0 + \beta_1 Age_i + \beta_2 Sex_i + \beta_3 Edu_i + \\ & + \beta_4 Maritalstatus_i + \beta_5 Farmsize_i + \\ & + \beta_6 Experience_i + \beta_7 FBO_i + \beta_8 HHsize_i + \\ & + \beta_9 Ins.Prompt\ paytm_i + \beta_{10} Ins.Awarnes_i + \\ & + \beta_{11} Weather.info_i + \beta_{12}\ Ext.Serv_i + \\ & + \beta_{13} CreditAcess_i + \beta_{14} RiskEf.Inc_i \end{aligned} \tag{9}$$

Truncated Negative Binomial Model:

$$\begin{aligned}\textbf{Sub.Intensity}_{\mathbf{i}} = {} & \beta_0 + \beta_1 Age_i + \beta_2 Sex_i + \beta_3 Edu_i + \\ & + \beta_4 Maritalstatus_i + \beta_5 Farmsize_i + \\ & + \beta_6 Experience_i + \beta_7 FBO_i + \beta_8 HHsize_i + \\ & + \beta_9 Ins.Prompt\ paytm_i + \beta_{10} Ins.Awarnes_i + \\ & + \beta_{11} Weather.info_i + \beta_{12}\ Ext.Serv_i + \\ & + \beta_{13} CreditAcess_i + \beta_{14} RiskEf.Inc_i \end{aligned} \tag{10}$$

Study variable

Dependent variable

The nature of the dependent variable was a continues variable. The dependent variable was measured as the ratio of land insured over the total number of land cultivated. Hence, for the purpose of estimation, the dependent variable was converted into a count variable (0,1,2,3,…10), (Kalmijn, 2012). This was done by first multiplying the dependent variable, which is ratio in nature by 10 (for instance 0.25 × 10 =2.5). The second part is to approximate the continues values into the nearest whole number (for instance, 2.5 ~ 3 and 2.2~2). Therefore, the dependent variable is now count variable (number of land insured) and requires the use of count models for its estimation.

Explanatory Variables

Sex of farmer (coded as male 1, female 0), Marital status (coded as married = 1, not married = 0), education (years of education), household size (number of persons in the household), FBO access (Yes = 1 or No = 2), Experience (years), Risk efficient income (T-MOTAD- amount), Weather Information (Yes = 1, No = 0), Insurance awareness (Yes = 1, No = 0), Extension service (Yes = 1, No = 0), Insurance prompt payment = Yes = 1, No = 0), and Credit access (Yes = 1, No = 0).

Results and discussion

Existing plan, optimum plan and risk efficient farm plans on various crops

The major four crop enterprise mix produced in the area became the basis for the farmer's plan and the LP/T-MOTAD selected crop mix. These were maize, sorghum, soya bean and groundnut (GSS, 2016). Table 1 presents the results of the farmer's plan (I), risk efficient farm plans (II and III) and profit maximization plan (IV). The result from Table 1 shows that the farmer's plan (I) is to produce maize (0.54 hectare), soya bean (1.00 hectare), groundnut (0.56 hectare) and sorghum (0.5 hectare) to obtain an expected income of GH¢7,412.97[1] ($673.29). From the Table 1, the result of the profit maximization plan (IV) also shows that to obtain the optimum income of GH¢11168.10 ($1014.36), the farmer should produce 1.50 hectares of soya bean and 0.74 hectare of groundnut. Comparably, the profit maximization plan (IV) gives the farmer about 33.62% increase in income more than the farmer's plan (I). From the Table 1, the risk efficient farm plan (II and III) shows that the farmer should produce soya bean and sorghum in their respective hectares (1.50 ha and 0.33 ha (Plan II) /1.50 ha and 0.42 ha (Plan III) to obtain a risk efficient income of GH¢9,403.42 ($854.08) and GH¢9,835.10 ($893.29) respectively. The risk efficient income obtained by the risk efficient farm plans (II and III) is higher than the farmer's plan by 21.17% and 24.63% respectively. This implies that the farmer can obtain an increased income with less level of risk. However, comparing the risk efficient plans (II and III) and the profit maximization plan (IV), there is a significant decrease in income by 15.80% and 11.94% (risk efficient farm plan II and III) respectively. This significant decrease in the risk efficient farm plans (II and III) is known to be the risk premium for averting a riskier plan.

Subscription of the Weather Index Insurance Product

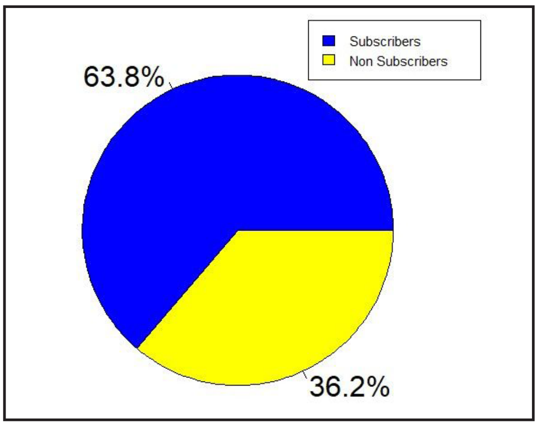
From the Figure 1, out of 450 food crop farmers interviewed, 287 (64%) noted that they have subscribed to the Weather Index Insurance policy. Approximately 36% (163) of the farmers interviewed also noted that they have not subscribed to the Weather Index. The farmers interviewed asserted that their low income, lack of preferred attributes, and prompt payments, among other factors, is what is constraining them from subscribing to the weather insurance.

[1] As of August, 2023, when the data was taken, the exchange rate was approximately GH¢ 11.01 to 1 USD. NB: Current exchange rate is GH¢ 14.33 to 1 USD (Source: https://www.bog.gov.gh/economic-data/exchange-rate/).

	Farmer´s Plan (I)	Risk Efficient Plan (II)	Risk Efficient Plan (III)	Profit Maximization Plan (IV)
Optimal Value (GH¢)	7412..97	9403.42	9835.10	11168.10
Enterprises				
Maize (ha)	0.54	0.00	0.00	0.00
Groundnut (ha)	0.56	0.00.	0.00	0.74
Soyabean (ha)	1.00	1.50	1.50	1.50
Sorghum (ha)	0.50	0.33	0.42	0.00
Total Crop Area	**2.60**	**1.83**	**1.92**	**2.24**

Source: Field survey, (2023)

Table 1: Farmer's Plan, Optimum Plan and Risk Efficient Plan of Crops.



Source: Field survey, (2023)

Figure 1: Distribution of subscribers and non-subscribers of WII in UWR.

Subscription Intensity of the Weather Index Insurance Product

From Table 2, the average land size owned by the farmers is 2.60 ha which is higher than the national average farm size of 2.20 ha for smallholder farmers (MoFA, 2015). The plausible reason is that farmers do not have enough income as well as credit access to expand their farm production activity. Table 2, the average land size insured against these climate extremes using the weather index insurance was 0.65 ha out of the 1.67 ha used for cultivation. Therefore, the subscription intensity of the weather index insurance is 0.39 ha (Area of land insured per land cultivated). By implication it means that for every hectare of farm size cultivated, the farmer insures 0.39 ha. The plausible reason is that most of the farmers interviewed asserted that they are constrained financially, making it difficult to expand their land insured.

Agricultural activity	Mean	Subscription Intensity
Area of land insured using WII (Hectares)	0.65	
Area of land cultivated (Hectares)	1.67	
Area of land owned (Hectares)	2.60	
Subscription Intensity of Weather Index Insurance		0.39

Source: Field survey, (2023)

Table 2: Subscription Intensity of the Weather Index Insurance Product.

Best Fit Model between PRM ZINBM NBDHM using AIC, BIC, LL

In reference to the Table 5 which present the results of the PRM, NBHM and ZINBM in estimating the effect of risk optimum income on subscription and subscription intensity of the WII. The AIC, BIC, and LL from the three count models (PRM, NBHM and ZINBM) employed in the Table 5 have been presented in the Table 3. The results in the Table 3 is to show the performance of all the three count models employed in the study. The results show that NBHM has AIC and BIC values comparatively smaller than that of ZINBM which values are also smaller than that of PRM (i.e. 2557.469<2559.325<10851.4 for AIC and 2693.074<2694.930<10917.15 in the case of BIC). As the model with the minimum computed AIC and BIC, NBHM appears to have empirical superiority than ZINBM which is also empirically superior than PRM. Further, the Log-Likelihood results in the Table 3 also portray that NBHM has the biggest log likelihood value of -1246 compared with -1247 for ZINBM and that of PRM which is -5410. This also suggests that NBHM has empirical superiority for the data set than ZINBM and PRM respectively.

Count Models	AIC	BIC	Log-likelihood
PRM	10851.4	10917.15	-5410
ZINBM	2559.325	2694.930	-1247
NBHM	2557.469	2693.074	-1246

Source: Field survey, (2023)

Table 3: Best Fit Model between PRM ZINBM NBDHM using AIC, BIC, Log-likelihood

Vuong test results based on pair comparisons of PRM, NBHM and ZINBM

In the study, PRM was paired as first model with NBHM and ZINBM respectively. Further, the ZINBM was paired as first model with NBHM. The results are presented in the Table 4. The results in Table 4 show that all the computed Vuong test z-statistic values are negative and highly significant. The Vuong test result of -20.2716*** between the Poisson Regression Model (PRM) and the Negative Binomial Hurdle Model (NBHM), implies that NBHM is preferred statistically to PRM. Similarly, test result of -20.2669*** between Poisson Regression Model (PRM) and Zero-Inflated Negative Binomial Model (ZINBM), implies that The ZINBM is statistically preferred to the PRM. Also, between the Negative Binomial Hurdle Model (NBHM) and the Zero Inflated Negative Binomial Model (ZINBM), the Vuong test result of -2.3414*** indicates that NBHM is preferred statistically to ZINBM. Given the study results, Negative Binomial Hurdle Model (NBHM) is selected as the best count model in dealing with excess zeros and over dispersion in the weather index insurance data set.

Count Regression Models	Vuong test z-statistic	p-value
PRM vs NBHM	-20.2716***	2.22e-16
PRM vs ZINBM	-20.2669***	2.22e-16
ZINBM vs NBHM	-2.3414***	0.0026

Source: Field survey, (2023)

Table 4: Vuong test results based on pair comparisons of PRM, NBHM and ZINBM.

Hanging rootogram of the PRM, NBHM and ZINBM for the study's count data

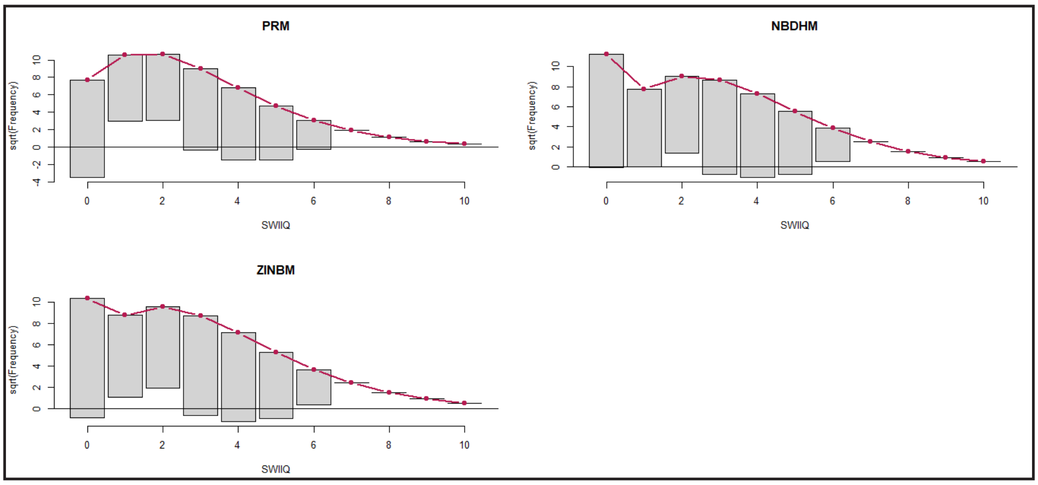
Following the discussions from the Table 3 and the Table 4 in finding the best fit model for the study, that could address the issue of excess zero, under and over dispersion in the WII data set. This study went further to use a hanging rootogram to show which among the three count regression models best fits the study's count data, addresses excess zeros, and treats over and under dispersion in the count data. This is shown in the Figure 2. From Figure 2, Poisson Regression Model (PRM) is at the top-left, Negative Binomial Hurdle Model (NBHM) to the top-right and Zero-inflated Negative Binomial Model (ZINBM) to the bottom left. The rootogram for PRM (top-left) shows that the counts (1, and 2) are over fitted while zero (0) and most count from 3 going are under fitted. This clearly shows over dispersion and a high number of under dispersion in the data. Therefore, a clear lack of fit for zero (0) count means that there is still a possibility of excess zeros in the study's count data.

Also, the rootogram for ZINBM (bottom-left) shows that there is under fitting of zero (0) and counts (3 going) indicating the presence of excess zeros and under dispersion in the count data. Comparably, the Zero-inflated Negative Binomial Model (ZINBM) is a much better fit than the Poisson Regression Model (PRM). However, the rootogram for NBHM (top-right) shows that the model perfectly fits the count zero (0). This clearly indicates that NBHM completely treats the excess zeros. Also, the deviations between the observed frequencies and the predicted frequencies are quiet small for most of the positive counts. Which means that NBHM is the best fit model.

Risk Efficient Income on Subscription and Subscription Intensity of Weather Insurance

In reference to the Table 3 which shows the results of (AIC, BIC, and Log-likelihood), The table 4 which shows the results of the Vuong statistical test and the Figure 2 which presents the results of the rootogram, all results show that the Negative Binomial hurdle model is the best model for this study rather than its competing models (PRM and ZINBM). Therefore, the results of the NBHM on the effect of risk efficient income on subscription and subscription intensity presented in the Table 5 is discussed. From the Table 5, the results of the Negative Binomial Hurdle Model (NBHM) indicate the estimate with their associated standard errors in bracket. In the first regression stage of the NBHM (Zero-hurdle model), the results show that variables such as the age of a farmer, sex, farm size, insurance prompt payment, extension service, credit access and risk efficient income are statistically significant in influencing food crop farmer's decision to subscribe to the weather index insurance. In the second regression stage of the NBHM (Count model), the results show that age, sex, education, farm size, experience, FBO, household size, insurance prompt payment, insurance awareness, credit access, risk efficient income are the variables that are statistically significant in influencing the intensity of farmer's subscription to the weather index insurance.

From the Table 5, the results of zero hurdle and count model of the NBHM show that the age of a farmer has a negative relationship with subscription and subscription intensity



Source: Field survey, (2023)

Figure 2: Hanging rootogram of different count models for the study's count data (0, 1,2,3,4….10).

and is significant at 1% and 10% respectively. This implies that older food crop farmers have extensive knowledge and skills, have dealt with many crop failures and losses, and have gained a lot of experience dealing with risky situations such as climatic or production risk. Therefore, they are more likely not to subscribe to the weather index insurance, let alone increase the number of subscriptions. The results of the zero-hurdle model of the NBHM show that farm size has a negative effect on the subscription for WII insurance and is statistically significant at 5%. This implies, it is more likely that a hectare increase in farm size will reduce the number of people who will subscribe to the weather insurance product. Also, the results of the zero-hurdle model of the NBHM show that access to extension services is found to have a positive effect on the subscription of WII and is statistically significant at 5% level. This implies that increasing extension service access to farmers is more likely to increase the number of farmers who will subscribe to the weather insurance product. This is consistent with a study by Ankrah et al. (2021).

Accordingly, from the Table 5, the results of the count model of NBHM, show that insurance awareness was found to have a negative relationship with subscription intensity of WII and is statistically significant at 1% level. This implies that, it is likely they may be aware of the WII but do not have the purchasing power to increase their subscription intensity. Insurance prompt payment has a positive effect on subscription intensity of the WII and is significant at 10%. This means, it is likely that immediate payment of insurance compensation will attract food crop farmers to increase the proportion of the land size insured. Access to credit was found to have a positive relationship with subscription and subscription intensity, and is statistically significant at 1% and 5%, respectively. This implies that making credit available to the farmers to be able to access is likely to increase the number of farm lands they will insure.

From the Table 5, the results of the zero-hurdle model of NBHM show that risk efficient income has a positive and statistically significant effect on subscription of weather index insurance product. This implies that an increase in the income of the farmer (Risk efficient income) is likely to increase the number of farmers who will subscribe to the insurance product. Interestingly, the count model results of the NBHM shows a negative coefficient for risk efficient income and is statistically significant at 1% level. This means that as the farmer gets a higher income (risk efficient income) than his farm income, it is likely he will no longer be willing to expand the land size insured. The plausible reason is that financial situations are getting better and therefore it serves as enough security to carter for the cost of any unforeseen circumstance.

Variable	Subscription of Weather Index-Based Insurance			Subscription Intensity of Weather Index-Based Insurance		
	PRM	NBHM (Zero Hurdle)	ZINBM (Zero Model)	PRM	NBHM (Count Model)	ZINBM (Count) Model
Intercept	6.9861*** (0.1808)	7.9162*** -1.3987	-12.8891*** (2.4122)	- -	3.9678*** (0.2479)	3.9679*** (0.2479)
Age	-0.0316*** (0.0017)	-0.0467*** (0.0113)	-0.0777*** (0.019)	- -	-0.0046* (0.0027)	-0.0046* (0.0027)
Sex	-0.3563*** (0.023)	-0.6582*** (0.1798)	1.1078*** (0.3093)	- -	-0.0522* (0.0317)	-0.0522* (0.0317)
Education	0.0490*** (0.0116)	-0.0487 (0.0806)	0.0822 (0.1378)	- -	0.0784*** (0.0159)	0.0784*** (0.0159)
Farm Size	-0.0202*** (0.0051)	-0.0938** (0.0406)	0.1478* (0.0672)	- -	0.0220** (0.0068)	0.0220** (0.0068)
Farm Experience	0.0122*** (0.0027)	0.0044 (0.0176)	-0.0087 (0.0294)	- -	0.0118** (0.0039)	0.0118** (0.0039)
FBO	0.0744** (0.0240)	0.0021 (0.1596)	-0.0289 (0.2681)	- -	0.0724* (0.0313)	0.0724* (0.0313)
Household Size	-0.0177*** (0.0043)	-0.0265 (0.0280)	0.0407 (0.0476)	- -	-0.0109* (0.0061)	-0.0109* (0.0061)

Source: Field survey, (2023)

Table 5: Risk Efficient Income and Risk Aversion on Subscription and Subscription Intensity Weather Index-Based Insurance.
(To be continued).

Variable	Subscription of Weather Index-Based Insurance			Subscription Intensity of Weather Index-Based Insurance		
	PRM	NBHM (Zero Hurdle)	ZINBM (Zero Model)	PRM	NBHM (Count Model)	ZINBM (Count) Model
Insurance Prompt	-0.0848*** (0.0215)	0.3191** (0.1485)	0.5356* (0.2493)	- -	0.0565* (0.0279)	0.0565* (0.0279)
Insurance Awareness	-0.1308*** (0.0210)	-0.0726 (0.1443)	0.1105 (0.2397)	- -	-0.1374*** (0.0292)	-0.1374*** (0.0292)
Weather Information	0.1272*** (0.0206)	0.3386** (0.1474)	-0.5164* (0.2473)	- -	-0.0316 (0.0296)	-0.0316 (0.0296)
Extension Service	0.1910*** (0.0211)	0.2925** (0.1442)	-0.5021* (0.2418)	- -	0.0255 (0.0275)	0.0255 (0.0275)
Credit Access	0.3328*** (0.0220)	0.5372*** (0.1560)	-0.8782*** (0.2602)	- -	0.0638* (0.0287)	0.0638* (0.0287)
Risk Efficient Inc.	-0.2872* (0.0178)	0.5209*** (0.1372)	0.8430*** (0.2359)	- -	-0.0602* (0.0246)	-0.0602* (0.0246)
Log (Theta)				- -	4.1618*** (0.2170)	4.1618*** (0.2170)
AIC	10851.4	2557.469	2559.325			
BIC	10917.15	2693.074	2694.93			
Log-likelihood	-5409.7	-1245.735	-1246.662			

Source: Field survey, (2023)

Table 5: Risk Efficient Income and Risk Aversion on Subscription and Subscription Intensity Weather Index-Based Insurance. (Continuation).

Conclusion

Farm income, aside from other factors, remains a key challenge when it comes to the subscription and subscription intensity of the weather index insurance. The paper bridges a literature and methodological gap by looking at risk efficient income obtained using the stochastic risk optimization model (T-MOTAD). The paper also analyses subscription and subscription intensity of weather index insurance. It further analyses the influence of the risk efficient income, prompt payout, insurance awareness, weather information, credit access and extension service among factors on subscription and subscription intensity using the negative binomial hurdle model. Furthermore, the study empirically tested the Negative Binomial Hurdle Model and two other count models (Poisson Regression Model and Zero-inflated Negative Binomial Model) using the AIC, BIC, Log-likelihood ratio test and Vuong statistical test to determine which among them is the best fit model for the study. The result from the T-MOTAD shows that the risk optimum plan was for the farmer to produce soya beans and sorghum to obtain a risk efficient income. The results from subscription and intensity also show that about 64% of the farmers have subscribed to the weather index insurance. Therefore, the proportion of the farm insured per land cultivated by the subscribers was 0.39 ha. The results from the negative binomial hurdle model shows that factors such as risk efficient income, insurance prompt payout, credit access, extension service, education, age, farm size and experience are statistically significant in influencing food crop farmer's subscription and subscription intensity of the weather index insurance.

The study contributes to the literature by adding to the limited number of studies on subscription, and subscription intensity. This study is unique as it integrates a risk-efficient farm plan with subscription of the weather index insurance product as a support policy, marking it the first initiative of its kind within the Ghana empirical context. The study also bridged the methodological gap by testing the empirical superiority of the negative binomial hurdle model and the zero-inflated negative binomial model as advancements over the Poisson regression model in analyzing the study's count data. This will benefit the research community in that it will provide a reference literature for further work relating to subscription and subscription intensity as well as risk optimum farm plan. This study suggests collaboration between government agencies, insurers, and extension officers to educate farmers about weather index insurance. Prompt payouts and focusing on crops identified by the T-MOTAD model could incentivize participation. Further research is needed on how risk-reducing farm plans affect farmers' willingness to pay for this insurance.

Acknowledgments

The authors wish to express their gratitude and sincere appreciation to Samuel and Emelia Brew-Butler Foundation for their valuable financial contributions.

Corresponding author:
Augustine Koufie, Graduate Assistant
Department of Agricultural Economics and Extension, School of Agriculture, College of Agriculture and Natural Sciences, University of Cape Coast, Ghana
Phone: +233 533 050 0258, E-mail: augustine.koufie@stu.ucc.edu.gh

References

[1] Abdul-Razak, M. and Kruse, S. (2017) "The adaptive capacity of smallholder farmers to climate change in the Northern Region of Ghana", *Climate Risk Management*, Vol. 17, No. 12, pp. 104-122. ISSN 2212-0963. DOI 10.1016/j.crm.2017.06.001.

[2] Addey, K. A., Jatoe, J. B. D. and Kwadzo, G. T. M. (2020) "Adoption of crop insurance in Ghana: an application of the complementary log-log truncated Poisson double-hurdle model", *Agricultural Finance Review*, Vol. 8, No. 1, pp. 76-93. ISSN 0002-1466. DOI 10.1108/AFR-06-2019-0062.

[3] Akinola, B. D. (2014) "Determinants of farmers' adoption of agricultural insurance: The case of poultry farmers in Abeokuta Metropolis of Ogun State, Nigeria", *British Journal of Poultry Sciences*, Vol. 3, pp. 36-41. ISSN 1995-901X. DOI 10.5829/idosi.bjps.2014.3.2.83216.

[4] Amponsah, E., Afful-Mensah, G. and Ampaw, S. (2018) "Determinants of cigarette smoking and smoking intensity among adult males in Ghana", *BMC Public Health*, Vol. 18, pp. 1-10. ISSN 1471-2458. DOI 10.1186/s12889-018-5872-0.

[5] Ankrah, D. A., Kwapong, N. A., Eghan, D., Adarkwah, F. and Boateng-Gyambiby, D. (2021) "Agricultural insurance access and acceptability: examining the case of smallholder farmers in Ghana", *Agriculture & Food Security*, Vol. 10, No. 1, pp. 1-14. ISSN 2048-7010. DOI 10.1186/s40066-021-00292-y.

[6] Antwi, K. (2016) "Optimal resource allocation decision among women farmers in the Northern Region of Ghana", *African Journal of Agriculture and Food Security*, Vol 4, No. 3, pp. 161-166. ISSN 2375-1177.

[7] Dai, H., Xue, Y., He, N., Wang, Y., Li, N., Schuurmans, D. and Dai, B. (2023) "Learning to optimize with stochastic dominance constraints", *International Conference on Artificial Intelligence and Statistics*, Vol. 206, pp. 8991-9009. PMLR. [Online]. Available: https://proceedings.mlr.press/v206/dai23b/dai23b.pdf. [Accessed: July 21, 2024].

[8] Dembele, B. (2018) "Income, crop diversification strategies and agricultural practices in crop and livestock production systems in Southern Mali", Ph.D. Thesis, Egerton University. [Online]. Available: http://41.89.96.81:8080/xmlui/handle/123456789/1726 [Accessed: July 21, 2024].

[9] Ellis, E. (2017) "Farmers' Willingness to Pay for Crop Insurance: Evidence from Eastern Ghana", *International Journal of Agricultural Management and Development (IJAMAD)*, Vol. 7, No. 4, pp. 447-463. ISSN 2159-5860. DOI 10.22004/ag.econ.292508.

[10] Feng, S., Han, Y. and Qiu, H. (2021) "Does crop insurance reduce pesticide usage? Evidence from China", *China Economic Review*, Vol. 69, p. 101679. ISSN 1043-951X. DOI 10.1016/j.chieco.2021.101679.

[11] Fiala, N. (2017) "Business is tough, but family is worse: Household bargaining and investment in microenterprises in Uganda", *Working Paper Series*, 5. University of Connecticut. [Online]. Available: https://econpapers.repec.org/RePEc:uct:uconnp:2017-05 [Accessed, July 21. 2024].

[12] Ghana Agricultural Insurance Programme (2013) "Developing Sustainable financial solutions to the Challenge of Climate Change", GAIP, Accra, Ghana. [Online]. Available: https://gaip-info.com/. [Accessed, July 21, 2024].

[13] Kalmijn, M. (2012) "Longitudinal analyses of the effects of age, marriage, and parenthood on social contacts and support", *Advances in Life Course Research*, Vol. 17, No. 4, pp. 177-190. ISSN 1569-4909. DOI 10.1016/j.alcr.2012.08.002.

[14] Koufie, A. (2020) "Optimum combination of food crop farm enterprise among smallholder farmers in the Assin north district of Ghana". Ph.D. Thesis, University of Cape Coast. [Online]. Available: http://hdl.handle.net/123456789/6570. [Accessed: July 21, 2024].

[15] MoFA (2015) "*Ministry of Food and Agriculture: Northern Region Agricultural Development Unit*", July 2015. Report. [Online]. Available: https://mofa.gov.gh/site. [Accessed: Jul. 21, 2024].

[16] Udo, U. J., Onyenweaku, C. E., Igwe, K. C. and Salimonu, K. K., (2015) "Formulating optimal farm plans with child farm labour reduction for arable crop farmers in Akwa Ibom State, Nigeria: an application of Linear Programming and T-Motad models", *Asian Journal of Agricultural Extension, Economics and Sociology*, Vol. 7, No. 1, pp.1-13. ISSN 2320-7027. DOI 10.9734/AJAEES/2015/18634.

Agris on-line Papers in Economics and Informatics

Volume XVI Number 4, 2024

Challenges and Trends in Agricultural Employment: The Case of Hungary

Zalán Márk Maró[1], Áron József Borda[2], Jeremiás Máté Balogh[1]

[1] Department of Agricultural Economics, Institute of Sustainable Development, Corvinus University of Budapest, Hungary

[2] Doctoral School of Business and Management, Corvinus University of Budapest, Hungary

Abstract

The agriculture and food industry faces many challenges, including a shortage of skilled and seasonal workers, low productivity, and a demographic shift towards an ageing agricultural population. The agricultural productivity and efficiency of Central and Eastern European countries, including Hungary, are relatively low compared to that of Western Europe. This study explores the complex landscape of agricultural employment in Hungary by analysing its situation and challenges that are in line with international standards. Using national- and company-level data, the study applies an analytical framework comprising descriptive statistics and a non-parametric Kruskal-Wallis test to explore patterns and trends in the sector's performance. In Hungary, more than 70% of farm managers are over 45 years old. Furthermore, despite the increase in the number of people with an agricultural education, around 150,000 farms still rely on experience-based management. We identify statistically verifiable and notable differences in the investigated indicators (sales revenue in proportion to number of employees, wage efficiency, personnel expenses per capita, assets value per capita) according to the founding period (pre-1989, 1989-2004, post-2004). The study concludes by arguing for generational change, better agricultural education and emphasis on the concentration of skills and capital within families as a sustainable solution, thereby addressing the complex challenges of the agricultural labour market and creating flexibility in the sector by attracting younger and educated people.

Keywords

Agricultural employment, rural employment labour, migrant labour, employment problems, labour productivity, efficiency, Kruskal-Wallis tests, Hungary.

Maró, Z. M., Borda, Á. J. and Balogh, J. M. (2024) "Challenges and Trends in Agricultural Employment: The Case of Hungary", *AGRIS on-line Papers in Economics and Informatics*, Vol. 16, No. 16, pp. 109-128. ISSN 1804-1930. DOI 10.7160/aol.2024.160409.

Introduction

In recent years, climate change, the fourth industrial revolution, and the growing middle class globally have posed increasingly greater challenges for agriculture and the food industry (Iglesias et al., 2012; Prisecaru, 2016; Wheeler and Von Braun, 2013). These challenges have appeared simultaneously on the market and with regard to technology. It is a market-related problem that in EU countries and, more narrowly, Central and Eastern European (CEE) ones, the development and productivity of the food industry exceeds that in Hungary (Bozsik and Magda, 2018; Fogarasi, 2007; Latruffe et al., 2012). A completely new technological environment is expected to be decisive in the coming years. At the same time, agriculture and the food industry play a significant role in CEE and the Hungarian economy for historical reasons and due to geographical location (Harangi-Rákos and Szabó, 2013; Ritter, 2004).

Despite their decreasing number, family farms are still crucial elements of agricultural employment in many developed countries (Klikocka et al., 2021; Smędzik-Ambroży et al., 2021). In Western and Northern Europe, the average size of farms is increasing due to greater efficiency pressure on modern farms (Hubert, 2018; Rye et al., 2018). Along with the increase in farm size, non-family employment also appears in the agricultural industry, especially in Central and Eastern Europe, although the number of family members working on family farms is decreasing (they prefer to work in other sectors of the economy). Family labour can be more favourably replaced using seasonal workers than workers with permanent contracts (e.g., income tax is more favourable with short-term contracts; several programs support seasonal work) (Alarcón, 2021; Darpeix et al., 2014). In the case of Central and Eastern Europe, several studies (Biernat-Jarka, 2015; Dries and Swinnen, 2002; Górny and Kaczmarczyk, 2018; Labrianidis and Sykas, 2009) have highlighted that, due to structural change, the number of farms of less than five hectares (mainly family farms) has decreased to the greatest extent, as size significantly influences productivity. In turn, the number of immigrant seasonal workers is increasing in agriculture, including in Poland. During the high season, 80-90% of the workforce employed on Polish farms are immigrant workers, mainly from Ukraine (Górny and Kaczmarczyk, 2018). The proportion of migrant workers in agriculture is also rising in Greece; the primary reason is the movement of young people and women from the agricultural sector to other, more profitable sectors (Papadopoulos et al., 2021). In the case of Romanian agriculture (Mateoc-Sîrb et al., 2014; Tocco et al., 2012), the presence of a Western European agricultural model cannot yet be observed since agriculture accounts for a very large share of GDP and family farms are dominant and employ a significant amount of people. However, as in all European countries, in Romania young and skilled people are more likely to leave agriculture.

One primary means of increasing labour productivity is reducing the labour cost associated with creating agricultural products. For this, the use of new equipment and new technologies is essential, which may affect the workforce. Therefore, the development of human capital is essential in agriculture as well (Babenko and Vasilyeva, 2017). American farmers report that the recent wave of mechanisation and digitisation will reduce the use of migrant labour in agriculture (Carolan, 2020, D'Antoni et al., 2012), while according to German farmers, it will take a long time for machines to completely replace migrant workers (Prause, 2021). The rapid development of technology and smart agriculture and the collection and processing of an incredible amount of data require different knowledge and skills from agricultural workers than before. One of the most essential means of managing this change is education, which, however, must also adapt to this challenge (e.g., practice-oriented or dual training). Having professionals with the right knowledge and experience has become crucial. At the same time, it should also be noted that the education of the agricultural workforce is generally lower than in other sectors (Dries and Swinnen, 2002; Górny and Kaczmarczyk, 2018), and members of the highly educated workforce often do not spend a long time in the agricultural sector, instead looking for job opportunities in non-agricultural sectors (Bousmah and Grenier, 2022, Tocco et al., 2012, Unay-Gailhard and Bojnec, 2019).

As in other sectors, important goals include increasing profits and productivity. The need to increase productivity is further reinforced by the generally widely observed labour shortage in developed countries. Agricultural investment, innovation and capital per employee are directly correlated with agricultural gross domestic product per employee, highlighting the importance of investing in raising labour productivity (Herrendorf and Schoellman, 2015). In addition, decreases in labour due to technological developments require increasing employees' level of education (Babenko and Vasilyeva, 2017). However, the productivity of agricultural land grows more slowly than the increase in labour force, and growth in agricultural productivity lags behind that of input-producing sectors, which is especially true for smaller producers (Kołodziejczak, 2020). As a result, it is necessary to concentrate production, optimise the production structure, develop technology, and support young people in starting agricultural activities (Kuznets and Murphy, 1966; Duarte and Restuccia, 2010).

Kijek et al. (2020) examined the EU Member States based on agricultural productivity. The authors constructed three groups: countries with low- (the new Member States, except for Cyprus, Malta, and Slovenia), medium- (Greece, Italy, Portugal, Spain, and Cyprus, Malta, and Slovenia) and high- (the remaining old Member States) productivity. In the first two groups (low and medium), the values gradually converged within the groups, while the differences increased within the third group (high productivity), i.e., economic and structural conditions are very important from this point of view. The role of agriculture and the food industry is more significant in the new Member States of the EU than in the old ones, but the opportunities for employment growth are limited in the case of both groups of countries (Donnellan and Hanrahan, 2017). Another regional difference is that the role of the food industry in gross added value is typically greater in the old Member States, while the share of agriculture is more significant in the new Member States.

Hungary's transition from a centrally planned economy to a market-oriented one in the 1990s brought forth challenges and opportunities regarding the efficiency of agricultural employment. The agricultural workforce in Hungary has experienced a steady decline, primarily due to modernisation and structural changes in the sector. The level of education and skills among Hungarian agricultural workers is integral to employment efficiency (Mészáros and Szabó, 2014). The mechanisation and adoption of modern agricultural technologies have significantly enhanced labour efficiency (Schmitz and Moss, 2015). Sectoral productivity, capital accumulation, and total factor productivity contribute to sectoral performance, especially in key areas of the sector (Yasmin et al., 2019). Efficiency analyses of agriculture in Central and Eastern Europe, and mainly in Hungary, show less efficiency and less labour productivity in comparison to the EU-15 (Nowak et al., 2015; Đokić et al., 2022), and a decreasing trend over time (Kočišová, 2015). Different specialisation patterns and policy measures (e.g., subsidies) in the Central and Eastern European countries contribute to filling this gap (Górny and Kaczmarczyk, 2018; Csaki and Jambor, 2019).

Overall, the efficiency of agricultural employment in Hungary and other countries is influenced by a combination of the following factors: structural changes, education level, adoption of technology, investment, and government policies, each playing a significant role in shaping the productivity and competitiveness of the sector. In recent years, the listed problems have not been solved due to the fragmentation of the production structure of Hungarian agriculture, the ageing farming community, urbanisation and the migration of the rural population, the relatively low agricultural incomes, and the spread of the coronavirus pandemic along with the Russian-Ukrainian conflict. The purpose of the present study is to assess the situation and challenges of Hungarian agricultural employment in line with international standards and to provide relevant policy recommendations concerning the new challenges of agricultural employment and the education system. In this paper, the authors address the following questions: (1) How is agricultural employment developing in Hungary and? (2) What are the main trends in agricultural employment? (23) What challenges does Hungarian agricultural employment face? (34) What are the differences between companies operating in Hungarian agriculture in terms of time of foundation? We answer these questions in the Results and Discussion section. Finally, the last section provides conclusions and policy implications, notes limitations, and suggests future research based on the article.

Materials and methods

In this chapter, we describe the structure of the database selected and the methodological approaches used for the analysis. First, the Hungarian agricultural employment situation is analysed based on national data from the Hungarian Central Statistical Office (HCSO). More specifically, descriptive statistics are calculated, with the help of the Excel and SPSS softwares, for the period from 2011 to 2020. However, this 9-year period was selected for the examination of the national data, since company-level data were available for three years (2011, 2015, 2020) obtained from OPTEN Informatics Ltd. In the first part of the paper (see Results and Discussion), the distribution of people employed in Hungary by economic sector, the number of Hungarian agricultural employees, the gender and age distribution of Hungarian agriculture, and the education level of farm managers were investigated. In this part, we seek to answer the following research questions: How is agricultural employment developing in Hungary and what are the main trends in agricultural employment? What challenges does Hungarian agricultural employment face?

We also used a company-level database containing 23,414 observations referring to various Hungarian agricultural enterprises. This firm-level data comes from OPTEN Informatics Ltd., which provides company data and information services. The OPTEN database contains the following variables about the companies: (1) name, (2) headquarters, (3) number of locations, (4) main activity, (5) headcount data, (6) location according to county, (7) net sales revenue, (8) equity, (9) personnel expenses, (10) assets, (11) year of foundation, and (12) the year the financial report was prepared.

Table 1 provides comprehensive details of the accounting data received from OPTEN, expressed in nominal prices for the examined enterprises. The indicators in this series relate directly and indirectly to the balance sheet, through the profit after tax. These indicators show a significant dispersion, reflecting the variability within the data. In order to deal with this variability and to achieve a more accurate representation,

Accounting data (thousands of HUF)	Mean (Standard deviation) [5% trimmed mean] (median)		
	2011	2015	2020
Net revenue	609,814 (3,579,851) [226,993] (90,713)	615,641 (3,904,126) [214,551] (84,675)	715,060 (4,860,263) [232,726] (91,368)
Personnel expenses	52,292 (234,960) [21,372] (9,305)	57,524 (296,722) [22,307] (10,018)	67,246 (380,480) [26,593] (12,457)
Assets	582,415 (2,272,136) [287,529] (114,388)	629,476 (2,495,063) [301,197] (109,886)	794,104 (3,700,645) [353,081] (131,318)
Owners' equity	288,074 (1,039,840) [148,433] (45,589)	334,334 (1,149,360) [168,898] (49,786)	428,493 (1,582,843) [207,170] (67,374)

Source: Author's composition based on Opten (2023)

Table 1: Accounting data of the examined agricultural enterprises.

a 5% reduced average has been calculated by excluding the extreme values at the beginning and at the end of the data series. This adjustment results in a significantly corrected and refined comparison that provides insights, similar to the median.

In the second part of the article (see Results and Discussion), the main emphasis is on presenting the basic characteristics of the companies (e.g., distribution of investigated enterprises by county or agricultural sector, the number of employees), as well as conducting a variance analysis for some accounting indicators (sales revenue in proportion to number of employees, wage efficiency, personnel expenses per capita, value of assets per capita) according to the founding period. Three years (2011, 2015, 2020) have been analysed, due to the data collection and transfer of OPTEN, highlighting the differences between the periods.

Descriptive statistics and non-parametric Kruskal-Wallis tests, in the case of the company data received from OPTEN, were applied using Excel and SPSS software. The Kruskal-Wallis test is used to determine whether there is a significant difference between three or more groups when the conditions of normal distribution are not met and the variances between independent samples are unequal. The Kruskal-Wallis test works by ranking data and then comparing the sum of the data ranks between groups. If there is no difference between the groups, then the differences between the statistical values calculated as the sum of the rankings of each group are random (Ostertagova et al., 2014, Breslow, 1970). In this paper, with the help of the Kruskal-Wallis test, a statistically significant (at the 5% level) difference was investigated in the above mentioned indicators in line with year of foundation (pre-1989, 1989-2004, post-2004). These periods and years were chosen because Hungary had a political and economic system change in 1989 and the country became the member of the European Union in 2004. Kruskal-Wallis test was used to answer the research question of 'What are the differences between companies operating in Hungarian agriculture in terms of time of foundation?'.

Results and discussion

The situation of Hungarian agricultural employment - based on national data

In Hungary, the democratic transformations that occurred in 1989-1990 fundamentally changed the organisation of the economy and society, accompanied by the appearance and permanence of unemployment. On the one hand, the number of economically inactive people increased; on the other hand, production fell. The economic activity of the population decreased due to the closure and transformation of various companies and (production) cooperatives. According to Halmos (2006), nearly one and a half million jobs were lost between 1989 and 1992, and the number of employed people continued to decrease until 1997. After the regime change, the structure of employment was radically transformed; the weight of the classical production sectors decreased, while the role of the service sector increased. This transformation resulted in a substantial reduction in the number of workers in agriculture.

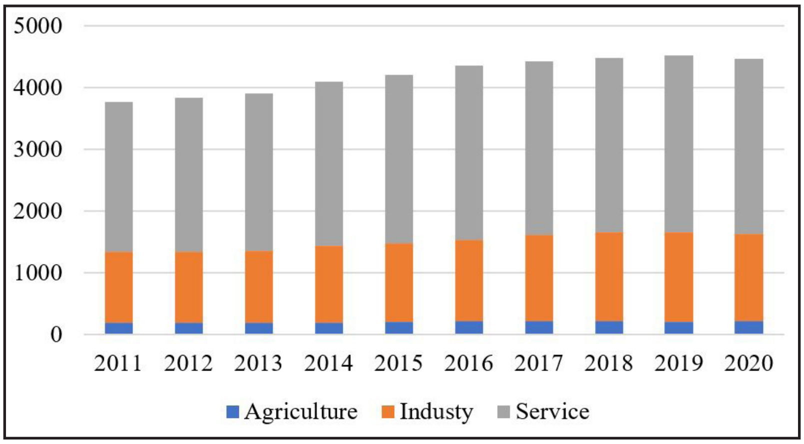
Using the data of the Hungarian Central Statistical

Office (HCSO), we sought to find out the trends in agricultural employment in Hungary between 2011 and 2020. The proportion was nearly two-thirds, approximately 30% in the industrial sector, and only 4.74% in the agricultural industry (Figure 1). The number of people employed in the agricultural sector has increased from 186,5 thousand in 2011 to 213,9 thousand in 2020, indicating the important role of the sector in the labour mark. However, the share of agricultural employment in total employment has slightly decreased from 4.78% in 2011 to 4.65% in 2020, indicating an expansion in other sectors. Based on Avincz et al. (2002), the number of people living from agriculture, or those connected to it at some level, may be much higher than in the official statistics. The share of the agricultural workforce in the EU varies across Member States, with a generally decreasing trend due to factors such as ageing and rural-to-urban migration, particularly among the younger generation seeking higher-paying employment (Popescu et al., 2021). In general, a small share of agricultural employment is a feature of European countries (Garrone et al., 2019, Megyesiova, 2021). Empirical evidence on the impact of subsidies on agricultural employment is mixed, with some studies showing positive effects (Breustedt and Glauben, 2007, Olper et al., 2014), while others find no or negative effects (Berlinschi et al., 2014). However, the CAP-related budgetary cost of maintaining jobs in agriculture is very high (Garrone et al., 2019).

Observing the distribution of employment by area, most people work in the Northern and Southern Great Plains and Southern Transdanubia (Table 2). The latter two regions are classically rural areas where the share of agriculture in GDP is the highest. After the regime change, relations between settlements were also transformed. Due to urbanisation, the labour force began to flow from rural (mainly agricultural) areas to towns. This process has affected the proportion of agricultural employees in villages and small towns since larger ones attract workforce from neighbouring settlements. As a result, most inhabitants do not participate in local production (Weber, 2014).

In addition to changes at national level, the data were used to examine how agricultural employment has changed at regional level. Regionally, agriculture is significant in all regions of Hungary except Budapest, where agricultural employment is lowest, but increased slightly from 3.1 thousand in 2011 to 4.5 thousand in 2020. In Central Hungary, the number of agricultural employees remained stable, but their share decreased. In Central Transdanubia region, the number of employees increased but their share decreased slightly. In Western Transdanubia, the number of employees remained stable but its share decreased, indicating a declining role of agriculture.

In South Transdanubia, fluctuations in the number of agricultural workers were observed. In Northern Hungary, the share of agricultural workers decreased, despite fluctuations in the number of employees. The Northern Great Plain showed a steady increase in both the number and the share of agricultural workers, highlighting the growing importance of agriculture in this region. The Southern Plain has also seen a steady increase in the number of agricultural employees, maintaining its dominant role in the region's labour market. The latter two regions are classically rural areas where the share of agriculture in GDP



Source: Author’s composition based on HCSO (2023) data

Figure 1: Distribution of people employed in Hungary by economic sector (thousands of people).

is the highest. After the regime change in 1989-1990, relations between settlements were also transformed. Due to urbanisation, the labour force began to migrate from rural (mainly agricultural) areas to towns. This process has affected the proportion of agricultural employees in villages and small towns since larger ones attract workforce from neighbouring settlements. As a result, most inhabitants do not participate in local agricultural production processes (Weber, 2014).

Overall, the increase in the number of agricultural workers points to the continued importance and stability of the agricultural sector in the different regions of Hungary, despite a slight decline in its share of total employment. This may indicate a diversification of the economy, with other industries developing alongside agriculture.

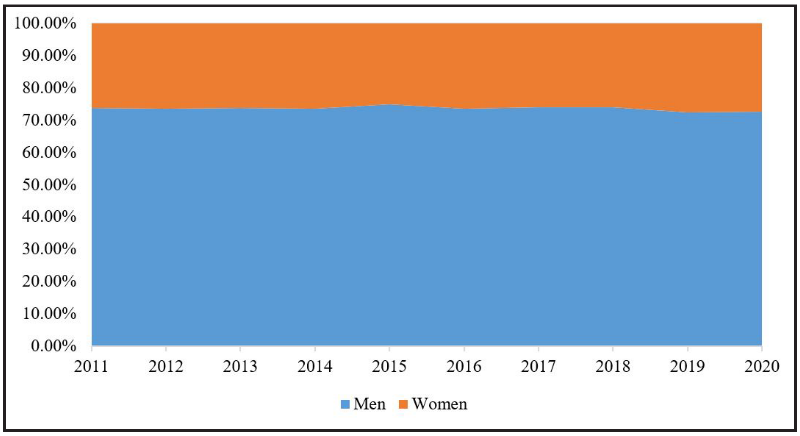
In Hungary, there have been no significant changes in terms of gender since men have always been disproportionately represented in agriculture due to the predominantly physical nature of the industry (Figure 2). In 2010 and 2011, after a continuous decrease, the proportion of men started to increase again and reached 76%. Since 2015, the proportion of men compared to women has continuously decreased; in 2020, 26.5% of the employed were women. It is clear from the literature that women are engaged in monotonous, less appreciated and less profitable agricultural activities (de Castro et al., 2020; Cortignani et al., 2020).

In addition to changes at national level, the data were used to examine how agricultural employment has changed at regional level. The age structure of agriculture (Figure 3) is very different from that of other sectors, as the proportion of the older age group is outstanding. While in 2011 and 2015, 55-64-year-olds were in the majority, by 2020, the over-65s accounted for 35% of managers of agricultural enterprises. Twenty-seven per cent of managers are between the ages of 60 and 69, but the age group between 70 and 75 also accounts for a significant 10%. Overall, more

Regions	2011		2015		2020	
	Agriculture, thousand people	Share	Agriculture, thousand people	Share	Agriculture, thousand people	Share
Budapest	3.1	0.41%	3,7	0.44%	4.5	0.51%
Central Hungary	12.6	2.48%	12.5	2.22%	13	2.02%
Central Transdanubia	19.6	4.26%	23.1	4.61%	22.8	4.39%
Western Transdanubia	23.6	5.56%	23.5	5.07%	23.7	4.76%
Southern Transdanubia	25.6	7.59%	30.2	8.17%	28.6	7.64%
Northern Hungary	17.1	4.24%	20.5	4.43%	18.5	3.83%
Northern Great Plain	38.5	7.35%	43.1	7.14%	48.7	7.59%
Southern Great Plain	47.6	9.63%	50.1	9.28%	54.2	9.59%
Total	186.5	4.78%	205.3	4.74%	213.9	4.65%

Source: Author's composition based on HCSO (2023)

Table 2: Number of domestic employees in Hungary by region (2011, 2015, 2020).



Source: Author's composition based on HCSO (2023)

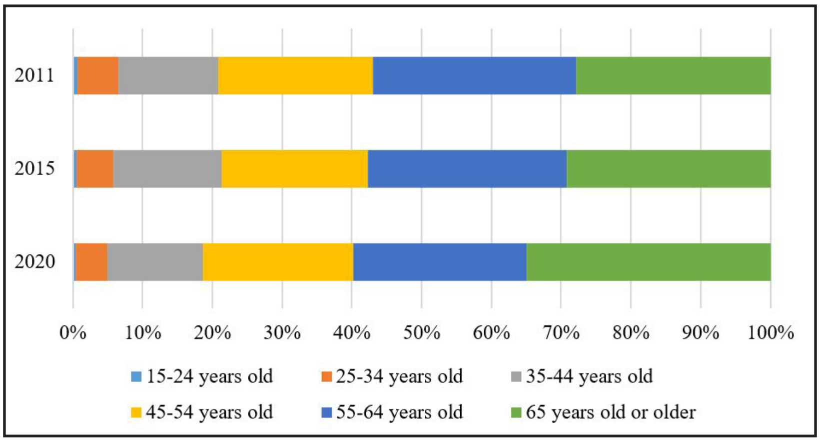
Figure 2: Gender distribution in Hungarian agriculture.

than 80% of farm leaders are between 45 and 74 years old in 2020. Demographic challenges pose a significant social obstacle for family farms, which is particularly evident concerning the issue of ageing managers, as predominantly observed in developed nations. Approximately one-third of family farm managers in the European Union are 65 or older, with notable percentages observed in specific countries such as Portugal (50%), Romania (44%), Cyprus (43%), and Italy (40%). Young farm managers (under 40) accounted for only about 10% of all managers (Eurostat, 2019). Overall, the increase in the share of the older generation and the decrease in the share of the younger generation indicate that the agricultural sector is a highly ageing. The ageing workforce is leading to structural changes in the agricultural sector, and concerns are being raised about its negative impact on the food economy. However, it should be noted that the survey is intended to show the manager of the farm. It is possible that a part of the younger generation is also active on family farms, but they are not participating in the management of farms. Younger farmers are associated with more efficient production practices (Leonard et al., 2017). Additionally, Potter and Lobley (1992) highlight that old age is linked to the transition from intensive to extensive production and the potential disappearance of family farms, especially when the successor is unknown. The challenge of ageing and inter-generational succession in the EU may impact the sustainability of family farming and rural areas.

Regarding the education of people employed in agriculture, only 5.5% of workers in 1990, 7.2% in 1996, and almost 7.7% in 2001 had completed higher education (Avincz et al., 2002). Among those managing farms, by 2020 (compared to 2011), the proportion without agricultural training or education had decreased by nearly 20% (Figure 4). Although the number of managers with agricultural qualifications has increased, there are approximately 150,000 farms that are managed based on experience alone. The education level of the agricultural workforce is generally lower than in other sectors (Dries and Swinnen, 2002, Górny and Kaczmarczyk, 2018), and members of the highly educated workforce typically do not stay long in the agricultural sector, largely for financial reasons (Tocco et al., 2012, Bousmah and Grenier, 2022).

The intensive mechanisation, automation, and robotisation that can also be observed in agriculture make it increasingly necessary to employ a workforce with new types of knowledge. Instead of manual workers, there is a growing need for specialists who can handle and service machines, which requires the development of other skills through education and technology-oriented training (Carolan, 2020). Operating constantly developing agricultural technology requires higher level qualifications (Putićová and Mezera, 2008). Additionally, education and various forms of training have a vital role to play in the employment of the workforce this frees up (Marinoudi et al., 2019).

Today, the younger generation has access to more learning and educational opportunities, which significantly impacts generational change. Farrell et al. (2021) observed that young individuals who leave farming for educational pursuits have the option to return, especially, if they receive subsidies or central support in agricultural areas of interest, such as organic farming. According

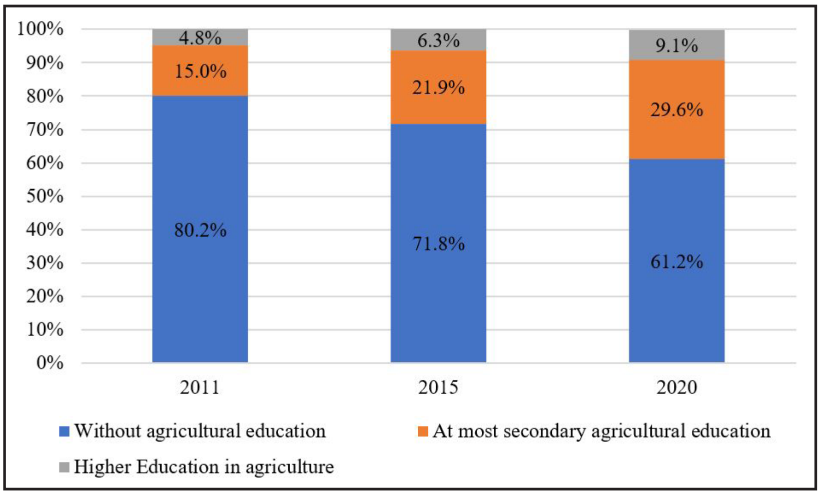


Source: Author’s composition based on HCSO (2023)

Figure 3: Age distribution of farm managers in agricultural enterprises.

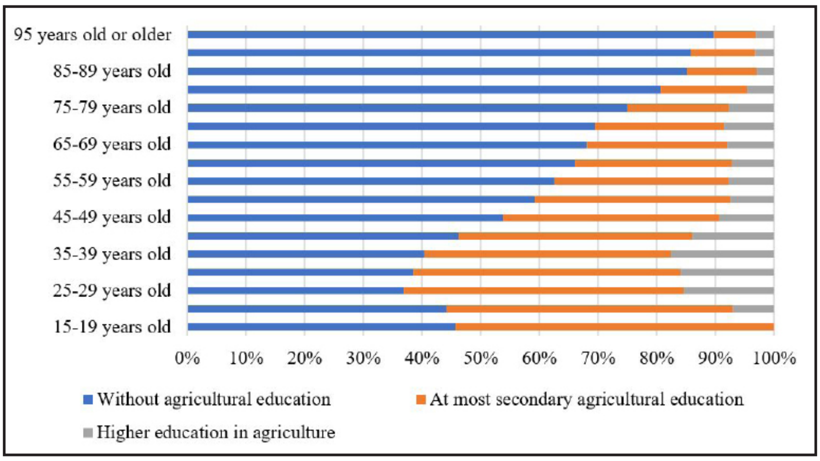
to Popa and Turek Rahoveanu (2021), education plays a crucial role in the decision to start or continue farming, with highly educated young farmers more likely to seek investment and farm establishment support. Popescu (2021) found a link between productivity and farmers' education, concluding that young people are keen to enhance their knowledge to improve their skills. Various studies have highlighted the increasing skill levels of farmers and the role of education in generational change and rural development (Elahi et al., 2022; Osterhoudt, 2018).In addition, Heider et al. (2021) identified the lack of modernization and development as another barrier to generational change. Chiswell and Lobley (2018) noted that older farmers often struggle to delegate farm management tasks, whilemodernization and digitalization offer solutions, as digitalizing administrative tasks allows young people to be more involved in daily farm operations. The adoption of innovative practices, precision agriculture, Agriculture 4.0 (or 5.0), and more sustainable farming methods can encourage the younger generation to take over farms and improve farm viability (Farrell et al. 2021). Modernization can enhance working conditions in agriculture and make the sector more appealing to young people. Research consistently shows that young people are more inclined to modernize the agricultural economy, with financial support being a critical factor (Karttunen et al., 2016; Widiyanti et al., 2018).

Comparison of the distribution according to age and education shows that more younger people have completed higher education (between 25-44 years), and the older a manager is, the greater the probability that they will not have completed agricultural education (Figure 5). According to Karácsony (2010), the low level of education of those employed in agriculture has hindered



Source: Author's composition based on HCSO (2023)

Figure 4: Distribution of farm managers by education.



Source: Author's composition based on HCSO (2023)

Figure 5: Age distribution of farm managers by education and age, 2020.

the development opportunities of Hungary's agriculture. Despite the increase in professional qualifications, today, middle-aged farmers who do not have a professional qualification (or other work experience outside of agriculture) have quite limited options and, if possible, want to continue farming until their retirement. In contrast, if members of the younger, more educated generation decide not to continue agricultural production, the structure of the agricultural workforce may undergo a significant transformation. This process is hindering the necessary restructuring processes in several Central and Eastern European countries (Ritter, 2018).

The situation of Hungarian agricultural employment based on company data

The distribution of the examined enterprises by county is shown in Table 3. In the analysed sample, the largest proportion of enterprises were based in Pest, Bács-Kiskun and Hajdú-Bihar counties and Budapest. In contrast, the smallest proportion is located in Nógrád, Komárom-Esztergom, Fejér and Heves counties.

County	2011	2015	2020
	Distribution (%)		
Bács-Kiskun	9.80	9.47	8.91
Baranya	4.93	5.43	5.72
Békés	6.66	5.81	5.55
Borsod-Abaúj-Zemplén	4.94	5.28	5.26
Budapest	6.08	7.46	7.89
Csongrád	4.35	4.35	4.55
Fejér	2.52	2.49	2.73
Győr-Moson-Sopron	5.14	4.89	4.71
Hajdú-Bihar	7.91	7.36	7.32
Heves	2.62	2.58	2.36
Jász-Nagykun-Szolnok	5.14	4.98	5.17
Komárom-Esztergom	2.37	2.27	2.18
Nógrád	1.23	1.06	1.05
Pest	12.91	12.70	12.59
Somogy	4.87	4.90	5.13
Szabolcs-Szatmár-Bereg	4.99	4.92	4.98
Tolna	3.49	3.70	3.87
Vas	3.31	3.15	2.98
Veszprém	3.74	3.80	3.86
Zala	2.97	3.40	3.19
No data	0.03	0.00	0.00

Note: Counties with the largest proportion of agricultural businesses are shown in bold. Counties with the smallest proportion of businesses are shown in italics.
Source: Author's composition based on OPTEN (2023)

Table 3: Distribution of enterprises by county in Hungary.

Table 4 provides descriptive statistics about the number of employees and the year of establishment of the companies. Regarding the number of employed people, the standard deviation is notable, which indicates that the degree of heterogeneity in the sample is high. A decrease in the number of employed people was typical during the analysed period, while in terms of the year of foundation, enterprises established after 1989 dominate. Market-based companies established after the regime change clearly operate and perform better than non-market-based companies established before 1989 (Martin, 2002).

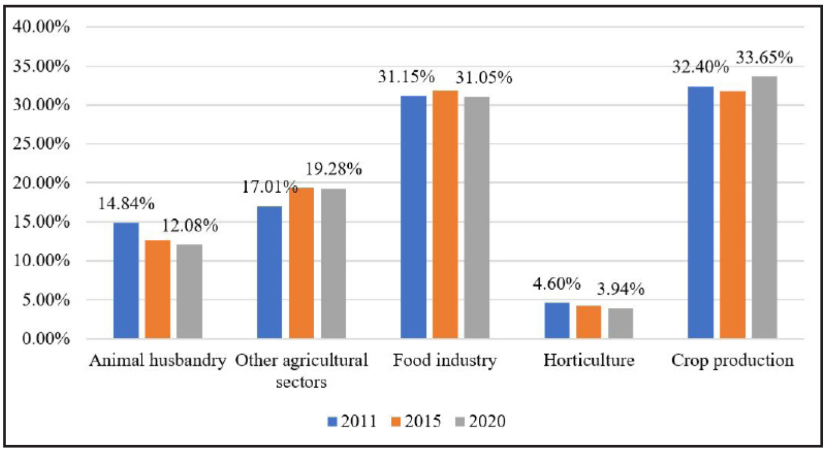
	Mean (standard deviation)		
	2011	**2015**	**2020**
Number of employees	23.99 (79.95)	19.77 (70.44)	17.40 (70.55)
Year of establishment	**Distribution (%)**		
	2011	**2015**	**2020**
-1989	2.89	1.6	1.26
1989-2004	77.2	59.7	49.36
2004-	19.91	38.7	49.38

Source: Author's composition based on Opten (2023)

Table 4: Descriptive statistics of Hungarian agricultural companies in the sample.

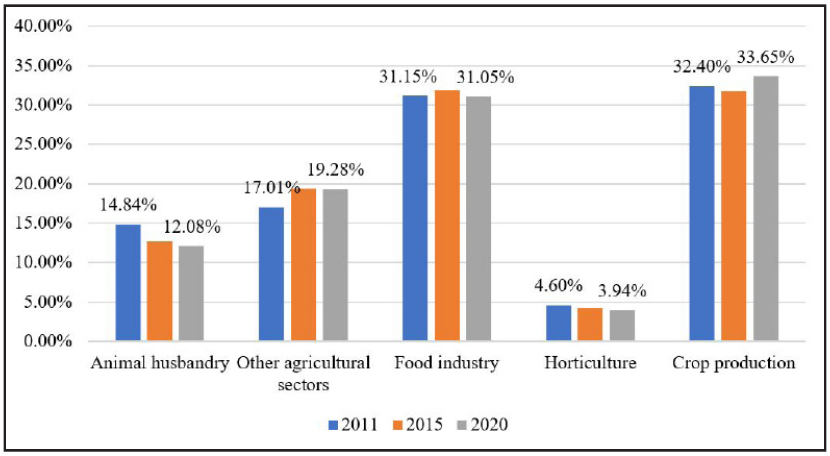
The distribution of the investigated enterprises according to sector is illustrated in Figure 6. The proportion of enterprises in crop production and the food industry is the largest, and those in the horticultural sector the smallest in the analysed sample.

In terms of the number of employees by sector, crop production does not stand out significantly (Figure 7), which shows that this sector is not overly labour-intensive, and mechanisation is present to a high degree.



Source: Author's composition based on Opten (2023)

Figure 6: Distribution of investigated enterprises by agricultural sector in Hungary.



Source: Author's composition based on Opten (2023)

Figure 7: Development of number of employees by sector in Hungary.

Variance analysis based on period of establishment

In the next stage of our analysis, we investigated whether there is a statistically verifiable (significant at the 5% level) difference in the indicators (sales revenue in proportion to number of employees, wage efficiency, personnel expenses per capita, and assets value per capita) according to the founding period (-1989, 1989-2004, 2004-).

A significant difference at the 5% level was found between the period of foundation and sales revenue in relation to number of employees for the three years (Table 5). There are significant differences in revenue per employee by the year of establishment, highlighting how economic and political changes have affected business productivity over time. Enterprises established between 1989 and 2004 had consistently higher turnover per employee than those established before 1989 and after 2004. In 2011, enterprises established between 1989 and 2004 performed better in terms of turnover per employee, significantly outperforming enterprises established before 1989 and after 2004. This period benefited from the immediate effects of market reforms following the collapse of socialism and integration into the European Union, which boosted business growth through an inflow of resources and modernisation efforts.

The trend of outstanding performance of the 1989-2004 cohort continued in 2015. These enterprises maintained their leading position in terms of turnover per employee, underlining the lasting benefits of the various support programmes initiated during and after economic restructuring and EU accession. The ranking scores of companies from this period remained significantly higher than those of companies established in the other periods, confirming the idea that the initial reforms and support programmes have had a long-lasting positive impact

Category	Test statistics	Average rank value	Test statistics (pairwise comparison)	Period of comparison
2011				
-1989	8.65*	2307.82	-1.37	(-1989) – (2004-)
1989-2004		2647.31	-1.98	(-1989) – (1989-2004)
2004-		2544.26	2.34	(2004-) – (1989-2004)
2015				
-1989	34.98*	3066.90	-2.2	(-1989) – (2004-)
1989-2004		3727.53	**-3.63***	**(-1989) – (1989-2004)**
2004-		3470.54	**5.03***	**(2004-) – (1989-2004)**
2020				
-1989	22.15*	3318.04	**-4.17***	**(-1989) – (2004-)**
1989-2004		4132.81	**-4.64***	**(-1989) – (1989-2004)**
2004-		4059.64	1.34	(2004-) – (1989-2004)

Note: *Significant at the 5% level.
Source: Author's composition based on Opten (2023)

Table 5: Variance analysis: period of establishment of companies in relation to sales revenue in proportion to number of employees.

on the productivity of companies.

By 2020, the dominance of firms from 1989-2004 in terms of turnover per employee has been maintained, although the gap between them and firms established in other periods has started to narrow. In particular, enterprises born before 1989 showed the most significant improvement in their turnover per employee. This improvement is probably due to the extensive restructuring and investments made in the previous decades, which allowed these older companies to catch up with more recently established companies.

The improved performance of enterprises created between 1989 and 2004 can be attributed to several key factors. Market reforms following the collapse of socialism created a more favourable business environment, while the inflow of EU funds provided financial support for growth and modernisation. These firms were able to take advantage of these benefits, resulting in higher productivity levels. In contrast, companies established before 1989 had to undergo significant restructuring to adapt to new market conditions, which initially hampered their productivity.

In addition, the creation of larger farms in the period 1989-2004 also contributed to the better performance of enterprises from this period. Although smaller farms, which are more prevalent in Hungary, have achieved faster growth rates, they remain generally less productive than their larger counterparts. This differentiation between smaller and larger farms further explains the differences in turnover per employee between different periods. Overall, the results show how historical economic and political changes have had a long-lasting impact on business productivity, with the period 1989-2004 proving to be a particularly favourable for business creation and growth.

What are the key factors driving the differences in wage efficiency among Hungarian enterprises founded in different periods? The analysis in Table 6 shows significant differences in wage efficiency between different categories of companies, at the 5% significance level. Enterprises established before 1989 have significantly lower wage efficiency than those established after 1989. In 2011, data showed that the wage efficiency of firms established before 1989 was significantly lower compared to those established later, while firms established after 1989 were more efficient in their use of labour costs. This trend continued in 2020, where pre-1989 enterprises show the lowest wage efficiency. In contrast, enterprises born between 1989 and 2004 showed the highest efficiency, closely followed by those which born after 2004. The lower wage efficiency observed in pre-1989 enterprises underlines the long-term impact of socialist economic policy, which often prioritised employment over productivity. In contrast, post-1989 born enterprises benefited from market-driven incentives and EU support, leading to more efficient practices and better use of labour costs. However, despite these improvements, overall wage efficiency in Hungarian agriculture remains significantly below Western European standards. On average, a Hungarian

Category	Test statistics	Average rank value	Test statistics (pairwise comparison)	Period of comparison
2011				
-1989	12.97*	1857.07	**-3.56***	**(-1989) – (2004-)**
1989-2004		2623.89	**-3.40***	**(-1989) – (1989-2004)**
2004-		2664.81	-0.94	(2004-) – (1989-2004)
2015				
-1989	26.97*	2462.37	**-5.10***	**(-1989) – (2004-)**
1989-2004		3645.48	**-5.19***	**(-1989) – (1989-2004)**
2004-		3630.42	0.30	(2004-) – (1989-2004)
2020				
-1989	53.47*	2679.21	**-7.10***	**(-1989) – (2004-)**
1989-2004		4109.55	**-6.47***	**(-1989) – (1989-2004)**
2004-		4260.63	**-2.78***	**(2004-) – (1989-2004)**

Note: *Significant at the 5% level.
Source: Author's composition based on Opten (2023)

Table 6: Variance analysis: founding period of companies in relation to wage efficiency.

farm worker produces roughly half as much as his or her Western European counterpart. Despite the major events of the past decades and Hungary's accession to the EU, this trend does not show any significant improvement, as detailed by Csáki and Jámbor (2018). The persistence of this gap highlights the continuing challenges in achieving parity with productivity levels in Western Europe, indicating that further reforms and support are needed to improve the efficiency and productivity of Hungarian agriculture.

Per capita personnel expenditure shows the average expenditure on staff, reflecting the level of investment in human resources. How do different periods of establishment influence per capita personnel expenditure among Hungarian enterprises, and what factors contribute to the varying levels of investment in human capital across these periods? Table 7 shows significant differences between enterprises created in different periods. Enterprises created after 1989 had higher per capita personnel expenditure in 2011 than those created before, and the average ranking values suggest that enterprises created after 1989 put more emphasis on investment in human resources. This trend was maintained in 2015, with enterprises created after 1989 continuing to have higher per capita personnel expenditure, reflecting efforts to improve the quality and productivity of their workforce. By 2020, the pattern remained consistent, with per capita personnel expenditure being highest for enterprises created after 2004, followed by enterprises created between 1989 and 2004, and lowest for enterprises created before 1989.

The higher per capita personnel costs of enterprises after 1989 reflect a strategic shift towards investment in human capital, driven by the need to remain competitive in a more market-oriented and technologically advanced agricultural sector. These enterprises are likely to take advantage of market incentives and potential EU support to increase their labour skills and productivity. In contrast, older enterprises, established before 1989, are often constrained by legacy structures and have limited access to capital, resulting in lower investment in labour. Their lack of investment in human capital may prevent them from competing effectively with more modern, better financed enterprises. The general trend underlines the importance of investing in human capital to increase productivity and competitiveness in the agricultural sector, especially, in adapting to today's market and technological demands.

In the following paragraph, we seek to answer the question: What factors have influenced the differences in per capita asset values among Hungarian enterprises founded in different periods, and How have historical and economic contexts shaped the capital investment patterns and modernisation efforts in these enterprises?

The value of assets per capita, which serves as an indicator of capital intensity, shows significant differences between enterprises founded in different periods, as detailed in Table 8. In 2011, enterprises founded between 1989 and 2004 had a higher value of assets per capita compared to enterprises founded before 1989 and after 2004, indicating a concerted effort towards modernisation and capital investment

Category	Test statistics	Average rank value	Test statistics (pairwise comparison)	Period of comparison
2011				
-1989	10.08*	2081.65	**-3.17***	**(-1989) – (2004-)**
1989-2004		2605.95	**-3.06***	**(-1989) – (1989-2004)**
2004-		2630.50	-0.56	(2004-) – (1989-2004)
2015				
-1989	24.13*	2866.39	**-3.75***	**(-1989) – (2004-)**
1989-2004		3681.85	**-4.48***	**(-1989) – (1989-2004)**
2004-		3555.45	**2.47***	**(2004-) – (1989-2004)**
2020				
-1989	10.72*	3542.33	**-3.00***	**(-1989) – (2004-)**
1989-2004		4116.76	**-3.26***	**(-1989) – (1989-2004)**
2004-		4076.55	0.70	(2004-) – (1989-2004)

Note: *Significant at the 5% level.
Source: Author's composition based on Opten (2023)

Table 7: Variance analysis: period of establishment of companies in relation to personnel expenses per capita.

Category	Test statistics	Average rank value	Test statistics (pairwise comparison)	Period of comparison
2011				
-1989	100.93*	2462.46	0.81	(-1989) – (2004-)
1989-2004		2763.47	**10.01***	**(-1989) – (1989-2004)**
2004-		2323.14	-1.76	(2004-) – (1989-2004)
2015				
-1989	170.10*	3671.23	**2.54***	**(-1989) – (2004-)**
1989-2004		3871.18	**13.04***	**(-1989) – (1989-2004)**
2004-		3204.83	-1.10	(2004-) – (1989-2004)
2020				
-1989	79.16*	3916.87	0.74	(-1989) – (2004-)
1989-2004		4269.39	**8.84***	**(-1989) – (1989-2004)**
2004-		3784.79	-2.01	(2004-) – (1989-2004)

Note: *Significant at the 5% level.
Source: Author's composition based on Opten (2023)

Table 8. Variance analysis: period of establishment of companies in relation to value of assets per capita

during this transitional period. This trend continued in 2015 and 2020, with enterprises from the 1989-2004 period consistently maintaining the highest per capita asset values. This sustained advantage can be attributed to the significant investments made during Hungary's transition from planned economy to a market economy and accession to the European Union, which provided substantial financial support and incentives for infrastructure development and modernization initiatives. However, pre-1989 enterprises struggled with inherited structural weaknesses and limited resources for substantial capital investment, resulting in relatively lower per capita asset values. Meanwhile, post-2004 enterprises, despite their relative newness and potential flexibility, have not yet reached the same level of capital intensity, probably due to a more competitive financing environment and changing market dynamics. These results underscore the profound impact of the historical and economic context on the capital investment patterns of Hungarian agriculture, highlighting the critical role of targeted investment in promoting modernisation and enhancing competitiveness.

In 2022, agricultural income, measured according to the income of deflated factors per annual work unit (AWU) expressed as an index, increased by 12.5% compared to 2021. This rise was driven by a higher factor income (+10.3%) achieved with less total agricultural labour input, which decreased by -1.9%. Across the EU, many Member

States recorded increased or unchanged income per AWU, with notable rises for several key agricultural producers. Conversely, the sharpest declines were observed in Romania (-26.0%), Portugal (-11.7%), Malta (-8.7%), and Lithuania (-8.0%). Overall, agricultural income per AWU for the EU in 2022 continued its upward trend since 2009, reflecting both a steady factor income and, notably in 2022, a sharp increase (Eurostat, 2023).

Recommendations and policy implications

Overall, the labour shortage observed in the agricultural and food industry is not a unique phenomenon, as these sectors face challenges similar to other sectors of the economy (Causa et al., 2022; Bollérot, 2002). In the agricultural sectors where the demand for manual labour is greater (e.g., the fruit or vegetable sector or animal husbandry), the lack of skilled or even career-starting labour is more pronounced. The wage demands of newly graduated applicants with no experience are unrealistic, even for those applying for simpler jobs. The supply of skilled labour (e.g., workers who know and can use precision technology, plant protection methods, or animal health specialists) is constantly decreasing. At the same time, the operation of modern machines requires an increasingly higher level of training (Erickson et al., 2018). A significant proportion of the older generation of workers does not know how to learn or does not want to finance the transition to modern technologies. **Technological development and digitisation and its impact on transformation can make the entire sector much more attractive to labour market participants.** However, attracting young people to the sector cannot be considered easy in other countries either (Som et al., 2018).

Companies attempt to overcome the problem of a lack of suitably qualified and experienced workforce by choosing from those less qualified and inexperienced during the selection process and then bringing employees up to the required professional level with the help of internal training since their education is usually not adequate in many cases (Carolan, 2020). **Greater emphasis should be placed on teaching skills that are often sought after (e.g., GIS, laboratory tests, the use of different software).** However, rapid technological development can be observed in the sector, and constantly staying up to date is an unrealistic expectation for secondary or higher education. Mid-year or summer internships are essential for acquiring the necessary practical knowledge, which training should not be allowed to deteriorate but be systematically organised under the supervision of the state or business chambers. At individual companies, participants of mandatory internships can represent a labour supply. There are already good examples of industry-university cooperation and dual training in many countries (Ankrah and Omar, 2015), including in Hungary (e.g., cooperation between Audi and István Széchenyi University in Győr). However, there should be many more such initiatives modelled on very well-functioning dual training.

Continuous generational change can be observed, and fluctuation is constantly present in the sector (Borda et al., 2023). At the same time, the career path model lacks harmony with the limitations associated with natural ageing processes and the performance of activities, for example. In many cases, exploiting retired people's professional and life experiences and transferring these to appropriate groups is not even called for. With retirement, significant accumulated experiential knowledge leaves companies and sectors. Another aspect of generational change concerns management. A significant number of domestically owned agricultural companies and food manufacturers are under family control. They typically started their independent activities in the years after the regime change, and the generation that is about to retire will not followed by the next generation within the family (in many cases, grandchildren take over the company directly from grandparents). In such cases, the issue of succession is difficult, and the involvement of an external manager can be critical. However, in some countries, generational change is already a well-established practice; successors must first prove themselves at other companies and play a leading role elsewhere, and only then can they come ‘home’ to work on the family farm or business. Furthermore, the return of young individuals after education to farming hinges on the availability of subsidies and central support. The attraction of advanced agricultural technologies, such as drones and milking robots, positively impacts the younger generation’s interest (Guerra, 2018, Farrell et al., 2021).

By encouraging generational change, the appropriate expertise and capital can be concentrated within families in the long term. **The government must consciously address**

generational change and ensure that the sector is an attractive alternative for young people in the long term. Hungarian agricultural policy should encourage the creation of the size of farms capable of supporting single families by consolidating agricultural areas and reducing fragmentation. Ownership structure strongly limits the possibilities of use (e.g., modern machines with high-performance capacity cannot be used everywhere). However, precision and environmentally friendly technologies are gaining ground, and it would be worthwhile strongly pursuing this direction of development. By properly using subsidies and investing in the future, an economy can become competitive in the long term. A complete review of systems based on subsidies is needed to reduce the effects of distorting competition (Berlinschi et al., 2014).

Conclusion

Based on the results and the literature, it can be seen that Hungarian agriculture does not differ significantly from the agriculture of other Central and Eastern European countries. Agriculture lags behind other sectors in terms of employment and proportional GDP. The Hungarian agricultural society can be considered an ageing society, however, it can be seen as a positive issue that the small number of young people who are entering into the sector have a higher overall education level, and thus better abilities and skills. In the past ten years, the proportion of total employees working in the sector without agricultural employment decreased by 20 percentage points. Despite that the number of managers with agricultural education has increased, they still manage approximately 150,000 farms in Hungary based on their experience. The number of employees in the Hungarian agricultural enterprises is constantly decreasing, in 2011 an average agricultural enterprise employed 24 people, while in 2020 it employed 17 people, with median values of 3-8 people. Along every dimension, enterprises founded before 1989 have significantly lower efficiency and productivity than those founded after (mainly founded after the EU accession of Hungary in 2004). Moreover, most Hungarian agricultural enterprises are lagging behind the majority of Western European companies in terms of labour, territorial and wage productivity.

Overall, the tasks facing the agricultural and food industry labour market are multifaceted. On the one hand, work in the sector must be made attractive to young people by providing role models and career advice guidance and developing educational programmes. As a result of technological development, there is a need for highly practice-oriented training courses that respond to rapidly changing needs. In addition, it is necessary to provide adequate and competitive wages to those who choose a career in the competitive agriculture and food industry. The effects of the pandemic and the Ukrainian-Russian crisis are only exacerbating the employment-policy (and agricultural-policy)-related problems listed above. The crises of recent years have shown that countries with a fundamentally competitive agriculture and food industry remain the most resistant. As Csáki and Jámbor (2018) also showed, those countries that are sufficiently brave and quick enough to implement agricultural and employment policy reforms are more successful in the long term than their neighbours who focus on short-term benefits.

A limitation of this research is that Hungarian employment was examined only between 2011 and 2020 due to the availability of company data. Hungarian agricultural employment was explored before the 2010s with the help of the literature and secondary sources. It would also be worth examining how agricultural employment developed after 2020, when significant economic and political changes took place in the world, including in the states of Central and Eastern Europe.

Corresponding author:
Zalán Márk Maró
Department of Agricultural Economics, Institute of Sustainable Development
Corvinus University of Budapest, Fővám tér 8, 1093 Budapest, Hungary
E-mail: zalan.maro@uni-corvinus.hu

References

[1] Alarcón, C. (2021) "Agrarian questions, digitalisation of the countryside, immigrant labour in agriculture and the official discourses on rural development in the Uppsala region, Sweden", *Italian Review of Agricultural Economics*, Vol. 76, No. 1, pp. 19-32. ISSN 2281-1559. DOI 10.36253/rea-12824.

[2] Ankrah, S. and Omar, A.-T. (2015) "Universities–industry collaboration: A systematic review", *Scandinavian Journal of Management*, Vol. 31, No. 3, pp. 387-408. ISSN 0956-5221. DOI 10.1016/j.scaman.2015.02.003.

[3] Avincz, J., Bognár, I., Erdész, F., Kamarásné Hegedűs, N., Kapronczai, I., Kartali, J., Kertész, R., Radóczné Kocsis, T., Stauder, M. and Tóth, E. (2002) "A magyar mezőgazdaság az adatok tükrében a rendszerváltás után", *Agrárgazdasági Kutató Intézet,* Budapest. ISSN 1418 2130. (in Hungarian).

[4] Babenko, A. and Vasilyeva, O. (2017) "Factors of labour productivity growth in agriculture of the agrarian region", *Baltic Journal of Economic Studies*, Vol. 3, No. 4, pp. 1-6. ISSN 2256-0742. DOI: 10.30525/2256-0742/2017-3-4-1-6.

[5] Berlinschi, R., Swinnen, J. and Van Herck, K. (2014) "Trapped in agriculture? Credit constraints, investments in education and agricultural employment", *The European Journal of Development Research*, Vol. 26, pp. 490-508. ISSN 0957-8811. DOI 10.1057/ejdr.2014.30.

[6] Biernat-Jarka, A. (2015) "Structural changes and labour input in Polish agriculture after the accession to the European Union", *Scientific Papers: Management, Economic Engineering in Agriculture & Rural Development*, Vol. 15, No. 3, pp. 73-78. E-ISSN 2285-3952, ISSN 2284-7995.

[7] Bojnec, Š. and Fertő, I. (2021) "The growth of farms: A Hungarian-Slovenian comparison", *Post-Communist Economies*, Vol. 33, No. 1, pp. 79-93. ISSN 1463-1377. DOI 10.1080/14631377.2020.1727265.

[8] Bollérot, P. (2002) "Labour shortages and employability: A European and international approach", *International Social Security Review*, Vol. 55, No. 3, pp. 19-38. ISSN 0020-871X. DOI 10.1111/1468-246X.00130.

[9] Borda, Á. J., Sárvári, B. and Balogh, J. M. (2023) "Generation Change in Agriculture: A Systematic Review of the Literature", *Economies*, Vol. 11, No. 5, pp. 129. ISSN 2227-7099. DOI 10.3390/economies11050129.

[10] Bousmah, I. and Grenier, G. (2022) "Labor shortages and immigration: The case of the Canadian agriculture sector", *Agribusiness*, Vol. 38, No. 1, pp. 220-235. ISSN 0742-4477. DOI 10.1002/agr.21719.

[11] Bozsik, N. and Magda, R. (2018) "Labour productivity in the Hungarian agriculture", *Acta Agraria Debreceniensis*, Vol. 150, pp. 119-128. ISSN 2416-1640. DOI 10.34101/actaagrar/150/1708.

[12] Breslow, N. (1970) "A generalized Kruskal-Wallis test for comparing K samples subject to unequal patterns of censorship", *Biometrika*, Vol. 57, No. 3, pp. 579-594. ISSN 1464-3510. DOI 10.1093/biomet/57.3.579.

[13] Breustedt, G. and Glauben, T. (2007) "Driving forces behind exiting from farming in Western Europe", *Journal of Agricultural economics*, Vol. 58, No. 1, pp. 115-127. ISSN 0021-857X. DOI 10.1111/j.1477-9552.2007.00082.x.

[14] Carolan, M. (2020) "Automated agrifood futures: Robotics, labor and the distributive politics of digital agriculture", *The Journal of Peasant Studies*, Vol. 47, No. 1, pp. 184-207. ISSN 0306-6150. DOI 10.1080/03066150.2019.1584189.

[15] Causa, O., Abendschein, M., Luu, N., Soldani, E. and Soriolo, C. (2022) "The post-COVID-19 rise in labour shortages", *OECD Economics Department Working Papers*, No. 1721, 22 p. ISSN 1815-1973. DOI 10.1787/e60c2d1c-en.

[16] Chiswell, H. M. and Lobley, M. (2018) "It's definitely a good time to Be a farmer: understanding the changing dynamics of successor creation in late modern society", *Rural Sociology*, Vol. 83, No. 3, pp. 630-653. ISSN 1549-0831. DOI 10.1111/ruso.12205.

[17] Cortignani, R., Carulli, G. and Dono, G. (2020) "COVID-19 and labour in agriculture: Economic and productive impacts in an agricultural area of the Mediterranean", *Italian Journal of Agronomy*, Vol. 15, No. 2, pp. 172-181. ISSN 2039-6805. DOI 10.4081/ija.2020.1653.

[18] Csaki, C. and Jambor, A. (2019) "Convergence or divergence–Transition in agriculture of Central and Eastern Europe and Commonwealth of Independent States revisited", *Agricultural Economics*, Vol. 65, No. 4, pp. 160-174. ISSN 1805-9295. DOI 10.17221/195/2018-AGRICECON.

[19] Csáki, C. and Jámbor, A. (2018) "Konvergencia vagy divergencia: Merre tart Kelet-Közép-Európa és a FÁK mezőgazdasága?", *Közgazdasági Szemle*, Vol. 65, No. 10, pp. 1048-1066. ISSN 0023-4346. DOI 10.18414/KSZ.2018.10.1048. (In Hungarian).

[20] D'antoni, J. M., Mishra, A. K. and Barkley, A. P. (2012) "Feast or flee: Government payments and labor migration from US agriculture", *Journal of Policy Modeling*, Vol. 34, No. 2, pp. 181-192. ISSN 0161-8938. DOI 10.1016/j.jpolmod.2011.10.002.

[21] Darpeix, A., Bignebat, C. and Perrier-Cornet, P. (2014) "Demand for seasonal wage labour in agriculture: what does family farming hide?", *Journal of Agricultural Economics*, Vol. 65, No. 1, pp. 257-272. ISSN 0021-857X. DOI 10.1111/1477-9552.12019.

[22] De Castro, C., Reigada, A. and Gadea, E. (2020) "The devaluation of female labour in fruit and vegetable packaging plants in Spanish Mediterranean agriculture", *Organization*, Vol. 27, No. 2, pp. 232-250. ISSN 1350-5084. DOI 10.1177/1350508419883387.

[23] Đokić, D., Novaković, T., Tekić, D., Matkovski, B., Zekić, S. and Milić, D. (2022) "Technical efficiency of agriculture in the European Union and Western Balkans: SFA method", *Agriculture*, Vol. 12, No. 12, pp. 1992. ISSN 2077-0472. DOI 10.3390/agriculture12121992.

[24] Donnellan, T. and Hanrahan, K. (2017) "Value added and employment growth in EU primary agriculture and food processing", *EuroChoices*, Vol. 16, No. 3, pp. 4-9. ISSN 1478-0917. DOI 10.1111/1746-692X.12174.

[25] Dries, L. and Swinnen, J. F. (2002) "Institutional reform and labor reallocation during transition: Theory evidence from Polish agriculture", *World Development*, Vol. 30, No. 3, pp. 457-474. ISSN 0305-750X. DOI 10.1016/S0305-750X(01)00118-8.

[26] Duarte, M. and Restuccia, D. (2010) "The role of the structural transformation in aggregate productivity", *The Quarterly Journal of Economics*, Vol. 125, No. 1, pp. 129-173. ISSN 1531-4650. DOI 10.1162/qjec.2010.125.1.129.

[27] Elahi, E., Khalid, Z. and Zhang, Z. (2022) "Understanding farmers' intention and willingness to install renewable energy technology: A solution to reduce the environmental emissions of agriculture", *Applied Energy*, Vol. 309, pp. 118459. ISSN 1872-9118. DOI 10.1016/j.apenergy.2021.118459.

[28] Erickson, B., Fausti, S., Clay, D. and Clay, S. (2018) "Knowledge, skills, and abilities in the precision agriculture workforce: an industry survey", *Natural Sciences Education*, Vol. 47, No. 1, pp. 1-11. ISSN 2168-8281. DOI 10.4195/nse2018.04.0010.

[29] Eurostat (2019) "*Agriculture Statistics – Family Farming in the EU", Brussels*. [Online]. Available: https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Agriculture_statistics-family_farming_in_the_EU#Structural_profile_of_farms_-_analysis_for_the_EU. [Accessed: Dec. 15, 2023].

[30] Eurostat (2023) "*Performance of the agricultural sector*". [Online]. Available: https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Performance_of_the_agricultural_sector#Agricultural_labour_productivity. [Accessed: Dec. 15, 2023].

[31] Farrell, M., Murtagh, A., Weir, L., Conway, S. F., Mcdonagh, J. and Mahon, M. (2021) "Irish organics, innovation and farm collaboration: A pathway to farm viability and generational renewal", *Sustainability*, Vol. 14, No. 1, pp. 93. ISSN 2071-1050. DOI 10.3390/su14010093.

[32] Fogarasi, J. (2007) "Efficiency and total factor productivity in post-EU accession Hungarian sugar beet production", *Studies in Agricultural Economics*, Vol. 105, pp. 87-100. ISSN 1418-2106. DOI 10.22004/ag.econ.107653.

[33] Garrone, M., Emmers, D., Olper, A. and Swinnen, J. (2019) "Jobs and agricultural policy: Impact of the common agricultural policy on EU agricultural employment", *Food Policy*, Vol. 87, pp. 101744. ISSN 0306-9192. DOI 10.1016/j.foodpol.2019.101744.

[34] Górny, A. and Kaczmarczyk, P. (2018) "A known but uncertain path: The role of foreign labour in Polish agriculture", *Journal of Rural Studies*, Vol. 64, pp. 177-188. ISSN 0743-0167. DOI 10.1016/j.jrurstud.2017.12.015.

[35] Guerra, A. I. N. (2018) "Young Farmers as Innovation Enablers in Rural Areas: The Role of EU's Support in a Portuguese Peripheric Region, Trás-Os-Montes", Universidade de Lisboa (Portugal).

[36] Halmos, C. (2006) "Foglalkoztatáspolitika–rendszerváltás", *Munkaügyi Szemle*, Vol. 7, pp. 31-37. ISSN 0541-3559. (In Hungarian).

[37] Harangi-Rákos, M. and Szabó, G. (2013) "The economic and social role of private farms in Hungarian agriculture", *APSTRACT: Applied Studies in Agribusiness and Commerce*, Vol. 6, No. 5, pp. 33-41. E-ISSN 1789-7874, ISSN 1789-221X. DOI 10.22004/ag.econ.147411.

[38] Heider, K., Rodriguez Lopez, J. M., Balbo, A. L. and Scheffran, J. (2021) "The state of agricultural landscapes in the Mediterranean: Smallholder agriculture and land abandonment in terraced landscapes of the Ricote Valley, southeast Spain", *Regional Environmental Change*, Vol. 21, No. 1, pp. 1-12. ISSN 1436-378X. DOI 10.1007/s10113-020-01739-x.

[39] Herrendorf, B. and Schoellman, T. (2015) "Why is measured productivity so low in agriculture?", *Review of Economic Dynamics*, Vol. 18, No. 4, pp. 1003-1022. ISSN 1094-2025. DOI 10.1016/j.red.2014.10.006.

[40] Hubert, C. (2018) "Capital/Labour separation in French agriculture: The end of family farming?", *Land Use Policy*, Vol. 77, pp. 553-558. ISSN 0264-8377. DOI 10.1016/j.landusepol.2018.05.062.

[41] Iglesias, A., Quiroga, S., Moneo, M. and Garrote, L. (2012) "From climate change impacts to the development of adaptation strategies: challenges for agriculture in Europe", *Climatic Change*, Vol. 112, pp. 143-168. ISSN 0165-0009. DOI 10.1007/s10584-011-0344-x.

[42] Karácsony, P. (2010) "A mezőgazdasági foglalkoztatottság regionális jellemzői", *Jelenkori Társadalmi és Gazdasági Folyamatok*, Vol. 5, No. 1-2, pp. 106-109. ISSN 2676-9867. DOI 10.14232/jtgf.2010.1-2.106-109.(In Hungarian).

[43] Karttunen, J. P., Rautiainen, R. H. and Lunner-Kolstrup, C. (2016) "Occupational health and safety of Finnish dairy farmers using automatic milking systems", *Frontiers in public health*, Vol. 4, pp. 147. ISSN 2296-2565. DOI 10.3389/fpubh.2016.00147.

[44] Kijek, A., Kijek, T. and Nowak, A. (2020) "Club convergence of labour productivity in agriculture: Evidence from EU countries", *Agricultural Economics,* Vol. 66, No. 9, pp. 391-401. ISSN 1805-9295. DOI 10.17221/178/2020-AGRICECON.

[45] Klikocka, H., Zakrzewska, A. and Chojnacki, P. (2021) "Characteristics of models of farms in the European Union", *Sustainability*, Vol. 13, No. 9, pp. 4772. ISSN 2071-1050. DOI 10.3390/su13094772.

[46] Kočišová, K. (2015) "Application of the DEA on the measurement of efficiency in the EU countries", *Agricultural Economics*, Vol. 61, No. 2, pp. 51-62. ISSN 1805-9295. DOI 10.17221/107/2014-AGRICECON.

[47] Kołodziejczak, W. (2020) "Employment and gross value added in agriculture versus other sectors of the European Union economy", *Sustainability*, Vol. 12, No. 14, pp. 5518. ISSN 2071-1050. DOI 10.3390/su12145518.

[48] Kuznets, S. and Murphy, J. T. (1966) "*Modern economic growth: Rate, structure, and spread*", Yale University Press New Haven. 46 p.. ISBN 10 0300006462

[49] Labrianidis, L. and Sykas, T. (2009) "Geographical proximity and immigrant labour in agriculture: Albanian immigrants in the Greek countryside", *Sociologia Ruralis*, Vol. 49, No. 4, pp. 394-414. ISSN 0038-0199. DOI 10.1111/j.1467-9523.2009.00494.x.

[50] Latruffe, L., Fogarasi, J. and Desjeux, Y. (2012) "Efficiency, productivity and technology comparison for farms in Central and Western Europe: The case of field crop and dairy farming in Hungary and France", *Economic Systems*, Vol. 36, No. 2, pp. 264-278. ISSN 0939-3625. DOI 10.1016/j.ecosys.2011.07.002.

[51] Leonard, B., Kinsella, A., O'donoghue, C., Farrell, M. and Mahon, M. (2017) "Policy drivers of farm succession and inheritance", *Land Use Policy*, Vol. 61, pp. 147-159. ISSN 0264-8377. DOI 10.1016/j.landusepol.2016.09.006.

[52] Marinoudi, V., Sørensen, C. G., Pearson, S. and Bochtis, D. (2019) "Robotics and labour in agriculture. A context consideration", *Biosystems Engineering*, Vol. 184, pp. 111-121. ISSN 1537-5110. DOI 10.1016/j.biosystemseng.2019.06.013.

[53] Martin, R. (2002) "Politicized managerial capitalism: enterprise structures in post-socialist central and Eastern Europe", *Journal of Management Studies*, Vol. 39, No. 6, pp. 823-839. ISSN 0022-2380. DOI 10.1111/1467-6486.00313.

[54] Mateoc-Sîrb, N., Mateoc, T., Mănescu, C. and Grad, I. (2014) "Research on the labour force from Romanian agriculture", *Scientific Papers Series Management, Economic Engineering in Agriculture and Rural Development*, Vol. 14, No. 1, pp. 215-218. E-ISSN 2285-3952, ISSN 2284-7995.

[55] Megyesiova, S. (2021) "Production, employment and productivity of agricultural sector in the European Union", *Bulgarian Journal of Agricultural Science*, Vol. 27, No. 5, pp. 846–858. ISSN 1310-0351.

[56] Mészáros, S. and Szabó, G. (2014) "Hatékonyság és foglalkoztatás a magyar mezőgazdaságban", GAZDÁLKODÁS: Scientific Journal on Agricultural Economics, Vol. 58, No. 01, pp. 58-74. ISSN 0046-5518. DOI 10.22004/ag.econ.201227. (In Hungarian).

[57] Nowak, A., Kijek, T. and Domańska, K. (2015) "Technical efficiency and its determinants in the European Union", *Agricultural Economics*, Vol. 61, No. 6, pp. 275-283. ISSN 1805-9295. DOI 10.17221/200/2014-AGRICECON.

[58] Olper, A., Raimondi, V., Cavicchioli, D. and Vigani, M. (2014) "Do CAP payments reduce farm labour migration? A panel data analysis across EU regions", *European Review of Agricultural Economics*, Vol. 41, No. 5, pp. 843-873. ISSN 1464-3618. DOI 10.1093/erae/jbu002.

[59] Osterhoudt, S. (2018) "Remembered resilience: oral history narratives and community resilience in agroforestry systems", *Renewable Agriculture and Food Systems*, Vol. 33. No. 3, pp. 252-255. ISSN 1742-1705. DOI 10.1017/S1742170517000679.

[60] Ostertagova, E., Ostertag, O. and Kováč, J. (2014) "Methodology and application of the Kruskal-Wallis test", *Applied Mechanics and Materials*, Vol. 611, pp. 115-120. ISSN 1662-7482. DOI 10.4028/www.scientific.net/AMM.611.115.

[61] Papadopoulos, A., Fratsea, L.-M., Spyrellis, S. and Baltas, P. (2021) "Exploring the contribution of migrant labour in Greek agriculture", *Italian Review of Agricultural Economics*, Vol. 76, No. 1, pp. 33-48. ISSN 2281-1559. DOI 10.36253/rea-12574.

[62] Popescu, A., Tindeche, C., Marcuță, A., Marcuță, L., Honțuș, A. and Angelescu, C. (2021) "Labour force in the European Union agriculture - Traits and tendencies", *Scientific Papers Series Management, Economic Engineering in Agriculture and Rural Development*, Vol. 21, No. 2, pp. 475-486. E-ISSN 2285-3952, ISSN 2284-7995.

[63] Popa, A. M. P. and Turek Rahoveanu, A. (2021) "Supporting young farmers and the sustainability of rural regions. Case study - Olt county, Romania", *Scientific Papers: Management, Economic Engineering in Agriculture & Rural Development*, Vol. 21, No. 3, pp. 651-657. E-ISSN 2285-3952, ISSN 2284-7995.

[64] Potter, C. and Lobley, M. (1992) "Ageing and succession on family farms: the impact on decision-making and land use", *Sociologia Ruralis*, Vol. 32, No. 2/3, pp. 317-334. ISSN 0038-0199. DOI 10.1111/j.1467-9523.1992.tb00935.x.

[65] Prause, L. (2021) "Digital agriculture and labor: A few challenges for social sustainability", *Sustainability*, Vol. 13, No. 11, pp. 5980. ISSN 2071-1050. DOI 10.3390/su13115980.

[66] Prisecaru, P. (2016) "Challenges of the fourth industrial revolution", *Knowledge Horizons - Economics*, Vol. 8, No. 1, pp. 57. ISSN 2069-0932.

[67] Putićová, M. and Mezera, J. (2008) "Food industry in the Czech Republic–with regard to labour force development", *Agricultural Economics*, Vol. 54, No. 6, pp. 285-292. ISSN 1805-9295. DOI 10.17221/282-AGRICECON.

[68] Ritter, K. (2004) "The Role of Agriculture in Rural Development in Hungary", *Eastern European Countryside*, Vol. 11, pp. 137-153. E-ISSN 2199-5877.

[69] Ritter, K. (2018) "A vidékgazdaság foglalkoztatási szerkezete Magyarországon", *Hadtudományi Szemle*, Vol. 11, No. 4, pp. 400-420. ISSN 2060-0437. (In Hungarian).

[70] Rye, J. F., Slettebak, M. H. and Bjørkhaug, H. (2018) "From family to domestic and global labour? A decade of proletarisation of labour in the Norwegian horticulture industry", *European Countryside*, Vol. 10, No. 4, pp. 528-542. E-ISSN 1803-8417. DOI 10.2478/euco-2018-0030.

[71] Schmitz, A. and Moss, C. B. (2015) "Mechanized agriculture: Machine adoption, farm size, and labor displacement", *AgBioForum*, Vol. 18, No. 3, pp. 278-296. ISSN 1522-936X.

[72] Smędzik-Ambroży, K., Guth, M., Majchrzak, A., Muntean, A. C. and Maican, S. Ș. (2021) "The Socio-Economics Factors in Family Farms with Different Economic Sustainability Levels from Central and Eastern Europe", *Sustainability*, Vol. 13, No. 15, pp. 8262. ISSN 2071-1050. DOI 10.3390/su13158262.

[73] Som, S., Burman, R. R., Sharma, J., Padaria, R., Paul, S. and Singh, A. (2018) "Attracting and retaining youth in agriculture: challenges and prospects", *Journal of Community Mobilization and Sustainable Development*, Vol. 13, No. 3, pp. 385-395. ISSN 2230-9047.

[74] Tocco, B., Davidova, S. and Bailey, A. (2012) "Labour adjustments in agriculture: evidence from Romania", *Studies in Agricultural Economics,* Vol. 116, No. 2, pp. 64-73. ISSN 2063-0476. DOI 10.7896/j.1406.

[75] Unay-Gailhard, İ. and Bojnec, Š. (2019) "The impact of green economy measures on rural employment: Green jobs in farms", *Journal of Cleaner Production*, Vol. 208, pp. 541-551. ISSN 0959-6526. DOI 10.1016/j.jclepro.2018.10.160.

[76] Weber, E. (2014) "A mezőgazdasági munkaerő változása (a Dél-Alföld és a Dél-Dunántúl összehasonlítása)", *Közép-Európai Közlemények*, Vol. 7, No. 3-4, pp. 133-141. ISSN 2676-878X. (In Hungarian).

[77] Wheeler, T. and Von Braun, J. (2013) "Climate change impacts on global food security", *Science*, Vol. 341, No. 6145, pp. 508-513. ISSN 0036-8075. DOI 10.1126/science.1239402.

[78] Widiyanti, E., Setyowati, N. and Ardianto, D. T. (2018) "Young generation's perception on the agricultural sector", In *IOP Conference Series: Earth and Environmental Science,* Vol. 200, No. 1, p. 012060, IOP Publishing. E-ISSN 1755-1315. DOI 10.1088/1755-1315/200/1/012060.

[79] Yasmin, T., El Refae, G. A. and Eletter, S. (2019) "Sectoral productivity in Hungarian economy: an input-output linkages approach", *Journal of Eastern European and Central Asian Research,* Vol. 6, No. 2, pp. 344-355. ISSN 2328-8280. DOI 10.15549/jeecar.v6i2.318.

Agris on-line Papers in Economics and Informatics

Volume XVI Number 4, 2024

Effect of Farm Size on the Structure of Crop Production

Anna Žovincová

Department of Statistics, Faculty of Economics and Management, Czech University of Life Sciences Prague, Czech Republic

Abstract

The study deals with the statistical analysis of crop production structure concerning farm size. Given the large-scale nature of Czech agriculture and the deepening structural imbalance, this is a topical issue. Firstly, the trends in the area of sown crops between 1993–2023 and their expected development between 2024–2025 were assessed. Subsequently, the weighted data of conventional farms focused on field crop production operating in the Czech Republic were analysed using the Kruskal–Wallis test. With the exception of peas, the share of crops grown depends on the size of the farm. There are statistically significant differences, mainly between small and very large farms and between small and large farms. At the same time, it is clear that in the long term, there has been a significant decline in the area sown to potatoes, rye, barley, and forage, which are crops that account for a higher proportion of the harvested area structure on small holdings.

Keywords

Agricultural policy, Czech Republic, field crops, nonparametric methods, time series.

Žovincová, A. (2024) "Effect of Farm Size on the Structure of Crop Production", *AGRIS on-line Papers in Economics and Informatics*, Vol. 16, No. 4, pp. 129-140. ISSN 1804-1930. DOI 10.7160/aol.2024.160410.

Introduction

Czech agriculture has a centuries-old tradition that has guaranteed both the self-sufficiency of the nation in basic agricultural commodities and the export of many of these commodities (Czech Statistical Office (CSO), 2011). Especially since the integration of the Czech Republic into the common market and the implementation of the Common Agricultural Policy (CAP), structural imbalances have been deepening. Species diversity has declined and changed, as have crop shares in the area sown. The cultivation of rye, barley and potatoes is declining, while the area of rape and industrial crops is expanding (Procházková et al., 2016). The authors Řezbová and Škubna (2012) mention in their paper the undeniable dependence of the world agricultural commodity market on biotech crops, with predictions confirming a further increase in the importance of this sector. Considering the level of self-sufficiency in basic crop commodities, we can state that we have an active balance in cereals. On the contrary, self-sufficiency is low in potatoes, temperate fruits and vegetables. Low food self-sufficiency can not only negatively affect price stability and food security, but limiting agricultural production also has negative impacts from an ecological and environmental point of view and on rural development in general (Svatošová et al., 2018). In response to the situation, the Ministry of Agriculture (MoA) defines sustainable food security and adequate food self-sufficiency as one of the main priorities within the Development Strategy with a view to 2030. The aim is to increase the area under perennial forage crops, potato production, vegetable cultivation and the area under orchards at the expense of the area under rapeseed. Analysis by Kolodziejczak (2018) shows that the EU as a whole is largely food self-sufficient. The only exception to this is fruit. At the same time, it is clear that self-sufficiency varies across EU countries. It is therefore necessary to ensure effective mechanisms for redistributing surpluses to regions suffering from shortages by promoting the exchange of goods within the EU, while maintaining the economic, social and natural sustainability of agricultural production. Within the neighbouring countries, the level of self-sufficiency in basic commodities is lowest in Slovakia. In contrast, Poland and Germany have higher levels of self-sufficiency in meat and potato production compared to the Czech Republic. Moreover, Polish agriculture shows a high level of self-sufficiency in all the basic commodities monitored.

Czech agriculture is also characterised by its large-scale production, with legal entities having an 11% share of the total number of agricultural entities farming over 69.5% of the land (MoA, 2021). There are significant differences in farm size between EU countries. In terms of farm size, the Czech Republic, together with Slovakia, is at the top of the ranking (Urbánová et al., 2018; Kryszak et al., 2021). Popescu et al. (2016) conducted an empirical analysis of the farm structure and land concentration in Romania and the EU-28. The results show that farms within the EU are characterized by a large number, diversity and show a wide range of sizes. In 2013, the average farm size in the EU was 16.2 ha and 65.9% of the agricultural area was farmed by farms with an area of more than 50 ha. The largest farms were recorded in the Czech Republic (133 ha) and Slovakia (80.7 ha), where the share of area farmed by farms over 50 ha was 93.3% and 92.7% respectively. On the other hand, the smallest farm sizes are found in Malta, Cyprus and Romania, which also have the lowest economic efficiency. Also in neighbouring Austria and Poland, farms tend to be smaller on average (19.4 ha and 10.1 ha respectively) and farms over 50 ha account for 37.9% and 30.8% of the utilised agricultural area.

One of the objectives of the reformed CAP applicable from 2023 is to provide more targeted support to smaller farms (Consilium.europa.eu, 2023). This objective is supported by the so-called European agricultural model, according to which the farm should be medium-sized, based on family labour, have a diversified, multi-directional production structure and, among non-economic functions, maintain cultural and social links in the countryside (Kowalczyk and Sobiecki, 2014). According to the authors of the CAP Strategic Plan for the Czech Republic, the current system of direct payments has long been unfair for small farms with lower incomes, and a redistributive payment should encourage a fairer distribution of payments that respects the benefits of large-scale production (Lososová and Zdeněk, 2023). Thus, 23% of the total amount of direct payments should go to redistributive payments favouring small farms, compared to 10-12% in neighbouring countries. It is clear that the preference for small enterprises over large ones is more distinctive in the Czech Republic than in other countries (Svobodová et al., 2022). Representatives of the Agrarian Chamber of the Czech Republic and the Agricultural Association of the Czech Republic have warned that the current set-up will lead to further food price increases and reduced production. On the other hand, the Association of Private Farming of the Czech Republic (APF CR) considers the changes to be a step in the right direction. Financial support favouring small farms in the Czech Republic is driven by the need to diversify agricultural activities in the countryside (Svobodová et al., 2022). APF CR has long pointed to the inappropriate structure of farms and agriculture in the Czech Republic, with cereals and rapeseed decisively shaping crop production and its structure. Western European family-type agriculture operates in a more or less balanced commodity structure and it can therefore be concluded that farm size also influences the structural composition. Several studies are also inclined to support smaller farms, especially with regard to ensuring higher biodiversity (Ricciardi et al., 2021). Increasing field size is an important but long-overlooked cause of biodiversity loss in European farmland (Clough et al., 2020). In large agricultural regions, the trend towards more specialised and larger farms growing fewer and fewer crops continues (Bennett et al., 2012). Although small farms contribute to biodiversity conservation and food security at the local level, they often face challenges related to productivity, market access and long-term sustainability (Marsden and Sonnino, 2008). Diversified crop production, while bringing environmental benefits, reduces crop yields and prevents the realisation of economies of scale (Fleisher and Liu, 1992). According to Žáková Kroupová et al. (2023), subsidies have a negligible positive impact on agricultural biodiversity and thus support farmers' incomes rather than agricultural biodiversity. Being a small or medium farmer means that the impact of subsidies on Simpson's index of diversity is rather less than being a very large farmer. The finding may be related to the current legislation that requires that a farm with more than 30 ha of arable land must grow at least three crops, the main crop does not take more than 75% of the arable land, and at the same time the two main crops do not take more than 95% of the arable land (MoA, 2022). Farm size is also discussed in relation to farm productivity and efficiency. Small farms lag behind large farms in both productivity and technical efficiency. Targeting support to small farms leads to relatively small increases in overall productivity compared to targeting larger farms (Čechura et al., 2022). Svobodová et al. (2022) state that the group of farms with significant economic size achieves substantially higher productivity than small and medium-sized farms. This is also true for different production-oriented groups, with farms focused on field crop production achieving higher total factor productivity. Field crop production is an important agricultural production specialisation and significantly influences the whole Czech agriculture (Rudinskaya and Náglová, 2020). Farms specialising in field crops have the highest average economic performance scores, which include productivity, cost and profitability indicators, but also have the worst average environmental sustainability scores, which include the use of organic fertilisers, greening, proportion of grassland and others. Due to the automation of production, these enterprises use relatively little labour, are highly profit-oriented and grow mainly cash crops. In terms of economic size, the highest environmental dimension scores are reported for small enterprises, which in turn have the worst economic dimension scores (Špička et al., 2020). Staniszewski and Borychowski (2020) report that the impact of subsidies on efficiency depends on the size of farms. A statistically significant, stimulating effect of subsidies was identified only in the group of the largest farms. The heterogeneity of small farms also leads to the question of whether acreage is an appropriate size criterion for subsidy degression and whether a more appropriate criterion would be economic size of the farm or its combination with acreage (Lososová and Zdeněk, 2023). A number of factors influence farm size. In our context, these factors include land consolidation, unemployment rates and soil fertility. At the European scale, a significant association between farm size and wheat production has been found (Janovská at al., 2017).

The aim of the paper is to verify whether the structure of crop production in the Czech Republic depends on the size of the farm. The first question concerns the identification of differences in the structure of crop production according to farm size. The second question deals with the shares of the harvested area of individual crops concerning farm size and the comparison of inter-group differences. The paper contributes to the current state of knowledge by applying statistical methods to compare four farm size groups in the field production specialisation. This study fills a gap in research on the structure of crop production in the Czech Republic, as most previous studies have examined farm size mainly in relation to efficiency, productivity, subsidies, or diversity.

Materials and methods

The data were drawn from the CSO and FADN and were processed using MS-Excel, Statistica 14 and IBM SPSS 29 statistical software. Within the sample of the FADN survey conducted in 2021, enterprises specialised in field production were the most represented group, 365 enterprises in total (32.5%). These enterprises represented 5 396 agricultural entities of the given specialization, farmed 36.2% of the total cultivated land in the Czech Republic and contributed 28.8% to the total production of the Czech agricultural sector and 44.3% to crop production. The following main crops were chosen to assess the percentage structure of cropland harvested: wheat, rye, barley, oats, maise, peas, sugar beet, potatoes, rapeseed, mustard, poppy and other feed crops. The sample covers one CAP period 2014–2021 and consists of conventional agricultural enterprises focused on field crop production operating in the Czech Republic. According to the total SO of the enterprise, the categories used were small enterprises (SO 8-25 thousand EUR), medium enterprises (SO 25-100 thousand EUR), large enterprises (SO 100-500 thousand EUR) and very large enterprises (SO over 500 thousand EUR). The number of enterprises sampled each year and size group is shown in the Table A1.

Statistical analysis

Using chain base and fixed base indices and regression analysis of time series, the development of the sown area in the Czech Republic in the period 1993–2023, according to the data of the CSO, was first assessed. The trend of the analysed time series was described using linear, quadratic, and logarithmic trend functions. The correlation index was used to decide on the appropriate type of trend function (Hindls, 2007). Based on the selected trend function, predictions of the sown area of individual crops for the period 2024–2025 were determined.

Subsequently, statistical hypotheses were tested. There are often situations where the conditions for using a standard parametric test are violated, or we want to avoid these assumptions in order to increase the generality of the findings (Pereira et al., 2015). To overcome these difficulties, nonparametric tests based on very general assumptions have been developed (Grofík et al., 1987). Thus, nonparametric tests have broader applicability than parametric tests. However, they have the disadvantage of lower test power (Hindls et al., 2007). The Shapiro-Wilk test was used to verify the assumption of normality and the assumption of homogeneity of variances was verified using the Levene's test (see the Table A2). Since the assumptions were not met, the nonparametric Kruskal–Wallis test, which is an alternative nonparametric procedure to the parametric one-factor analysis of variance, was used. The test is based on the following criterion:

$$\mathrm{H} = \frac{12}{N(N+1)} \sum_{i=1}^{k} \frac{T_i^2}{ni} - 3\,(N+1) \qquad (1)$$

Where n_1, n_2, ..., n_k = the ranges of each file; $N = n_1 + n_2 + ... + n_k$; k = the number of independent random samples; T_1, T_2, ..., T_k = the sums of the rank numbers of each observation for each sample separately after merging the samples into a single file and assigning a rank (Grofík et al., 1987). The test statistic for $n_i > 5$ has approximately χ^2 distribution with k - 1 degrees of freedom. We test the null hypothesis H_0 that all samples come from the same distribution (Jarošová, 2021). If the Kruskal–Wallis test rejects the tested hypothesis, we further assess which groups are statistically significantly different from each other using a post-hoc test. If we are working with unbalanced samples, according to Anděl (2011), we can complement the Kruskal–Wallis test with the so-called general multiple comparison method. Let us denote by $t_i = T_i/n_i$ the average ranking in the i-th sample. Let $h_{KW}(\alpha)$ be the critical value of the Kruskal-Wallis test at the α significance level contained in the special tables, which can be approximated at larger ranges by the quantile of the χ^2 distribution with k - 1 degrees of freedom for a given α. If the inequality holds

$$|t_i - t_k| \geq \sqrt{\frac{N(N+1)}{12}\left(\frac{1}{n_i} + \frac{1}{n_k}\right) h_{KW}(\alpha)}, \qquad (2)$$

then, at the α significance level, we reject the null hypothesis that the distributions of the i-th and k-th samples are identical.

Results and discussion

Development of sown areas

It is clear from Table 1 above that there are significant changes in the area sown to individual crops in the long term. In terms of the share of the total sown area, wheat, grain maise, and rapeseed have increased in importance. At the same time, these are the only crops which, despite the decline in total sown area, have not fallen below the value recorded in 1993 and which have experienced an average annual increase of 0.14%, 3.08% and 2.77% respectively over the period under review. On the other hand, in terms of the share of the total sown area, barley, potatoes, and forage crops on arable land showed a significant decrease. Compared to 1993, the areas of potato (19.96%), flax (20.33%), rye (36.81%) and barley (50.31%) were at their lowest levels in 2023.

Table 2 shows the expected development of the area of each crop based on the calculated trend functions. Only functions whose correlation index is higher than 0.6 and whose result is statistically significant are analysed. These conditions were not met only in the case of wheat. The other results are statistically significant, and according to the values of the correlation index, it is clear that there is a strong dependence between the variables and that the chosen trend functions explain the variability of the time series very well. According to the calculated predictions, it can be expected that in the following years 2024–2025 there will be a slight increase in the sown areas of rye, oats, legumes, industrial sugar beet, flax, forage crops and potatoes, which can be considered as a positive indicator in response to the set

	Average (ha)	Average absolute increment (ha)	Average growth coefficient	Fixed base index 2023/1993	Fixed base index 2004/1993	Fixed base index 2013/1993	Share of total sown area 1993 (%)	Share of total sown area 2023 (%)
Wheat	830487	1152.13	1.0014	1.0441	1.1021	1.0590	24.63	33.85
Rye	41231	-1410.77	0.9672	0.3681	0.8840	0.5599	2.11	1.02
Barley	452576	-10570.97	0.9774	0.5031	0.7348	0.5468	20.08	13.29
Oats	53638	-832.53	0.9848	0.6326	0.8617	0.6408	2.14	1.78
Grain maise	73261	1468.23	1.0308	2.4853	2.9613	3.7743	0.93	3.05
Leguminous crops	40116	-1407.83	0.9804	0.5514	0.3017	0.1896	2.96	2.15
Potatoes	41551	-2799.47	0.9477	0.1996	0.3428	0.2211	3.3	0.87
Technical sugar beet	68770	-1614.67	0.9802	0.5483	0.6629	0.5819	3.37	2.43
Rapeseed	326374	7084.03	1.0277	2.2694	1.5497	2.5015	5.27	15.73
Flax	4889	-208.70	0.9483	0.2033	0.9567	0.1925	0.25	0.07
Arable forage crops	562311	-16886.57	0.9754	0.4733	0.5204	0.4537	30.25	18.84

Source: CSO and author's procession (2023)

Table 1: Basic characteristics of the area sown to each crop between 1993 and 2023.

	Trend function	Correlation index	F p-value	2024 prediction (ha)	-95% +95% prediction	2025 prediction (ha)	-95% +95% prediction
Rye	y´= 83°234.25 – 4°311.97t_i + 80.32t_i^2	0.9078	65.606 0	27 501	17 988 37 014	28 410	17 636 39 184
Barley	y´= 638°131.9 – 11°597.3 t_i	0.9502	269.48 0	267 019	240 534 293 505	255 422	227 667 283 178
Oats	y´= 77°650.8 – 21°948.6 log t_i	0.745	36.172 0	44 614	40 513 48 715	44 321	40 145 48 497
Grain maise	y´= - 1°036.6 + 9°382.53t_i – 225.66 t_i^2	0.9185	75.505 0	68 126	54 680 81 572	62 840	47 613 78 068
Leguminous crops	y´= 85°467.47 – 6°509.41t_i + 175.0 t_i^2	0.9318	92.236 0	56 365	49 156 63 573	61 230	53 066 69 394
Potatoes	y´= 103°296.3 – 6°812.2t_i + 140.6 t_i^2	0.9707	228.62 0	29 306	22 248 36 364	31 634	23 641 39 627
Technical sugar beet	y´= 106°792.1 – 4°559.5t_i + 104.0 t_i^2	0.8779	47.07 0	67 341	58 347 76 336	69 539	59 353 79 725
Rapeseed	y´= 174°907.1 + 16°197.5t_i – 320.5 t_i^2	0.8685	42.993 0	365 019	324 060 405 979	360 383	313 996 406 770
Flax	y´= 12°185.54 – 6°669.22 log t_i	0.6483	21.026 0.0001	2 147	512 3 781	2 058	393 3 722
Arable forage crops	y´= 1°028 202 – 57°413t_i + 1 347 t_i^2	0.9701	223.57 0	570 691	521 005 620 377	600 856	544 586 657 127

Source: CSO and author's procession (2023)

Table 2: Analysis of crop area trend functions and their expected evolution between 2024-2025.

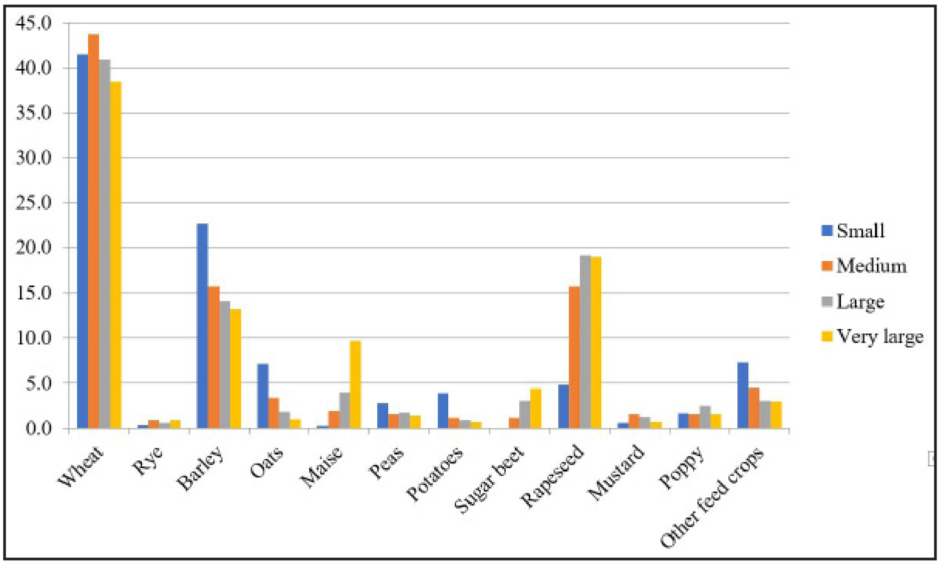
measures. On the other hand, a decrease in the area sown to rapeseed and grain maise can be expected.

The identification of trends can help to identify commodities that require special attention from agricultural policy. Alternatively, the effectiveness of the agrarian policy measures can be assessed, which should lead to an increase in the sown area of sensitive commodities.

Farm size and structure of crop production

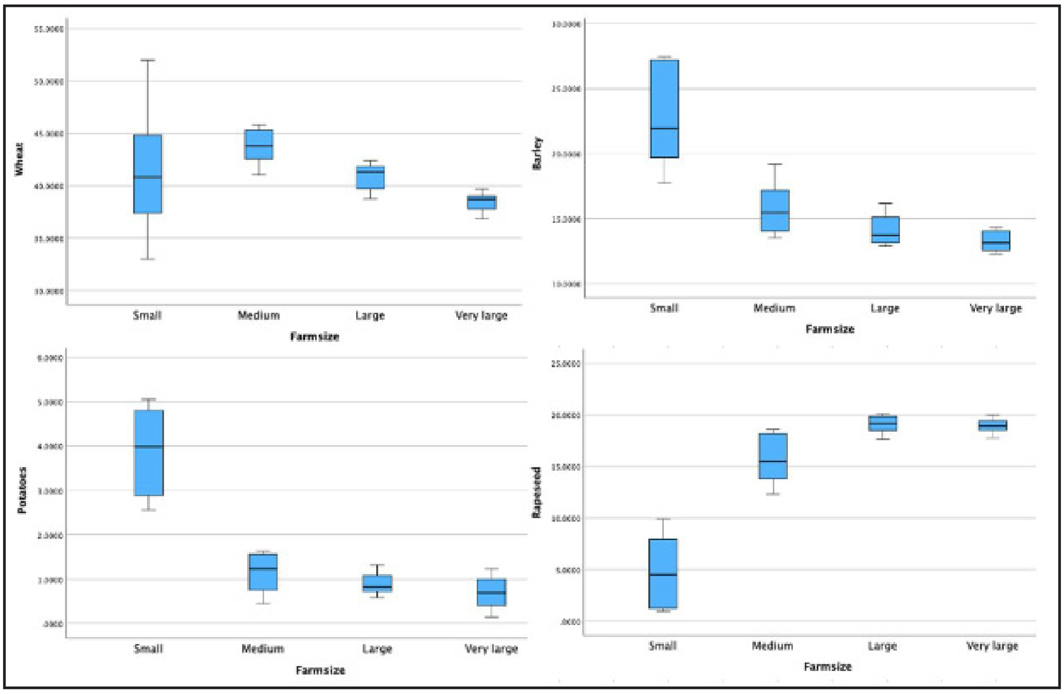
The size of farms is influenced by several factors (Janovská et al., 2017). One of them is demonstrably the structure of crop production. The following Figure 1 shows the average structure of harvested area per arable land for different farm size groups, between which there is a significant difference. The largest differences are observed for barley, maise, potatoes, oilseed rape and other fodder crops. On the other hand, the average percentages of wheat, rye, peas, mustard, and poppy are similar. In the overall crop production structure, there was a slight increase in the share of wheat, poppy, peas, and other feed crops in 2019 compared to 2014. The share of barley, potatoes and maise decreased. These findings are in line with the claims of the APF CR, which has long pointed out that cereals and oilseed rape decisively shape the structure of crop production. According to Malinovský (2021), the production of barley, oats, and rye will decline in the following years in favour of wheat and maise. From the analyses carried out, it is clear that the crops whose importance in terms of sown area in the Czech Republic has been declining for a long time have a higher share in the structure of harvested arable land in small farms.

The different structures between the different farm sizes are also evident in Figure 2 below, which includes box plots of the percentages of wheat, barley, potatoes, and rapeseed in the structure of each farm size group. The highest variability over time is observed for small enterprises, while the lowest variability is observed for the largest enterprises. In the case of barley, potatoes and rapeseed, small enterprises are the outliers in terms of their shares, and they are also the most variable over time. The share of these crops in the structure of large and very large enterprises is similar and relatively stable compared to small enterprises. While the share of rapeseed is the lowest for small enterprises, averaging 4.84%, this average share rises to 19.09% and 18.94% for large and very large enterprises respectively. On the other hand, barley and potatoes reach the highest share for small enterprises, at 22.65% and 3.88% respectively. In comparison, for very large enterprises, the average share of barley and potatoes is 14.20% and 0.87% respectively. This fact is related to the findings of Procházková et al. (2016), according to which the cultivation of rye, barley and potatoes, which are predominant in the structure of small enterprises, is receding.



Source: FADN and author's procession (2023)

Figure 1: Average structure of harvested area per arable land (%).



Source: FADN and author's procession (2023)

Figure 2: Categorised box plot of percentage of wheat, barley, potatoes and rapeseed.

On the contrary, in the long run, the areas of rapeseed and industrial crops are expanding, whose harvested areas reach higher shares in very large and large enterprises. This fact is also linked to the low level of self-sufficiency in potatoes (Svatošová et al., 2018). Potatoes, together with sugar beet, selected fruit and vegetables, hops, and protein crops, are among the sensitive sectors supported by EU resources through voluntary coupled support (MoA, 2021). The introduction of aid in the potato sector has slowed down the rate of decline in potato areas (Žovincová, 2019).

According to the results of the Kruskal–Wallis test in Table 3, it is clear that for almost all crops H_0 cannot be accepted, and therefore, the share of the crop grown depends on the size of the farm. The only crop for which no dependence between share of cultivation and farm size was found is peas. Thus, farm size influences the proportion

Crop	K-W test	P-value	Hypothesis	Post-hoc test	P-value
Wheat	13.6532	0.0034**	H1	M x VL	0.0013**
Rye	9.0303	0.0289*	H1	S x VL	0.0769
Barley	18.9193	0.0003***	H1	S x L S x VL	0.0085** 0.0002***
Oats	25.2796	0.0000***	H1	S x L S x VL M x VL	0.0128* 0.0000*** 0.0030**
Maise	26.3801	0.0000***	H1	S x L S x VL M x VL	0.0137* 0.0001*** 0.0026**
Peas	0.6806	0.8777	H0	x	x
Potatoes	16.2871	0.0010**	H1	S x L S x VL	0.0096** 0.0007***
Sugar beet	26.4024	0.0000***	H1	S x L S x VL M x VL	0.0061** 0.0000*** 0.0029**
Rapeseed	21.0419	0.0001***	H1	S x L S x VL	0.0004*** 0.0010**
Mustard	14.5848	0.0022**	H1	M x S M x VL	0.0194* 0.0180*
Poppy	9.1038	0.0279*	H1	L x VL	0.0496*
Other feed crops	13.8141	0.0032**	H1	S x L S x VL	0.0128* 0.0089**

Note: If p-value < 0.05, then H0 cannot be accepted at the chosen significance level, and the proportion of cultivation of a given crop depends on the size of the farm. Furthermore, if the p-value < 0.05, then there is a statistically significant difference just between the indicated size groups of enterprises, where S = small, M = medium, L = large, VL = very large. The level of significance is indicated as P < 0.05 *, P < 0.01 **, P < 0.001***. The post-hoc test includes only groups of enterprises between which there is a statistically significant difference.

Source: FADN and author's procession (2023)

Table 3:Results of Kruskal–Wallis test (K-W test) and post-hoc multiple comparison test.

of crops grown, respectively, the structure of crop production and agricultural policy should take this into account in measures relating to farm size and self-sufficiency. The new redistributive payments favouring small farms in the Czech Republic are to go to 23%, which critics argue could impact medium-sized farms (Lososová and Zdeněk, 2023). An administrative division of large farms into smaller ones can be expected. This will result in a higher number of enterprises and a decrease in their size rather than a change in the structure of crop production. At the same time, this raises the question of whether SO would be a better indicator for subsidy payments than the agricultural area used (Urbánová et al. 2018). The level of production, hence self-sufficiency, especially for commodities not regulated by agricultural policy measures, can be largely linked to the level of their aggregate profitability achieved and to the competitiveness of downstream processing industries (Procházková et al., 2018). At the same time, the smallest producers lag behind the largest ones due to scale effects (Čechura et al., 2022).

The multiple comparison method found a statistically significant difference mainly between small-sized enterprises and large and very large enterprises. In a similar direction, the findings of Janovská et al. (2017) suggest that there is a significant association between wheat production and farm size on a European scale. The most significant differences are observed between the smallest and the largest farms, especially for barley, oats, maise, potatoes, sugar beet and rapeseed. There is also a significant difference between medium-sized and very large enterprises for wheat, oats, maise, sugar beet and mustard. With respect to farm size, the main issues examined so far have been biodiversity (Ricciardi et al., 2021), wheat production (Janovská et al., 2017; Skalicky et al., 2021), the impact of subsidies on agricultural diversity (Žáková Kroupová et al., 2023), the impact of subsidies on farm efficiency (Staniszewski and Borychowski, 2020), and efficiency and productivity (Čechura et al., 2022; Svobodová et al., 2022), which are significantly higher for enterprises with high economic size than for small and medium-sized enterprises, and in terms of overall productivity growth, policy support for small enterprises is a trade-off. It is clear from the various studies that there is no uniform view on the issue of farm size. Significant differences in the structure of crop production according to farm size are another indicator that should be addressed and also targeted by CAP measures. Compared to other EU Member States, the Czech Republic and Slovakia have the largest farm size (Urbánová et al., 2018) and it is therefore clear that large farms significantly influence the structure of crop production.

It is important to mention that many other factors play a role in the structure of production and farm size, which have already been the subject of some studies or create space for further research. In relation to the structure of crop production and farm size, other areas of interest are level of production, self-sufficiency, regulatory measures for individual commodities, profitability and the competitiveness of downstream processing industries. The impact of farm size on production structure could be further explored across production orientations or selected countries.

Conclusion

This study investigated the relationship between farm size and crop production structure of conventional arable farms in the Czech Republic. The analysis was based on the application of statistical methods from the field of nonparametric testing and time series. In contrast to previous studies that assessed farm size mainly in relation to production, efficiency, biodiversity, or subsidies, this study assessed the importance of individual crops in the overall cropping structure of small, medium, large, and very large farms.

The results show that there have been significant and often negative changes in the structure of crop production in the Czech Republic during the period under review. It is also clear that farm size influences the structure of crop production. Given the large-scale nature of Czech agriculture, the structure of crop production is largely defined by large enterprises. For all the crops evaluated, with the exception of peas, it is not possible to accept H_0, and therefore, the share of the crop grown depends on the size of the holding. A statistically significant difference was found mainly between small enterprises and large and very large enterprises. Compared to large and very large enterprises, small enterprises have a predominant share of barley, oats, potatoes and other feed crops. In contrast, large and very large enterprises have a higher share of maise, rapeseed and sugar beet.

The results also have important policy implications. Measures should not focus purely on the size of the holding, but the production structure of the holding should also be assessed alongside the size. If one of the objectives of the reformed CAP applicable from 2023 is to provide more targeted support to smaller farms, the proposals should also include approaches to increase their efficiency and productivity. At the same time, one of the main priorities of the Ministry of Agriculture is sustainable food security and adequate food self-sufficiency, with the aim of increasing the area under permanent fodder crops, potatoes, orchards and vegetables at the expense of the area under rapeseed. Appropriate measures should thus be set up to support both the productivity of small farms and changes in the structure of crop production on large farms, which decisively shape Czech agriculture. Here, the established legislation requiring a farm larger than 30 ha of arable land to grow at least three crops seems sensible. Voluntary coupled support for sensitive commodities also plays an important role. In order to increase the productivity of small farms, increasing support should also be linked to the purchase of agricultural equipment. Increased investment in research and development leading to higher yields also seems to be a possible solution in terms of ensuring an adequate level of self-sufficiency.

Acknowledgements

This article is a part of the dissertation in the doctoral study program Quantitative Methods in Economics at the Faculty of Economics and Management, Czech University of Life Sciences Prague. The dissertation is entitled "Changes in the production dimension and structure of Czech agriculture".

Corresponding author:
Ing. Anna Žovincová
Department of Statistics, Faculty of Economics and Management, Czech University of Life Sciences Prague
Kamýcká 129, 165 00 Praha – Suchdol, Czech Republic
Phone: +420774214413, E-mail: zovincova@pef.czu.cz

References

[1] Anděl, J. (2011) "Základy matematické statistiky", 3rd ed. Prague: Matfyzpress. ISBN 978-80-7378-162-0. (In Czech).

[2] Bennett, A. J., Bending, G. D., Chandler, D., Hilton, S. and Mills, P. (2012) "Meeting the demand for crop production: the challenge of yield decline in crops grown in short rotations", *Biological Reviews*, Vol. 87, pp. 52-71. ISSN 1469-185X. DOI 10.1111/j.1469-185X.2011.00184.x.

[3] Collective of office and external authors of APF CR (2021) "*On the problem of self-sufficiency of Czech agriculture*", Oct. 2021. [Online]. Available: https://www.asz.cz [Accessed: Sept. 21, 2023].

[4] Clough, Y., Kirchweger, S. and Kantelhardt, J. (2020) "Field sizes and the future of farmland biodiversity in European landscapes", *Conservation Letters*, Vol. 13, p. e12752. ISSN 1755-263X. DOI.org/10.1111/conl.12752.

[5] Czech Statistical Office (2011) "*České zemědělství očima statistiky*", Czech Statistical Office, Prague, 83 p. ISBN 978-80-250-2110-1. (In Czech).

[6] Czech Statistical Office (2024) "*Agriculture – time series*", Czech statistical Office. [Online]. Available: https://www.czso.cz/csu/czso/zem_ts [Accessed: March 20, 2024].

[7] Čechura, L., Žáková Kroupová, Z. and Lekešová, M. (2022) "Productivity and efficiency in Czech agriculture: Does farm size matter?", *Agricultural Economics*, Vol. 68, pp. 1-10. ISSN 0139-570X. DOI 10.17221/384/2021-AGRICECON.

[8] European Commission (2022) "*Proposed CAP strategic plans - summary overview*". [Online]. Available: https://agriculture.ec.europa.eu/cap-my-country/cap-strategic-plans_en [Accessed: Oct. 27, 2022].

[9] European Commission-FADN (2020) "*Definitions of Variables Used in FADN Standard Results", RI/CC 1750*. [Online]. Available: https://circabc.europa.eu/ui/group/880bbb5b-abc9-4c4c-9259-5c58867c27f5/library/162fb4de-22c9-489a-a0f6-8cd9f75de730 [Accessed: May 8, 2022].

[10] Farm Accountancy Data Network (2020) "*Sample survey of economic results of agricultural holdings in the FADN CZ network for 2020*", Prague: Institute of Agricultural Economics and Information. ISBN 978-80-7271-254-0. (In Czech).

[11] Farm Accountancy Data Network (2023) "*Public database*", Institute of Agricultural Economics and Information. [Online]. Available: https://public.fadn.cz/ [Accessed: Oct. 27, 2023].

[12] Fleisher, B. M. and Liu, Y. (1992) "Economies of scale, plot size, human capital, and productivity in Chinese agriculture", *Quarterly Review of Economics and Finance*, Vol. 32, pp. 112-124. ISSN 1062-9769.

[13] Grofík, R., Kubíček, J., Hrubý, J., Dufek, J., Kába, B. and Zeipelt, R. (1987) "*Statistika*", Bratislava: Príroda. 284 p. (In Czech).

[14] Hindls, R. (2007) "*Statistika pro ekonomy*", Professional Publishing, 8th ed. Prague. ISBN 978-80-86946-43-6. (In Czech).

[15] Janovská, V., Simova, P., Vlasak, J. and Sklenicka, P. (2017) "Factors affecting farm size on the European level and the national level of the Czech Republic", *Agricultural Economics*, Vol. 63, pp. 1-12. ISSN 0139-570X. DOI 10.17221/317/2015-AGRICECON.

[16] Jarošová, E. (2021) "*Návrhy a vyhodnocení průmyslových experimentů*", Professional Publishing, Prague. ISBN 978-80-88260-54-7. (In Czech).

[17] Kolodziejczak, M. (2018) "Food self-sufficiency in EU countries: an attempted projection to 2080", International Scientific Conference *AP XXVII. Food safety - Food security.* Czech University of Life Sciences Prague, ISBN 978-80-213-2890-7.

[18] Kowalczyk, S. and Sobiecki, R. (2014) "The European model of agriculture in relation to global challenges", *Problems of Agricultural Economics*, Vol. 329, pp. 35-58. ISSN 0044-1600. DOI: 10.22004/ag.econ.235229.

[19] Kryszak, Ł., Guth, M. and Czyżewski, B. (2021) "Determinants of farm profitability in the EU regions. Does farm size matter?", *Agricultural Economics*, Vol. 67, pp. 90-100. ISSN 0139-570X. DOI 10.17221/415/2020-AGRICECON.

[20] Lososová, J. and Zdeněk, R. (2023) "Simulation of the impacts of the proposed direct payment scheme - The case of the Czech Republic", *Agricultural Economics*, Vol. 69, No. 1, pp. 13-24. ISSN 0139-570X. DOI 10.17221/328/2022-AGRICECON.

[21] Malinovský, V. (2021) "Predicting Trends in Cereal Production in the Czech Republic by Means of Neural Networks", *AGRIS on-line Papers in Economics and Informatics*, Vol. 13, No. 1, pp. 87-103. ISSN 1804-1930. DOI 10.7160/aol.2021.130107.

[22] Marsden, T. and Sonnino, R. (2008) "Rural development and the regional state: Denying multifunctional agriculture in the UK", *Journal of Rural Studies*, Vol. 24, No. 4, pp. 422-431. ISSN 1873-1392. DOI.10.1016/j.jrurstud.2008.04.001.

[23] Ministry of Agriculture of the Czech Republic (2016) "*Strategie resortu Ministerstva zemědělství s výhledem do roku 2030*", Ministry of Agriculture of the Czech Republic, Prague. ISBN 978-80-7434-356-8. (In Czech).

[24] Ministry of Agriculture of the Czech Republic (2014 – 2021) "*Zpráva o stavu zemědělství České Republiky*", Ministry of Agriculture of the Czech Republic. [Online]. Available: https://eagri.cz/public/web/mze/zemedelstvi/publikace-a-dokumenty/zelene-zpravy/?pos=0 [Accessed: Jan. 10, 2023]. (In Czech).

[25] Ministry of Agriculture of the Czech Republic (2021) "*Situační a výhledová zpráva - Půda*", Ministry of Agriculture of the Czech Republic, Prague. ISBN 978-80-7434-598-2. (In Czech).

[26] Ministry of Agriculture of the Czech Republic (2022) "*Metodická příručka k podmínkám poskytování přímých plateb v České republice v roce 2022*", Ministry of Agriculture of the Czech Republic, [Online]. Available: https://eagri.cz/public/portal/mze/dotace/prime-platby/metodicka-prirucka-pro-prime-platby-pro-3 [Accessed: Sept. 18, 2023]. (In Czech).

[27] Pereira, D. G., Alfonso, A. and Medeiros, F. M. (2015) "Overview of Friedman's Test and Post-hoc Analysis", *Communications in Statistics - Simulation and Computation*, Vol. 44, No. 10, pp. 2636-2653, ISSN 1532-4141. DOI 10.1080/03610918.2014.931971.

[28] Popescu, A., Alecu, I. N., Dinu, T. A., Stoian, E., Condei, R. and Ciocan, H. (2016) "Farm structure and land concentration in Romania and the European Union's agriculture", *Agriculture and Agricultural Science Procedia*, Vol. 10, pp. 566-577. ISSN 2210-7843. DOI 10.1016/j.aaspro.2016.09.036.

[29] Procházková, R., Prášilová, M. and Hloušková, Z. (2016) "Efficiency of agriculture as related to foodstuffs Autarky in the Czech Republic", In: *Proceedings from the International Scientific Conference AP XXV.*, Czech University of Life Sciences Prague. ISBN 978-80-213-2670-5.

[30] Ricciardi, V., Mehrabi, Z. and Wittman, H. (2021) "Higher yields and more biodiversity on smaller farms", *Nature Sustainability*, Vol. 4, pp. 651-657. ISSN 0028-0836. DOI 10.1038/s41893-021-00699-2.

[31] Rudinskaya, T. and Náglová, Z. (2020) "Position of the Czech republic in EU field crop production", In: *Proceedings from the International Scientific Conference AP XXIX. Trends and challenges of agrarian sector*. Czech University of Life Sciences Prague. ISBN 978-80-213-3041-2.

[32] Řezbová, H. and Škubna, O. (2012) "The role of transgenic crops in the future of global food and feed", *AGRIS on-line Papers in Economics and Informatics*, Vol. 4, No. 2. ISSN 1804-1930.

[33] Staniszewski, J. and Borychowski, M. (2020) "The impact of the subsidies on efficiency of different sized farms. Case study of the Common Agricultural Policy of the European Union", *Agricultural Economics*, Vol. 66, pp. 373-380. ISSN 0139-570X. DOI 10.17221/151/2020-AGRICECON.

[34] Svatošová, L., Köppelová, J. and Brož, D. (2018) "Trends in consumption of selected types of foodstuffs as related to nutrition recommendations and self-sufficiency", In: *Proceedings from the International Scientific Conference AP XXVII. Food safety - Food security*. Czech University of Life Sciences Prague, ISBN 978-80-213-2890-7.

[35] Svobodová, E., Redlichová, R., Chmelíková, G. and Blažková, I. (2022) "Are the Agricultural Subsidies Based on the Farm Size Justified? Empirical Evidence from the Czech Republic", *Agriculture*, Vol. 12, No. 10, p. 1574. ISSN 2077-0472. DOI 10.3390/ agriculture12101574.

[36] Špička, J., Vintr, T., Aulová, R. and Macháčková, J. (2020) "Trade-off between the economic and environmental sustainability in Czech dual farm structure", *Agricultural Economics*, Vol. 66, No. 6, pp. 243-250. ISSN 0139-570X. DOI 10.17221/390/2019-AGRICECON.

[37] Urbánová, M., Dobošová, Ľ., Kozáková, J., Ďurišová, E. and Čeryová, D. (2018) "Physical and economic size of farms in the EU - focus on Slovakia", In: *Proceedings from the International Scientific Conference AP XXVII. Food safety - Food security*. Czech University of Life Sciences Prague. ISBN 978-80-213-2890-7.

[38] Žáková Kroupová, Z., Čechura, L., Opatrný, M., Hloušková, Z. and Mlezivová, I. (2023) "Assessment of the impact of agricultural support on crop diversity", *Agricultural Economics*, Vol. 69, No. 3, pp. 89-100. ISSN 0139-570X. DOI 10.17221/387/2022-AGRICECON.

[39] Žovincová, A. (2019) "Importance of the potato market in the Czech Republic in comparison with selected EU countries" In: *Think together, Scientific Doctoral Conference*, Czech University of Life Sciences Prague. ISBN 978-80-213-2169-4.

Appendix

Year	Small		Medium		Large		Very large	
	n	ha	n	ha	n	ha	n	ha
2014	22	50 773	135	140 229	173	336 686	131	695 047
2015	21	55 461	135	142 150	168	347 717	128	635 095
2016	22	41 470	133	130 463	169	342 569	130	668 507
2017	13	47 146	106	124 143	175	351 414	162	750 293
2018	19	43 954	121	123 217	160	338 246	159	773 752
2019	20	38 029	106	132 414	167	337 851	148	800 541
2020	N/A	N/A	98	130 405	139	314 640	116	751 805
2021	N/A	N/A	111	139 989	144	348 810	104	801 727

Source: FADN (2023)

Table A1: Number of farms in the research sample and their acreage of agricultural land area.

In the FADN CZ survey, the economic size threshold for the survey area, i.e. for the inclusion of enterprises in the FADN CZ sample, has been increased from EUR 8 000 to EUR 15 000 of standard production, as defined in the amendment to Commission Implementing Regulation (EU) No 2015/220, since the accounting year 2020. Based on this change, small enterprises with an economic size of IV are no longer included in the survey since the financial year 2020. This has had an impact on the results for the 2020 accounting year, especially for natural person enterprises (FADN, 2020).

	Shapiro-Wilk test		Levene's test	
Wheat	SW-W = 0.8924	p = 0.2463	F = 10.203	p = 0.00013
Rye	SW-W = 0.7536	p = 0.0216	F = 3.2238	p = 0.03888
Barley	SW-W = 0.8739	p = 0.1644	F = 8.0416	p = 0.00059
Oats	SW-W = 0.7154	p = 0.0034	F = 10.053	p = 0.00014
Maise	SW-W = 0.7076	p = 0.0027	F = 2.4758	p = 0.08377
Peas	SW-W = 0.8056	p = 0.0659	F = 22.026	p = 0.00000
Potatoes	SW-W = 0.8848	p = 0.2090	F = 8.6679	p = 0.00037
Sugar beet	SW-W = 0.8849	p = 0.2095	F = 6.4282	p = 0.00211
Rapeseed	SW-W = 0.8305	p = 0.1085	F = 23.049	p = 0.00000
Mustard	SW-W = 0.6979	p = 0.0059	F = 4.8485	p = 0.00824
Poppy	SW-W = 0.8045	p = 0.0320	F = 13.168	p = 0.00002
Other feed crops	SW-W = 0.8803	p = 0.1898	F = 4.7385	p = 0.00911

Source: FADN (2023)

Table A2: Verification of the assumptions of normality and homogeneity of variances using the Shapiro-Wilk test and the Levene's test. If P < 0.05, then the normality/homogeneity of variances assumption was not met. The results of the Shapiro - Wilk's test report only the groups with the lowest p-value..

Agris on-line Papers in Economics and Informatics

Volume XVI Number 4, 2024

Agris on-line Papers in Economics and Informatics

The international reviewed scientific journal issued by the Faculty of Economics and Management of the Czech University of Life Sciences Prague.

http://online.agris.cz

ISSN 1804-1930