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Changes in the Slovak Plum Production and its Competitiveness on the Single Market

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Abstract

The article identifies the importance and development of production and related competitiveness in the EU single market of plum production in the Slovak Republic in the time horizon from Slovakia's accession to the EU until 2020. The research results show an overall positive development in the area of plum orchards (18% increase), which is in contrast to the overall development of the area of orchards in the Slovak Republic (7.12% decrease). However, the changes in the area under cultivation are not reflected in the increase in production (decrease of 45.22%) during the period under study. This fact was also reflected in the volatility of the identified competitiveness of Slovak plum production on the EU Single Market during the period under review. The trade balance was positive only to a limited extent in 2008 and 2009. Nevertheless, the measured RCA values point to a more significant degree of competitiveness of Slovak plum production on the EU single market, with a positive trend between 2008 and 2015. However, there is a decline in competitiveness after 2015, when this negative trend could not be reversed until the end of the period under consideration. In order to reverse this negative trend, further targeted measures will be necessary in the future, both in terms of policies, modernisation processes and improved agrotechnical practices.

Keywords

Fruit, plums, competitiveness, single market.

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Introduction

Agriculture has often been in the focus of researchers when studying its role in the economy, society or nature (Mizik, 2021). Although agriculture no longer plays a significant role in the composition of GDP in developed countries, there are available research results that highlight the important position of this sector within the world and national economy (Johnston and Mellor, 1961; Johnson, 1993; Gollin, Parente and Rogerson, 2002). Developed countries, including EU countries, support this sector to maintain its basic function in rural development (Potter, 2006).

There has always been an obvious interest in investigating the situation within the EU territory when dealing with the current situation of agriculture. The situation of the agricultural

sector is a common object of research from an economic, social or political point of view. The agenda of agriculture is usually investigated as the situation of trade within the EU countries (Szabo and Grznár, 2015; Szabo and Grznar, 2016; Špirková, Stehlíková and Zúbková, 2017, Hošková and Zentková, 2024.) or third countries and EU countries (Murray and Zolin, 2012). We can highlight the interest of researchers in EU countries in the area of overall productivity (Chrastinová and Burianová, 2009) or, more recently, sustainability (Kalinowska et al., 2022). On the other hand, the research objective is more focused on trade barriers when studying trade between third countries and EU countries (Elijah et al., 2017).

The competitive dynamics of agricultural products involve a complex interplay of technological,

economic, social and environmental factors. To enhance global competitiveness, countries need to prioritise investments in research and development, infrastructure and sustainable practices. Addressing challenges such as climate change and market volatility requires joint initiatives at national and international levels. This review provides a basis for policy makers, researchers and stakeholders to understand and navigate the constantly evolving terrain of agricultural competitiveness.

Research on agricultural and food competitiveness has undergone a significant change in terms of breadth and depth (Ball et al., 2010; Gorton, Davidova and Ratering, 2000). It is now not only a tool to identify changes in agri-food production and its competitiveness in less developed countries (Bouet et al., 2020; Esterhuizen et al., 2006), but also a tool to identify a contemporary role of the agri-food industry within developed countries (Nowak and Kaminska, 2016; Nowak, Rozanska-Boczula and Krukowski, 2020).

A new research object emerged after the V4 countries (Czech Republic, Hungary, Poland and Slovakia) joined the EU. The accession of these countries was part of the largest enlargement of the EU in history. This enlargement brought a new interest of researchers when considering the impact on agriculture (Drożdż and Zemeckis, 2009; Mizik and Meyers, 2013). The results of the research showed that accession had a different impact on agriculture in the individual V4 countries (Jambor, 2010; Věžník and Konečný, 2011; Tóth, 2019; Kusz, Kusz and Hydzik, 2022, Zdráhal, 2024). Further research was followed by the study of international trade and competitiveness of agriculture in other European countries that transform their production within the industry when adapting to new market conditions (Dukič and Glavaš-Trbic, 2017).

Contemporary research oriented towards agricultural production in a regional and global scope emphasises individual commodities and their performance in international trade between countries (Smutka, Pokorná, Pulkrábek, 2012) or national demand (Kubicova et al., 2021).

With regard to the previous research conducted, the main aim of the article will be to provide focused research on a particular period of time starting from 2004 and lasting up to the year when the data started to be affected by the COVID-19 pandemics.

Materials and methods

The data compared for the purposes of the article include fruit production on the one hand and plum production on the other. These data were collected within the Single market trade activities.

Data used for calculations we acquired from:

- Eurostat,
- Slovak Statistical Office.

Within the Eurostat databases the data was collected from the following datasets:

- Crop production in EU standard humidity (data code: apro_cpsh1),
- EU trade since 1988 by HS2-4-6 and CN8 (data code: ds-045409\$defaultview).

The abovementioned datasets were used for plum production analysis and final calculation of the revealed comparative advantage of the Slovak plum production in the Single market.

Regarding the dataset of the Slovak Statistical office the following datasets were used:

- Hectare yields of selected agricultural crops (data code: pl3001rr),
- Gross vegetable production by commodities (data code: pl2018rs).

Datasets of the Slovak statistical Office were used for calculation of the overall fruit production in the Slovak Republic.

The decisive period for the observations in this study was between the years 2004 and 2020. The commodity investigated within international trade will be plum production.

With regard to the research activities carried out within the framework of this article, the main objective of the article is to identify the position of Slovak plum production and its competitiveness on the EU internal market.

The methods described below represent the pattern in order to fulfil the objective of the article. Basic descriptive statistics were used to compare the data observed during the period under study. Besides the direct comparison, the yield (Y) was estimated on the basis of the formula:

$$Y_c^v = \left(\frac{P_c^v}{A_c^v} \right) \quad (1)$$

The competitiveness of plum production in the Slovak Republic was estimated on the basis of the data observed during our research.

The trend of measuring the competitive advantage started at the end of the sixties. At that time, various authors such as Liesner (1958) or Balassa (1965) wrote their approach to the measurement of competitive advantage. As far as the authors mentioned above are concerned, the most common formula for the revealed competitive advantage is Balassa's index. The calculation formula can be expressed as follows:

$$RCA1_a^i = \left(\frac{X_a^i}{X_c^i}\right) / \left(\frac{X_m^i}{X_n^i}\right) \quad (2)$$

In the above formula for the revealed comparative advantage ($RCA1_a^i$) we can identify the following variables:

X - represents exports,

i - subscript refers to particular observed country,

c - subscript refers to all observed countries,

m - subscript refers to combined exports.

Subsequent research has brought various modifications to the measurement of competitiveness. One of these modifications is the approach to measuring competitive advantage first introduced by Vollrath (1991). The formula for Vollrath's interpretation of competitiveness measurement can be defined as follows:

$$RXA_a^i = \left(\frac{X_a^i}{X_n^i}\right) / \left(\frac{X_a^r}{X_n^r}\right) \quad (3)$$

$$RMA_a^i = \left(\frac{M_a^i}{M_c^i}\right) / \left(\frac{M_m^i}{M_n^i}\right) \quad (4)$$

$$RCA2_a^i = \ln(RXA_a^i) - \ln(RMA_a^i) \quad (5)$$

The revealed competitive advantage ($RCA2_a^i$) is measured as the difference between the relative export advantage (RXA_a^i) and the relative import advantage (RMA_a^i). Within these formulae, the following variables are identified:

X - defines exports,

M - defines imports,

i - subscript refers to selected country,

r - subscript refers to all observed countries,

a - subscript refers to a specific product,

n - subscript refers to all products.

The revealed competitive advantage ($RCA2_a^i$) was used for the research purposes of this article when the calculated data were evaluated as:

$RCA2_a^i >$ country is competitive on the Single market,

$RCA2_a^i <$ country is not competitive on the Single market.

Data used for calculations we acquired from:

- Eurostat,
- Slovak Statistical Office.

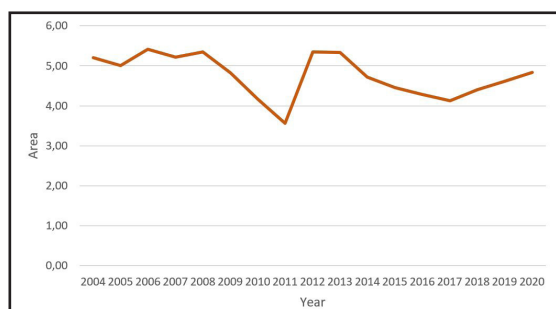
The time span of the research conducted within the study period was selected to be between 2004 and 2020. The beginning of the period of plum production in Slovakia is defined by the first year of the Slovak Republic's EU membership. Thus, the beginning of the reference period is still affected by a mixed effect before and after Slovakia's accession to the EU. The year 2020 has been chosen as the final period. After 2020, a number of economic and social changes have taken place which may have created additional factors in the competitiveness of plum production in Slovakia. Examples of such factors are the withdrawal of the United Kingdom from the EU and the resulting change in the size of the served market. On the other hand, there is a disruption in the market due to the COVID-19 pandemic measures. For the sake of consistency of the factors we have observed, the period under consideration has finally been terminated in 2020.

Results and discussion

Development of fruit production in the Slovak Republic

Text Fruit production is highly dependent on climatic conditions throughout the year. Numerous studies (Martins et al., 2021; Salama et al., 2021; Trbic et al., 2021) have shown the negative impact of current climate changes on traditional fruit production around the world. Plum production is facing the same challenges both in European countries (Vodá, 2019) and in other countries of the world.

Within the scope of the research, the first area investigated was the overall state of fruit production in the Slovak Republic. The data revealed two main indicators of the current state of fruit production in the country. The first observed indicator was the fruit production area and its changes over time within seventeen consecutive years. The changes observed (see Figure 1) within selected years show rather a decrease in the total harvested area. According to the available data, 5.2 thousand hectares of orchards were harvested.

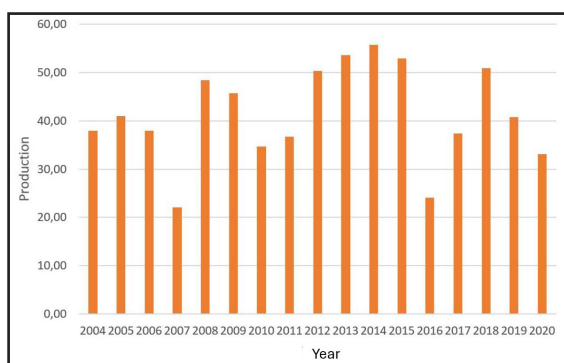


Source: Slovak Statistical Office, own calculations

Figure 1: Fruit production area in the Slovak Republic (1000 ha).

Despite the different changes observed in selected years, a relatively small decrease in the total harvested area was observed when comparing the year 2004 and 2020. The percentage change represents a decrease of 7.11% (or 370 ha). A significant decrease in the fruit production area was observed between the years 2008 and 2011, when the total fruit production area decreased by 33.46% (or 1.79 thousand hectares). A relatively steep increase in the production area was observed in 2012, which may be related to the high number of newly established orchards in the Slovak Republic. The relatively stable situation between the years 2012 and 2013 changed in the following years, when the decline of the fruit production area started again. Most of the decline was reversed in the last three observed years.

The second indicator examined was total fruit production over seventeen consecutive years. As shown in Figure 2, the volatility of production was higher than that of the production area.



Source: Slovak Statistical Office, own calculations

Figure 2: Total fruit production in the Slovak Republic (1000 tons).

This difference is a clear indication of the strong dependence of the fruit harvest on the overall climatic conditions throughout the year in each selected country. The relationship between fruit production and its dependence on weather

conditions is well supported by existing literature (Stöckle, 2009). The best harvest was achieved in 2014 (55.81 thousand tonnes of harvested fruit) and compared to the lowest observed value in 2007 (22.10 thousand tonnes of harvested fruit) we can see the volatility of fruit production in the Slovak Republic. In fact, fruit production in 2014 was 2.53 times higher than in 2007. We see a similar negative change between the years 2008 and 2011, as we found in the total fruit production area in the same period. More importantly, the last three years studied are in contradiction with the changes in the production area. We have observed a decrease of 34.98% (or 17.79 thousand tonnes) in the total fruit production between the years 2018 and 2020. The total fruit production during this period is in contradiction with the increase of the total fruit production area (+9.77% or 430 ha). This contradictory situation of the total fruit production compared to the increase of the total fruit production area could be caused by two main factors. The first could be the relatively high number of new, but not yet productive, orchards. The second cause may be the unfavourable weather situation within the mentioned years. Due to the significant changes in fruit production, we have examined the observed data within the framework of descriptive statistics.

If we look at the average production of 41.39 thousand tonnes of fruit (see Table 1).

Indicator	Value
Nbr. of observations	17.00
Minimum	22.10
Maximum	55.81
1 st Quartile	36.75
Median	40.78
3 rd Quartile	50.33
Mean	41.39
Variance (n-1)	98.38
Standard deviation (n-1)	9.92

Source: Slovak Statistical Office, own calculations

Table 1: Descriptive statistics of fruit production within years 2004 and 2020.

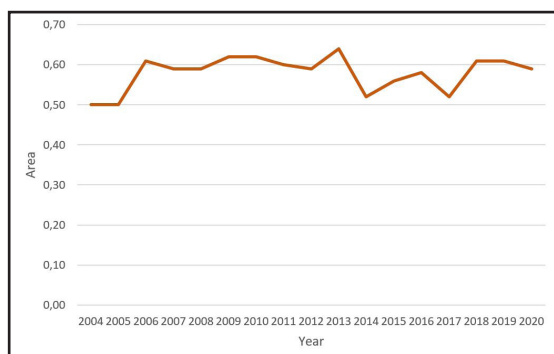
We can see that there is an almost even distribution between above average years (within 8 occasions) and below average years (also within 9 occasions). We have already highlighted in our study the significant volatility of fruit production within the observed period. This is supported by the measured standard deviation of 9.92 thousand tonnes of fruit. This value is relatively high compared to the mean of 41.39 thousand tonnes

of fruit. The measured value of the variance (see Table 1) supports our already mentioned assumption that the changes within the fruit production are relatively high compared to the average (median) production and the total production area itself.

Plum production in the Slovak Republic

Having recognised the development and current position of total fruit production in the Slovak Republic, the next research was devoted to a detailed study of Slovak plum production and its competitiveness on the internal market. The following research was carried out according to the same scheme as the research of the total fruit production in the Slovak Republic.

The plum production area has been studied in detail for seventeen consecutive years. We observed significant differences between the total fruit production and the plum production area in the Slovak Republic between the years 2004 and 2020. The difference between the largest registered plum production area (see Figure 3) of 0.64 thousand hectares in 2013 and the smallest registered plum production area of 0.52 thousand hectares in 2014 and 2017 was only 18.75%.



Source: Eurostat, own calculations

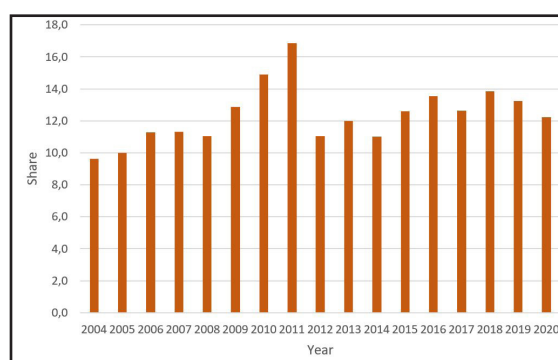
Figure 3: Plums production area (1000 hectares).

This observed value was lower compared to the same changes observed within the total fruit production area in the Slovak Republic, when the total fruit production area decreased by 33.46% (see Figure 1). This shows the difference in the volatility of the change in the total fruit production area and the plum production area in the Slovak Republic within seventeen consecutive years. In the case of plums, there was a positive change when comparing only the beginning and the end of the observed period. In 2004, the plum production area was 0.5 thousand hectares, while in 2020 it was 0.59 thousand hectares. This positive change observed in the study represents an 18% increase in the plum production

area. This result is contradictory to the changes in the total fruit production area in the Slovak Republic between 2004 and 2020, when we observed a decrease in the total fruit production area of 7.12%.

On the basis of the differences between the changes in the total fruit production area and the changes in the plum production area, the position and its development within the observed period have been carried out.

The share of the Slovak plum production showed heterogeneity (see Figure 4) when compared to the total Slovak fruit production within the years 2004 and 2020.

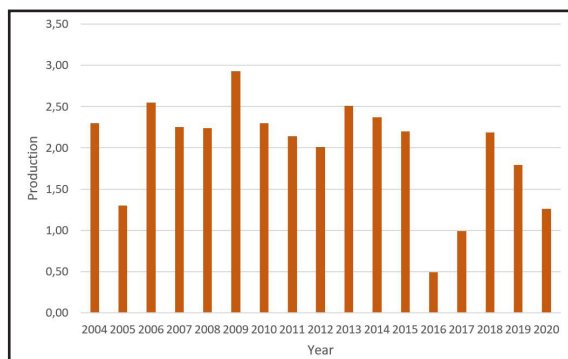


Source: Eurostat, own calculations

Figure 4: Plums production area share on the total orchard acreage (as percentage %).

These changes were mainly influenced by the volatility of the total fruit production area (see Figure 1) and not by the volatility of the plum production area (see Figure 3) within the studied years. This observation is supported by the comparison between the total fruit production area and the plum production area within each year. The lowest share of plum production in the total fruit production area was observed in 2004 and 2005 (8.5% of the total fruit production area in both years). The third and fourth highest values of the total fruit production area were recorded within the same years. On the other hand, the highest share of the plum production area was observed in 2011 (16.9% of the total fruit production area). The total fruit production area decreased rapidly and the lowest registered total fruit production area was also observed in this year. We also observed a high volatility in the share of plum production area in relation to the total fruit production area, if we compare the highest share observed in 2011 (16.9%) and the lowest share on the total fruit production area in 2004 and 2005 (8.5% for both years).

Similarly to the investigation procedure within the total Slovak fruit production, the investigation of the Slovak fruit production was carried out (see Figure 5).



Source: Eurostat, own calculations

Figure 5: Plums production (1000 tons).

The lowest quantity of harvested plums was observed in the year 2016 in the amount of 0.49 thousand tonnes. On the contrary, the highest quantity of harvested plums was reached in 2009. Plum production was 5.98 times higher in 2009 compared to 2016. This volatility of the production is higher compared to the volatility of the total fruit production, when the total fruit production was 2.53 times higher in the year 2014 compared to the year 2007. The changes observed in plum production may be caused by several factors. Two factors that may play a major role in plum production are the production area and the weather conditions. The influence of the production area can be weakened when examining the plum production in the Slovak Republic. This can be seen, for example, from the plum production in 2016 (0.49 thousand tonnes). Despite the lowest number of plums harvested in that year, the area under plum production was exactly the same as the seventeen-year average (0.58 thousand hectares). In relation to the simple average production (see Table 2) observed in the years under consideration, production should have been almost twice as high (real production 0.49 compared with average production 1.99). This can lead to the assumption that plum production is more vulnerable to climate change and is strongly influenced by weather conditions throughout the year. This assumption raises new questions that go beyond the research objectives of this article and the data available at the time of writing. Further research is needed in this area in the future.

The descriptive statistics was used to reveal more data related to the plum production and its changes within the observed years in the Slovak Republic.

This comparison was made in the same way as the descriptive statistics related to the total fruit production in the Slovak Republic. We observed 5 years when the plum production was below the mean value (see Table 2) related to seventeen observed years.

Indicator	Value
Nbr. of observations	17,00
Minimum	0,49
Maximum	2,93
1 st Quartile	1,79
Median	2,20
3 rd Quartile	2,30
Mean	1,99
Variance (n)	0,37
Standard deviation (n)	0,61

Source: Eurostat, own calculations

Table 2: Descriptive statistics of plum production within years 2004 and 2020.

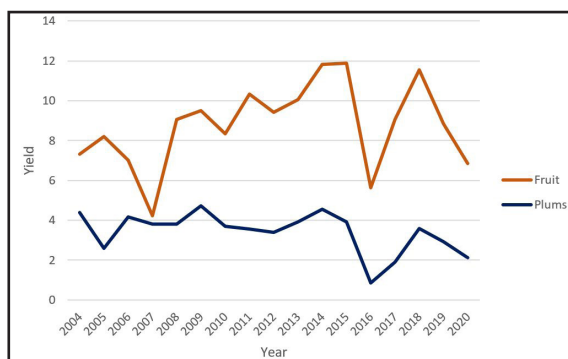
This value of underperforming years is lower compared to the total fruit production, when nine out of seventeen observed years showed underperforming values compared to the mean value. Based on this evidence, we concluded different paths for the total fruit production and the plum production between the years 2004 and 2020 in the Slovak Republic. The total fruit production shows lower volatility of production, but the number of years with lower production than the average is higher compared to the plum production.

The above-mentioned results concerning the differences in production development have raised the question of data availability both in terms of production area and production value. The most commonly used indicator is yield, which also meets the needs represented by the data studied.

The results of the yield comparisons between the years 2004 and 2020 represent differences in the total fruit yield per hectare compared to the harvested plum yield per hectare (see Figure 6).

The yield per hectare was higher within the group of species defined as the total fruit category compared to the plum harvest alone in each year observed. This comparison already suggests that the yield per hectare is not our performance within the total fruit category. The difference in yield per hectare between the total fruit category and the plum category was not stable. The percentage change in yield

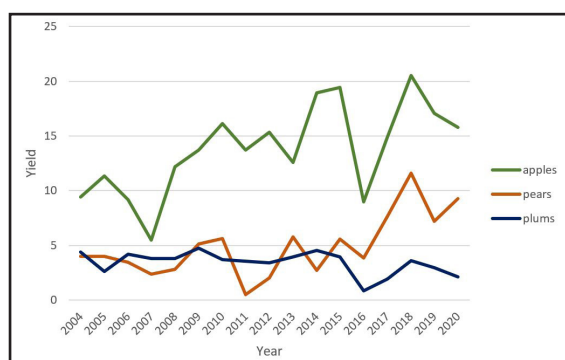
per hectare also did not follow the same path within the years observed.



Source: Eurostat, own calculations

Figure 6: Plums yield per hectare compared to average fruit yield per hectare in the Slovak Republic (tons per hectare).

We observed similar changes in yield, but also completely opposite developments in some observed years. For example, there were completely different changes between 2004 and 2005. The yield of harvested plums decreased significantly by 40.64%, but the yield of the total fruit harvest in the Slovak Republic increased by 12.18% between 2004 and 2005. On the other hand, there was a similar development between 2015 and 2016. The total fruit production decreased by 52.57%, but the change within the category of plum yield per hectare was even more significant at 78.50%. The average yield per hectare was 8.77 tonnes per hectare in the overall fruit category and 3.41 tonnes per hectare in the plum category. According to our measurements, there were six below average years within the total fruit category. This means that in the majority of occurrences (11 years) the current yield per hectare was higher than the average value measured between the years 2004 and 2020. The same situation was observed within the category of plum production. The current yield was lower than the average within six individual years (Figure 7).



Source: Eurostat, own calculations

Figure 7: Plums average yield per hectare compared to other mostly grown fruits in the Slovak Republic.

Slovak foreign trade in plums and its competitiveness on the internal market

In the context of foreign trade in the type of product under study, the research activity focused on its position in terms of absolute values of exports and imports. At the same time, the data were also evaluated in terms of the competitiveness of plum production in the Slovak Republic in the context of the wider EU single market.

When comparing exports and imports, the values of the foreign trade balance of plum production were taken into account (see Table 3).

Year	Fruit	Plums
2004	-1488735,00	-9813,00
2005	-1734500,00	-6541,00
2006	-1591324,00	-6730,00
2007	-2242888,00	-9852,00
2008	-2031706,00	18894,00
2009	-1923892,00	615,00
2010	-2050819,00	-2409,00
2011	-2192308,00	-7043,00
2012	-1912857,00	-4471,00
2013	-1954909,00	-2261,00
2014	-2019684,00	-10885,00
2015	-2187271,00	-11240,00
2016	-2469387,00	-19725,00
2017	-2390436,00	-18188,00
2018	-2254832,00	-18803,00
2019	-2537694,00	-24233,00
2020	-2871345,00	-28395,00

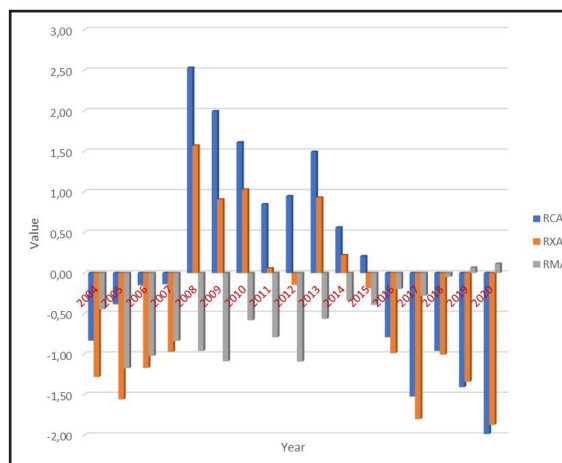
Source: Eurostat, own calculations

Table 3: Foreign trade balance with fruit and plums.

When comparing exports and imports, the values of the foreign trade balance of plum production were taken into account (see Table 3). Comparing the years 2004 and 2020, the same trend was observed in the form of an increase in the negative foreign trade balance for plum production and total fruit production in the Slovak Republic. In the case of total fruit production in the Slovak Republic, there is an increase of 92.87% in the negative external balance between 2004 and 2020. However, an even more significant negative trend was observed in the case of plum production and the external balance of this commodity. In this case, there is a 189.36% increase in the negative external balance between 2004 and 2020. A significantly different trend was also observed when comparing total fruit production and plum production within the different years studied in the research activity.

As in the case of production values, the year-on-year changes in the external trade balance for plums are more volatile than those for total fruit. The most significant negative change in the external balance was observed between 2006 and 2007. During this period, the negative external balance of fruit production decreased by 40.95%. In comparison, the most significant year-on-year change in the foreign trade balance for plum production occurred between 2013 and 2014. Within these years, there was a strong negative growth of 381.42% in the foreign trade balance within plum production. In the opposite spectrum of the observed data, the most significant reduction in the negative foreign trade balance within fruit production occurred in 2011 and 2012. The negative external trade balance was reduced by 12.75% in the years under review. From the above data it can be seen that the negative change in the foreign trade balance for fruit recorded higher values in the years under review compared to the positive changes, which resulted in a reduction of the negative value of the foreign trade balance for fruit production in the Slovak Republic compared to fruit production in the EU internal market. The most significant reduction in the negative value of the foreign trade balance for plum production occurred in 2007 and 2008. There was even a positive shift in this period, when the foreign trade balance of plum production recorded a positive value of 18 894 tonnes, compared with a negative foreign trade balance of 9 852 tonnes in 2007. In 2009, the foreign trade balance of plum production was also positive and, together with the positive value in 2008, represented the only two years in which the foreign trade balance of plum production of the Slovak Republic recorded positive values. This is a positive phenomenon compared to the development of the balance of foreign trade in total fruit production of the Slovak Republic, as in previous measurements no year was recorded with a positive value of the balance of foreign trade in fruit production. In the overall assessment, however, it should also be noted that the external balance of plum production also showed positive changes only in six years of the period under review. This value is therefore identical to that of the external trade balance of fruit production.

In connection with the competitiveness of plum production, we focused on the RXA, RTA and RCA indices in the last state of research. The measurement results show that plum production in the Slovak Republic reached both positive and negative values of the RCA index during the period under study (Figure 8).



Source: Eurostat, own calculations

Figure 8: Revealed comparative advantage in fresh plums within V4 countries between years 2004 and 2020.

The comparative advantage (RCA index) of plum production in the Slovak Republic was achieved between 2008 and 2015. In principle, this development is also directly related to the positive development of the RCA index over the period considered. The only exceptions are the years 2012 and 2015. The highest comparative advantage in plum production in the Slovak Republic was achieved in 2008. At the same time, the highest positive value of the RXA index was measured in the same year, which documents the increase in export competitiveness in that year. At the same time, the above export value is also in line with the increase in plum production in 2008, when the Slovak Republic achieved the highest level of positive foreign trade balance for this commodity. On the other hand, the worst measured value of the RCA index (-1.98) was recorded in 2020. In this year, the worst values of the RXA index and the best values of the RMA index were reached at the same time. The aforementioned facts measured for partial indices resulted in the most significant decrease in the competitiveness of Slovak plum production on the EU internal market in 2020.

Conclusion

The global agricultural sector is undergoing rapid change, with the competitiveness of agricultural products playing a crucial role in shaping the economic prosperity of nations. This study aims to provide a comprehensive analysis of the factors affecting the competitiveness of agricultural products, taking into account both domestic and international perspectives. The main research focused on changes in plum production in the Slovak Republic between 2004 and 2020.

In this area, the overall fruit production in the Slovak Republic was also measured. Based on a relative comparison of the two main indicators (orchard area and annual production), significant differences were found. The total area of plum orchards is relatively stable, with 500 ha of plum orchards recorded in 2004 and 590 ha in 2020. Over the period considered, the highest value of the area of registered plum orchards was recorded in 2013 (640 ha). On the other hand, the opposite trend was observed for the total area of orchards in the Slovak Republic, with a decrease of 7.12% over the period (compared to an increase of 18% in the area of plum orchards). Among these changes in the area of orchards and plum orchards, the share of plum orchards in the total area of orchards increased by 2.6% between 2004 and 2020. However, this positive trend was more dependent on the decrease in the total area of orchards (-370 ha) than on the increase in plum orchards (90 ha). Overall, however, the above-mentioned measurements clearly document a higher level of stability in the area of plum orchards compared to the total area of orchards in the Slovak Republic. The measurements focused on fruit and plum production in the Slovak Republic showed opposite results compared to the data measured in the case of the total area of orchards. In this case, the decrease in the production of plum orchards was more pronounced (-45.22%) compared to fruit orchards (-12.97%) in the years 2004 and 2020. There were also significant differences within the extreme values measured over the study period. The difference between the lowest and the highest plum production was 5.98. On the other hand, the difference in production within orchards was significantly lower at 2.53. The observed yields per hectare showed that plum production in the Slovak Republic is below the total fruit production yield. These results were caused by the interaction of two main indicators analysed in the paper. These indicators were fruit production area and total fruit production. This fact also contributed to the food insufficiency in this area when the trade balance recorded a negative value in fifteen out of seventeen observed years. Based on the results of the descriptive statistics and the international trade balance of the plum sector in the Slovak Republic, the revealed comparative advantage was determined. The competitiveness of the Slovak plum production has followed a different path in terms of measurements revealed by the RCA indicator. A positive value of this indicator was measured between the years 2008 and 2015, mainly supported by the growth of the relative export advantage

of the Slovak plum production. From the year 2016, there is an obvious decline in the revealed comparative advantage of the Slovak plum production. This decline was again mainly supported by the negative value of the relative export advantage within this commodity.

Slovak plum production has undergone significant changes during the period under review. On the basis of the measurements carried out within the framework of the research, an opinion was formed about a general decline. Stagnation of the production area, plum production, yield per hectare are all factors contributing to a negative competitiveness of this agricultural sector in the Slovak Republic. There are many factors that have contributed to this situation. Some of them are systematic problems of investment debt in this sector or slow adoption of new measures by farmers. Other factors, however, are global factors such as climate change or soil erosion. This factor has been already well documented by various authors (Zea et al., 2022; Nugroho et al., 2023) and could be applied for the territory of the Slovak Republic, while impacting its competitiveness within the broader EU territory. Among other possible drivers of Slovak plum competitiveness, we can find government policy instruments that play a role in shaping the national and international position of agricultural commodity competitiveness. These factors are documented by recent research results (Urbancová and Vrabčová, 2021; Kozelský et al., 2024) but are subject to further future research as an optional determinant of Slovak plum production competitiveness.

Among other factors that may play a role in the change in the competitiveness of the Slovak plum production there is the role of the market integration and trade policies within the EU. The integration of Slovak plum production into the EU single market has increased competition between plum producers in the Member States. This increased competition may have a significant impact on local producers as they face challenges from more competitive markets within the EU (Jarosz-Angowska, A., et al., 2022). Furthermore, the role of structural challenges and investment niveau may significantly contribute to the position of the Slovak plum production competitiveness. The competitiveness of the agricultural sector is influenced by structural factors such as farm size, specialisation and investment in modernisation. Larger farms and those with higher levels of investment are better able to adapt to market and policy changes. Evaluating these structural

aspects within Slovak plum production could shed light on production trends (European Parliament, 2024).

A more detailed study of these factors influencing plum production in the Slovak Republic is beyond the original scope of this article and represents an opinion for further scientific discussion and research.

The results of the research will have significant economic and social implications in the near future. A reduction in domestic supply will only increase dependence on imports. In the later stages, this may even affect market opportunities for local plum producers in the Slovak Republic. The observed situation within the Slovak plum production is in line with the increasing trade deficit, with Slovakia recording a trade deficit of EUR 700.60 million in December 2024 (Trading Economics, 2024).

The apparent decline in productivity growth figures indicates a possible lack of modernisation and investment in the sector (Cosmulescu et al., 2010). Necessary measures include the introduction of modern, advanced farming techniques, supported by targeted subsidies and other financial support mechanisms for replanting with high-yielding and climate-resilient varieties. Well-known studies also point to climate variability as a significant factor affecting fruit production. The implementation of climate adaptation strategies, such as the selection of frost-tolerant genotypes, will be essential to ensure the long-term stability of plum production.

The above challenges will require long-term action at regional, national and EU levels. Strategic investments, policy reforms and the adoption of modern agricultural practices are crucial to revitalise Slovak plum production and increase its competitiveness on the European Union's internal market.

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Shadow Values of Carbon Sequestration: A Case Study of the Czech Republic

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Abstract

This paper estimates the shadow values of total carbon sequestration in Czech cereal production. We use a production model with multiple outputs and inputs, using an input distance function (IDF) to estimate shadow price of land. The shadow prices of land and the amount of total carbon sequestration are then used to estimate the shadow values of carbon sequestration for a selected group of crops. The results present considerable differences in shadow values across both crops types and farm sizes.

Keywords

Carbon sequestration, shadow price, input distance function, FADN.

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Introduction

Carbon sequestration complements emission reduction efforts in aiding the European Union achieve its goal of becoming the first climate-neutral continent by 2050. In this context, the agricultural sector plays a unique role, as farming practices can both emit and absorb CO₂ (Aertsens et al., 2013). Policymakers have acknowledged this dual role, and carbon sequestration is now recognised and supported under the Common Agriculture Policy (CAP) as a means of achieving environmental objectives. The CAP 2023-2027 explicitly includes the objective: 'To contribute to climate change mitigation and adaptation, including by reducing greenhouse gas emissions and enhancing carbon sequestration, as well as to promote sustainable energy.'

However, carbon sequestration in agriculture faces several limitations that reduce its overall efficiency. The most significant challenge is the widespread practice of continuous cropping, which can severely degrade soil health. Continuous cropping often leads to the accumulation of autotoxic substances in the soil, causing harmful shifts in microbial community structure and diversity, and reducing soil nutrient levels. This degradation contributes to various soil health issues, including increased salinisation, acidification, and the spread of soil-

borne diseases all of which inhibit crop productivity and, consequently, the soil's carbon sequestration potential (Ma et al., 2024; Chen et al., 2022). Nutrient depletion and microbial imbalances further restrict the effectiveness of carbon sequestration practices (Bao et al., 2022; Li et al., 2022).

In contrast, sustainable agricultural practices such as agroforestry, crop diversification, crop rotation, and reduced tillage significantly encourage soil carbon sequestration by enhancing plant biodiversity, minimising soil disturbances, and establishing stable deep root systems that contribute to carbon storage in both biomass and soil organic matter (McCauley and Barlow, 2023; Kaushal et al., 2023; Andrés et al., 2022; Sprunger et al., 2020).

Conservation practices, particularly conservation tillage and cover cropping, have been shown to improve soil structure, retain soil moisture, and reduce erosion, all of which contribute to enhanced carbon sequestration (Kaushal et al., 2023; Bossio et al., 2020). In addition, the implementation of good nutrient management and residue management practices further promotes carbon retention in the soil, which is essential for maintaining soil health and sustaining agricultural productivity (Kaushal et al., 2023).

Empirical evidence supports these findings. For example, Pawłowska et al. (2019) highlight the role of catch crop cultivation in enhancing CO₂ sequestration in the agricultural sector, demonstrating how the biomass of these crops contributes to increased carbon capture in soils. Using the case of cereal production in Poland, the study estimated that if the entire area currently used for cereal cultivation were converted to catch crops, between 4.1 and 6.6 tonnes CO₂ per hectare per year could be sequestered, depending on the plant species. Similarly, research by Kwiatkowski et al. (2020), conducted between 2016 and 2018 under the soil and climatic conditions of the central Lublin region in Poland, found that catch crops can sequester between 4 and 6 tonnes of CO₂ per hectare per year.

The importance of supporting these promising agricultural practices for carbon sequestration is acknowledged in both EU and national policies. The greening payments and their associated conditions under Pillar I, for instance, support practices that contribute to carbon sequestration. Requirements related to diversification of crops, the preservation of permanent grassland areas, and the designation of ecological focus areas align with research findings that highlight how biodiversity enhances carbon sequestration (McCauley and Barlow, 2023; Sprunger et al., 2020; European Parliament, 2015).

In Czechia, additional measures are being implemented under Pillar I through eco-schemes, which promote organic farming, reduced tillage, and agroforestry. These practices aim to improve soil health, increase biodiversity, and consequently enhance carbon sequestration (Ministry of Agriculture of the Czech Republic, 2022). Pillar II is, however, more directly linked to climate change mitigation, and its measures are therefore more specifically targeted at supporting carbon sequestration. For example, the Czech Republic has voluntarily adopted a range of agri-environment-climate measures under this pillar (Ministry of Agriculture of the Czech Republic, 2022).

To support data-driven policy design, this paper provides estimates of the shadow values of carbon sequestration based on the estimated shadow prices of land. Specifically, it contributes to the ongoing discussion on carbon sequestration by proposing a method for its economic valuation in agriculture.

The estimation of shadow values concerning the carbon mitigation has been explored in various contexts. For example, Zhou et al. (2014) present a literature review on analyses of ‘bad’

and ‘good’ outputs, while Guan et al. (2018) estimate the shadow prices of carbon emissions in China’s planting industry. The economic dimension of carbon sequestration is also addressed in Bamiere et al. (2014), who analyse carbon policy from the perspective of farmers’ cost efficiency in France. In addition, Raj Kunwar et al. (2025) calculate different shadow prices for cover-crop fields and non-cover-crop fields, taking into account greenhouse gas emissions in order to promote the cover-crop adoption.

The novelty of this paper lies in the use of land shadow prices derived from a production model with multiple outputs and inputs, represented by an IDF. These are estimated using microeconomic data to calculate the shadow values of carbon sequestration.

The remainder of the paper is structured as follows. Chapter Material and methods presents data, theoretical model, and estimation procedure. Chapter Results and discussion discusses the results, and Chapter Conclusion provides concluding remarks.

Material and methods

Data

Our analysis relies on an unbalanced panel dataset of microeconomic data, comprising both physical and financial information on Czech agricultural producers. The data, sourced from the Farm Accountancy Data Network (FADN) and provided by the Institute of Agricultural Economics and Information, covers the period from 2008 to 2020. The sample includes farms classified according to the FADN typology as specialising in cereals, field crops, mixed cropping, and mixed crop-livestock operations.

The production technology is represented using an IDF, specified over vectors of outputs (y) and inputs (x). The output variables are defined as follows: cereal output (y_C) corresponds to the value of cereal production; other crop output (y_{AOC}) is calculated as the difference between total crop output and cereal output; and other agricultural output (y_{AOO}) represents the difference between total farm output and total crop output.

The input variables include land (x_L), measured in hectares of Utilised Agricultural Area (UAA); labour (x_W), expressed in Annual Work Units (AWU); capital (x_K), proxied by the sum of contract work and capital depreciation; and materials (x_M), defined as total intermediate consumption, which

refers to the sum of crop and livestock specific costs and general farming overheads, excluding contract work. The material input is used to normalise the remaining three input variables.

All monetary values for outputs and inputs are deflated using output and input specific price indices from Eurostat (base year 2010 = 100; Eurostat, 2021a–2021d). These deflators, together with farm characteristics such as a dummy variable for areas facing natural constraints (ANC), total subsidies per unit of output, and price indices of cereals, crops, and total output, are used as instrumental variables in the Generalised Method of Moments (GMM) estimation, alongside lagged IDF variables. Summary statistics for the input and output variables used in the analysis are presented in Table 1.

As the dataset does not contain complete information for all farms, observations from farms reporting negative or zero values for cereal production, land, labour, capital, or material inputs are excluded. To meet the requirements of the GMM estimator, producers with fewer than three observations are also removed. This approach helps to mitigate issues associated with unbalanced panel data. Additionally, in both models, the dependent variable and all covariates are log transformed and normalised by their respective means.

Theoretical model

The production process with multiple outputs and multiple inputs can, using production theory, be expressed in term of transformation function:

$$T(\mathbf{Y}_{it}, \mathbf{X}_{it}) = 1, \tag{1}$$

where \mathbf{Y} represents a vector of m outputs and \mathbf{X} is a vector of j inputs. The subscripts i and t denote farm ($i = 1, \dots, N$) and time period ($t = 1, \dots, T$), respectively.

The IDF is a special case of the transformation function that incorporates the behavioural

assumption that the farmer can control inputs and seeks to minimise costs. In this case, the production technology is expressed by the input requirement set $L(\mathbf{y}) = \{\mathbf{X}: \mathbf{X} \text{ can produce } \mathbf{y}\}$, with $\mathbf{X} \in \mathfrak{R}_+^J$ to produce $\mathbf{y} \in \mathfrak{R}_+^M$. The input requirement set is assumed to be closed, convex, and bounded by the input isoquant: $Isoq L(\mathbf{y}) = \{\mathbf{X}: \mathbf{X} \in L(\mathbf{y}), \lambda(\mathbf{X}) \notin L(\mathbf{y}), \lambda < 1\}$, where both inputs and outputs are assumed to be strongly, or freely, disposable (see Kumbhakar and Lovell, 2000).

According to Shephard (1970), the IDF is a radial measure of the distance from the output vector \mathbf{Y} to the input isoquant, $Isoq L(\mathbf{Y})$:

$$D_{L(\mathbf{Y}, \mathbf{X})} = \sup \{\mu > 0 : (\mathbf{Y}/\mu) \in L(\mathbf{Y})\}, \tag{2}$$

where μ represents the maximum possible proportional reduction in input vector \mathbf{X} for a given output level \mathbf{Y} (Zhou et al., 2014).

Under the assumption of linear homogeneity of degree one in inputs, the IDF satisfies:

$$D_I(\mathbf{Y}_{it}, \mathbf{X}_{it}) = 1. \tag{3}$$

In our empirical analysis, we assume that the transformation process can be well approximated by the translog multiple inputs and outputs IDF:

$$\begin{aligned} \ln D_{lit} = & \alpha_0 + \sum_{m=1}^M \alpha_m \ln y_{mit} + \\ & + \frac{1}{2} \sum_{m=1}^M \sum_{n=1}^M \alpha_{mn} \ln y_{mit} \ln y_{nit} + \sum_{k=1}^K \beta_k \ln x_{kit} + \\ & + \frac{1}{2} \sum_{k=1}^K \sum_{l=1}^K \beta_{kl} \ln x_{kit} \ln x_{lit} + \sum_{k=1}^K \sum_{m=1}^M \gamma_{km} \ln x_{kit} \ln y_{mit} + \\ & + \delta_t t + \frac{1}{2} \delta_{tt} t^2 + \sum_{m=1}^M \alpha_{mt} \ln y_{mit} + \\ & + \sum_k^K \beta_{kt} \ln x_{kit}, \end{aligned} \tag{4}$$

where α , β , γ and δ are vectors of the technology parameters to be estimated.

Variable	Obs	Mean	Std.Dev	Min	Max
yC	7,252	6617338	8925003	6303	93000000
yAOC	7,252	7310124	10900000	0	117000000
yAoo	7,252	10100000	18400000	0	172000000
xM	7,252	19600000	27600000	106503	232000000
xL	7,252	757.3	882.5	8.0	5980.1
xW	7,252	19.2	26.6	0.4	215.4
xK	7,252	3795198	5234101	7469	50100000

Source: FADN, own calculations

Table 1: Descriptive statistics of outputs and inputs.

We impose homogeneity¹ by normalising all the inputs by x_1 (material inputs, xM):

$$\begin{aligned}
 -\ln x_{1it} &= \alpha_0 + \sum_{m=1}^M \alpha_m \ln y_{mit} + \\
 &+ \frac{1}{2} \sum_{m=1}^M \sum_{n=1}^M \alpha_{mn} \ln y_{mit} \ln y_{nit} + \sum_{k=2}^K \beta_k \ln x_{kit} + \\
 &+ \frac{1}{2} \sum_{k=2}^K \sum_{l=2}^K \beta_{kl} \ln x_{kit} \ln x_{lit} + \sum_{k=2}^K \sum_{m=1}^M \gamma_{km} \ln x_{kit} \ln y_{mit} + \\
 &+ \delta_t t + \frac{1}{2} \delta_{tt} t^2 + \sum_{m=1}^M \alpha_{mt} \ln y_{mit} + \\
 &+ \sum_k \beta_{kt} \ln x_{kit} + \eta_i + \varepsilon_{it}, \quad (5)
 \end{aligned}$$

where $x_{kit}^* = \frac{x_{kit}}{x_{1it}}$, η_i captures the firm heterogeneity and ε_{it} is a stochastic noise, which is supposed to be i.i.d. $x_{kit}^* = \frac{x_{kit}}{x_{1it}}$, η_i .²

Estimation procedure

We estimate the IDF using the two-step system GMM estimator, which addresses potential endogeneity in equation (3). This approach relies on a system of two equations: one specified in first differences and the other in levels. It uses two types of internal instruments: lagged levels of the IDF variables for the differenced equation and lagged differences of the IDF variables for the levels equation. In addition, a set of external instruments (additional variables in levels) are employed to improve identification. The validity of the instruments is tested using the Hansen J-test (Hansen, 1982), which verifies the overall orthogonality of the instruments. We also conduct the Arellano-Bond test for autocorrelation (Arellano and Bond, 1991), which evaluates the appropriateness of using lagged variables as instruments.

Results and discussion

Table 2 presents the parameter estimates of the IDF. The signs of the first order coefficients are consistent with economic theory. Specifically, the estimates indicate that the IDF is non-increasing in outputs and non-decreasing in inputs. Furthermore, the model satisfies the requirement of concavity in inputs. The estimates also exhibit strong statistical properties, with most first order parameters statistically significant at the 5 percent

level. Moreover, the Wald test (at $\alpha = 0.05$) rejects the null hypothesis that all second order parameters are jointly equal to zero. This result supports the use of the translog functional form over the less flexible but widely used Cobb-Douglas production function. Specifically, the test suggests that adopting a Cobb-Douglas specification could yield biased estimates, as it does not account for variation in the first order parameters. For example, the second derivatives with respect to specific inputs or outputs are restricted to zero. The Hansen's J-test and the AR(2) test further support the validity of the GMM specification.

Since the translog IDF is estimated using logarithmic transformations of all variables, normalised by their sample means, the first order parameters can be interpreted as output and input elasticities or as shadow output and input shares, evaluated at the sample mean. Table 2 reports these shares, which reflect the relative contribution of each output and input to the production process. The results indicate a high level of specialisation in cereal production, which accounts for 51 percent of output (when evaluated under constant returns to scale). The share of other crop output is 34 percent, while other agricultural output accounts for approximately 15 percent. The estimates of economies of scale implies that the production process exhibits increasing returns to scale, with a scale elasticity of 1.143. This suggests that farms in the sample demonstrate minor economies of scale.

Moreover, agricultural production in the sample is material intensive, with material inputs dominating the cost structure. The material shadow share is 0.498, while the shadow shares of other material inputs range between 0.15 and 0.2. Specifically, land accounts for 0.145, labour for 0.196, and capital for 0.161.

The time variable parameter indicates technological regress; however, this regress slows over time. Hicks-neutral technological change was not rejected at the 5 percent significance level, suggesting that the technological change maintains the same input structure.

Table 3 presents the estimated shadow prices of land, calculated as the partial derivatives of the IDF with respect to land, alongside the actual rent paid by farms. The results indicate that shadow prices of land per hectare are higher than rent paid per hectare, suggesting considerable allocative inefficiencies in agriculture production. Specifically, land appears to be underutilised in farm production. This holds for the full sample

¹ Homogeneity of degree 1 in inputs implies:

$\sum_{k=1}^K \beta_k = 1, \sum_{k=1}^K \beta_{kt} = \sum_{k=1}^K \beta_{kt} = \sum_{k=1}^K \gamma_{km} = 0$

² Symmetry restrictions are: $\alpha_{mn} = \alpha_{nm}$ and $\beta_{kl} = \beta_{lk}$

Variable	Coefficient	Std.Err.	P-value	Variable	Coefficient	Std.Err.	P-value
ln_yC	-0.4494	0.0203	0.0000	t	0.0339	0.0027	0.0000
ln_yAOC	-0.2978	0.0176	0.0000	t_2	-0.0073	0.0011	0.0000
ln_yAOO	-0.1280	0.0068	0.0000	ln_yCt	-0.0004	0.0012	0.7080
ln_xL	0.1445	0.0354	0.0000	ln_yAOCt	0.0035	0.0016	0.0330
ln_xW	0.1962	0.0265	0.0000	ln_yAOOt	0.0003	0.0003	0.2360
ln_xK	0.1612	0.0208	0.0000	ln_xLt	0.0135	0.0072	0.0590
ln_yC_2	-0.0414	0.0021	0.0000	ln_xWt	0.0026	0.0052	0.6200
ln_yAOC_2	-0.0264	0.0017	0.0000	ln_xKt	0.0040	0.0045	0.3800
ln_yAOO_2	-0.0150	0.0010	0.0000	ln_yCxL	0.0274	0.0096	0.0040
ln_yCyAOC	0.0136	0.0038	0.0000	ln_yAOCxL	0.0036	0.0195	0.8550
ln_yCyAOO	0.0018	0.0004	0.0000	ln_yAOOxL	-0.0173	0.0035	0.0000
ln_yAOCyAOO	-0.0011	0.0007	0.0870	ln_yCxW	-0.0121	0.0066	0.0690
ln_xL_2	-0.6763	0.1324	0.0000	ln_yAOCxW	-0.0400	0.0163	0.0150
ln_xW_2	-0.0730	0.0694	0.2930	ln_yAOOxW	-0.0085	0.0027	0.0010
ln_xK_2	0.0880	0.0299	0.0030	ln_yCxK	-0.0038	0.0047	0.4200
ln_xLxW	-0.0228	0.0551	0.6790	ln_yAOCxK	0.0033	0.0047	0.4810
ln_xLxK	0.0009	0.0442	0.9830	ln_yAOOxK	-0.0013	0.0019	0.4780
ln_xWxK	-0.0918	0.0299	0.0020	constant	0.7698	0.0319	0.0000
Arellano-Bond test for AR(2) in first differences: z = -0.69 Pr > z = 0.493							
Hansen test of overid. restrictions: chi2(872) = 797.92 Prob > chi2 = 0.965							

Source: own calculations

Table 2: IDF parameter estimate.

Shadow prices of land according to the size (CZK/ha)					
	Full sample	0 - 99 ha	100 - 499 ha	500 - 999 ha	1000 and more ha
Mean	4377.8	2112.7	1310.2	5487.0	8725.0
Median	2570.9	955.3	431.2	3698.0	7988.0
Rent paid (CZK/ha)					
	Full sample	0 - 99 ha	100 - 499 ha	500 - 999 ha	1000 and more ha
Mean	2269.0	2029.0	2148.0	2563.4	2431.7
Median	2002.0	1610.0	1945.0	2427.4	2280.0

Source: own calculations

Table 3: Shadow prices of land and rent paid.

as well as for all size categories evaluated using mean values. However, when using the median, the results show that shadow prices of land are lower than the rent paid for farms up to 499 hectares. This suggests that smaller farms tend to overuse the land in comparison to their larger counterparts.

The considerable differences between the mean and median values are a result of a skewed distribution of shadow land prices towards smaller values. In light of this, we calculate the shadow values of total carbon sequestration using median values³.

Table 4 and 5 present the estimated shadow values of total carbon sequestration. The values are calculated based on the median values of land

shadow values and the total carbon sequestration in biomass—comprising the primary yield, secondary yield, and roots—for different crops (sourced from Kwiatkowski et al., 2020). Specifically, the shadow value of total carbon sequestration is determined by the ratio of the land shadow price to the total carbon sequestration for a given crop.

The results indicate that the shadow values of total carbon sequestration vary considerably across both crops and farm sizes. Differences across crops are primarily driven by variations in sequestration potential, while differences across farm sizes reflect variations in land shadow prices. Specifically, meadow hay exhibits the highest shadow value total carbon sequestration. By contrast, the lowest shadow values are for potato and sugar beet.

³ Note: the use of mean values of land shadow prices will considerably increase the shadow values of total carbon sequestration.

Crop	Total carbon sequestration in biomass of primary yield, secondary yield, and roots (CO ₂ t/ha a year)		Shadow values of total carbon sequestration (CZK t/ha)		
	Mean	Std.Dev	Point estimate	Interval estimate	
Winter wheat	16.6	2.77	154.87	132.73	185.89
Spring wheat	14.9	1.92	172.54	152.85	198.07
Spring barley	14.2	1.64	181.05	162.30	204.69
Winter rye	12.9	1.21	199.29	182.20	219.92
Oats	11.5	1.07	223.56	204.53	246.49
Maize	20.2	1.86	127.27	116.54	140.18
Winter oilseed rape	13	1.12	197.76	182.08	216.41
Potato	43.2	2.49	59.51	56.27	63.15
Sugar beet	80.4	3.75	31.98	30.55	33.54
Meadow hay	8.54	0.8	301.04	275.26	332.16

Source: Kwiatkowski et al. (2020); own calculations

Table 4: Shadow values of total carbon sequestration.

Crop	Shadow values of total carbon sequestration (CZK t/ha) - point estimate			
	0 - 99 ha	100 - 499 ha	500 - 999 ha	1000 and more ha
Winter wheat	57.55	25.98	222.77	481.20
Spring wheat	64.11	28.94	248.19	536.11
Spring barley	67.27	30.37	260.42	562.54
Winter rye	74.05	33.43	286.67	619.22
Oats	83.07	37.50	321.57	694.61
Maize	47.29	21.35	183.07	395.45
Winter oilseed rape	73.48	33.17	284.46	614.46
Potato	22.11	9.98	85.60	184.91
Sugar beet	11.88	5.36	46.00	99.35
Meadow hay	111.86	50.49	433.02	935.36

Source: own calculations based on Kwiatkowski et al. (2020) (Total carbon sequestration of different commodities – see also Table 4)

Table 5: Shadow values of total carbon sequestration according to the farm size.

In addition, the results suggest that larger farms tend to have higher shadow values of total carbon sequestration.

Conclusion

This study provides estimates of the shadow values of carbon sequestration based on the estimated land shadow prices. The aim is to contribute to the ongoing discussion on carbon sequestration by proposing a method for its economic valuation in agriculture. We suggest using a production approach to estimate the shadow prices of land, which can serve as the basis for calculating the shadow values of total carbon sequestration. Specifically, we apply a multiple outputs and inputs model of the transformation process, represented by an IDF, to estimate the shadow price of land. The resulting shadow price of land, together with the total amount of carbon sequestration, are then used to estimate the shadow values

of total carbon sequestration. Finally, we present and compare the shadow values of total carbon sequestration across a selected group of crops and farm sizes.

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Fuzzy Logic for Yield Prediction: Enhancing Decision-Making in Agricultural Economics

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Abstract

Accurate yield prediction is essential for optimizing decision-making in agricultural economics, enabling stakeholders to manage resources efficiently and respond to market demands. Traditional yield prediction models often struggle to handle the uncertainties and complexities inherent in agricultural systems, such as weather variability, soil conditions, and crop characteristics. This study introduces a fuzzy logic-based approach to yield prediction, offering a more flexible and robust method for addressing these uncertainties. By utilizing fuzzy sets and rules, the proposed model captures the intricate relationships between multiple factors influencing crop yield. The research demonstrates how fuzzy logic can enhance the accuracy and reliability of yield predictions, providing valuable insights for farmers, policymakers, and agricultural economists. Results indicate that this approach significantly improves decision-making processes in agricultural planning and risk management, making it a valuable tool for sustainable agricultural practices.

Keywords

Yield prediction, fuzzy logic, agricultural economics, decision-making, crop yield, uncertainty modeling.

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Introduction

Agricultural yield prediction is a critical aspect of decision-making in agricultural economics, influencing resource allocation, crop management, and market planning. Accurate yield predictions enable farmers, policymakers, and agricultural economists to optimize production strategies, mitigate risks, and respond effectively to market demands (El-Tabakh et al., 2024; Banerjee et al., 2024; Efremova et al., 2023; Mohammed et al., 2024). However, predicting crop yield is inherently challenging due to the complex and uncertain nature of agricultural systems, which are influenced by factors such as weather variability, soil conditions, crop characteristics, pest infestations, and technological interventions. Traditional statistical models, such as linear regression, often struggle to capture the non-linear relationships and uncertainties present in these systems, leading to less reliable yield predictions (Das et al., 2024;

Kumari et al., 2024; Roy and George et al., 2020; Rangasamy et al., 2023; Korol, 2024).

Fuzzy logic, a branch of artificial intelligence, offers a promising solution to this challenge by accommodating uncertainty and imprecision in data, making it well-suited for modeling complex agricultural systems (Polekhina and Polekhina, 2024; Adilova, 2020; Tóth et al., 2013; Imamguluyev et al., 2024; Tohidi et al., 2020). Unlike conventional models that rely on rigid assumptions and precise data, fuzzy logic allows for the incorporation of vague, ambiguous, and imprecise information, which is common in agriculture. By using fuzzy sets and rules, fuzzy logic can model the intricate and dynamic relationships between various factors influencing crop yield, providing a more flexible and adaptive approach to yield prediction (Zadeh and Aliev, 2018; Imamguluyev et al., 2024; Novák, et al., 2020, Aliev and Aliev, 2001; Ramiz and Vugar, 2022, Imamguluyev et al., 2024).

In this study, we present a fuzzy logic-based model for yield prediction, aiming to enhance decision-making in agricultural economics. By incorporating key variables such as weather variability, soil conditions, and crop characteristics, the proposed model captures the uncertainties inherent in agricultural processes, offering more accurate and reliable yield predictions. The research demonstrates how this approach can be applied to improve crop yield forecasting, ultimately contributing to sustainable agricultural practices and effective resource management. This article will compare the performance of the fuzzy logic model with a traditional linear regression model, highlighting the advantages of using fuzzy logic for handling uncertainty, non-linearity, and complexity in agricultural yield prediction.

This study introduces a fuzzy logic-based approach for yield prediction that captures the intricate relationships between multiple factors influencing crop yield. The research objectives include:

- Developing a fuzzy logic model for yield prediction based on key agricultural parameters.
- Evaluating its performance using real-world agricultural data and comparing it with traditional statistical models and advanced machine learning techniques.
- Demonstrating the model's effectiveness in addressing uncertainty, non-linearity, and complexity in agricultural yield prediction.

Materials and methods

Problem statement

Accurate yield prediction is a critical component of agricultural economics, directly impacting decision-making processes related to resource allocation, crop management, and market planning. However, traditional yield prediction models often face challenges in addressing the inherent uncertainties and complexities of agricultural systems. These systems are influenced by numerous factors such as fluctuating weather conditions, soil quality, and crop characteristics, all of which exhibit significant variability and interdependencies.

Conventional statistical and mathematical models tend to be rigid and struggle to accommodate the dynamic and uncertain nature of these variables, often resulting in inaccurate or unreliable predictions. This lack of precision can lead

to suboptimal decision-making, inefficient resource utilization, and increased financial risk for stakeholders such as farmers, policymakers, and agricultural economists.

To address this challenge, there is a pressing need for a more adaptable and intelligent approach that can effectively capture the intricate relationships and uncertainties within agricultural data. Fuzzy logic, with its ability to model imprecision and handle ambiguity, offers a promising solution. This study proposes a fuzzy logic-based model for yield prediction, aiming to enhance the accuracy and reliability of predictions by incorporating the vagueness and complexity inherent in real-world agricultural environments. By doing so, the research seeks to improve decision-making in agricultural planning and risk management, contributing to more sustainable and profitable agricultural practices.

Methodology

Defining Variables and Membership Functions

The fuzzy logic model incorporates three input variables: Weather Variability (WV), Soil Conditions (SC), and Crop Characteristics (CC), with Crop Yield (CY) as the output variable. The membership functions were selected based on agricultural data analysis and expert recommendations:

Triangular membership functions were chosen for variables with clear threshold values (e.g., WV and CC).

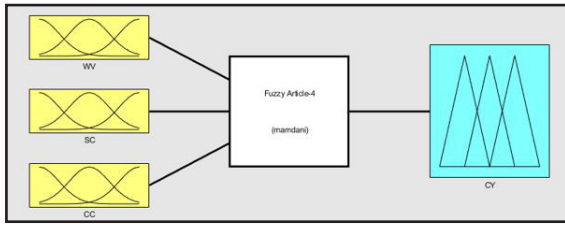
Trapezoidal membership functions were used for variables with gradual transitions (e.g., SC), as they allow for a smoother representation of conditions.

The rationale behind these choices is that triangular functions provide precise categorization for variables with well-defined breakpoints, while trapezoidal functions better capture the gradual nature of soil quality transitions.

Let's define input variables, output variables, membership functions, their ranges and rules using Fuzzy Toolbox in MATLAB.

Input and output variables (Figure 1):

- Weather Variability (WV)
- Soil Conditions (SC)
- Crop Characteristics (CC)
- Crop Yield (CY)

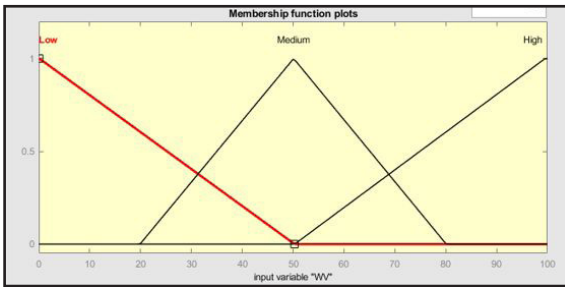


Source: MATLAB simulation, author's own elaboration, 2024

Figure 1: Graph of input variables.

Weather Variability (WV):

- *Description:* Represents variations in weather factors like temperature, rainfall, and humidity (Figure 2).
- *Range:* 0 to 100 (0: extremely unfavorable, 100: extremely favorable)
- *Membership functions:*
 - ◻ **Low:** Triangular [0, 0, 50]
 - ◻ **Medium:** Triangular [20, 50, 80]
 - ◻ **High:** Triangular [50, 100, 100]

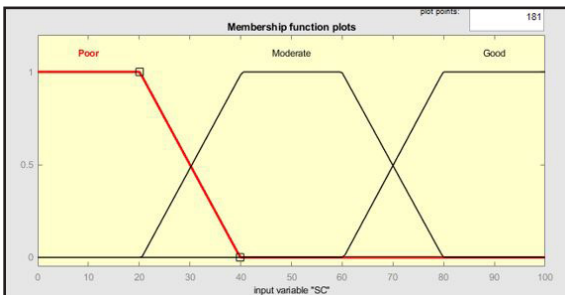


Source: MATLAB simulation, author's own elaboration, 2024

Figure 2: Fuzzy sets and membership functions for WV.

Soil Conditions (SC):

- *Description:* Represents soil properties such as fertility, moisture, and texture (Figure 3).
- *Range:* 0 to 100 (0: poor soil quality, 100: excellent soil quality)
- *Membership functions:*
 - ◻ **Poor:** Trapezoidal [0, 0, 20, 40]
 - ◻ **Moderate:** Trapezoidal [20, 40, 60, 80]
 - ◻ **Good:** Trapezoidal [60, 80, 100, 100]

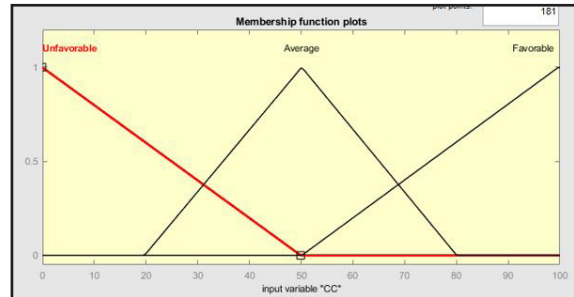


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Figure 3: Fuzzy sets and membership functions for SC.

Crop Characteristics (CC):

- *Description:* Represents factors such as crop variety, growth rate, and resistance to pests (Figure 4).
- *Range:* 0 to 100 (0: unfavorable characteristics, 100: highly favorable characteristics)
- *Membership functions:*
 - ◻ **Unfavorable:** Triangular [0, 0, 50]
 - ◻ **Average:** Triangular [20, 50, 80]
 - ◻ **Favorable:** Triangular [50, 100, 100]

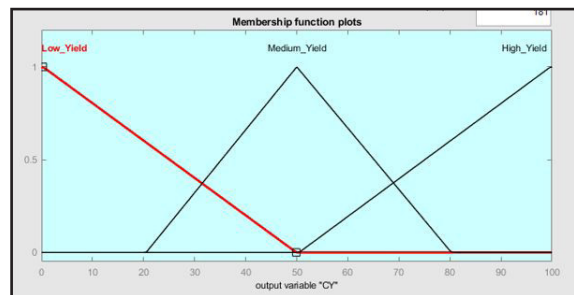


Source: MATLAB simulation, author's own elaboration, 2024

Figure 4: Fuzzy sets and membership functions for CC.

Output Variable: Crop Yield (CY):

- *Description:* Represents the predicted crop yield (Figure 5).
- *Range:* 0 to 100 (0: low yield, 100: high yield)
- *Membership functions:*
 - ◻ **Low Yield:** Triangular [0, 0, 50]
 - ◻ **Medium Yield:** Triangular [30, 50, 70]
 - ◻ **High Yield:** Triangular [50, 100, 100]



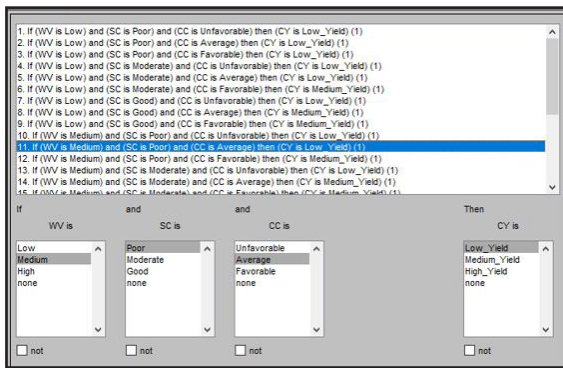
Source: MATLAB simulation, author's own elaboration, 2024

Figure 5: Fuzzy sets and membership functions for CY.

Fuzzy rules: (see Figure 6)

- If (WV is Low) and (SC is Poor) and (CC is Unfavorable) then (CY is Low Yield)
- If (WV is Medium) and (SC is Moderate) and (CC is Average) then (CY is Medium Yield)

- If (WV is High) and (SC is Good) and (CC is Favorable) then (CY is High Yield)
- If (WV is Low) and (SC is Good) and (CC is Average) then (CY is Medium Yield)
- If (WV is High) and (SC is Poor) and (CC is Unfavorable) then (CY is Low Yield)
- If (WV is Medium) and (SC is Good) and (CC is Favorable) then (CY is High Yield)
- If (WV is High) and (SC is Moderate) and (CC is Average) then (CY is Medium Yield)
- If (WV is Low) and (SC is Moderate) and (CC is Unfavorable) then (CY is Low Yield)



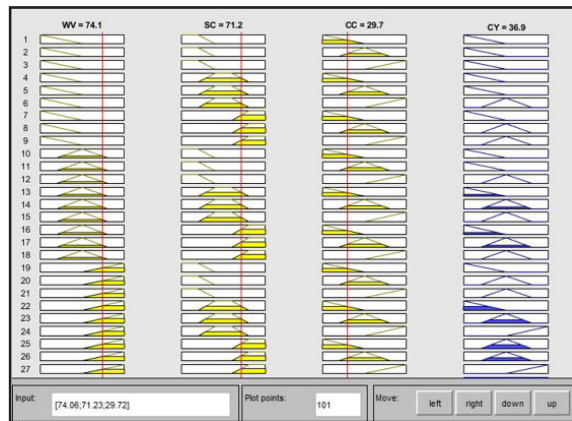
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Figure 6: Fuzzy rules.

Logical inference rules form the backbone of the fuzzy logic-based yield prediction model, enabling it to draw conclusions from the given input variables (Weather Variability, Soil Conditions, and Crop Characteristics) to predict crop yield. The rules utilize the "IF-THEN" structure to establish relationships between input and output variables, capturing the complex interactions and uncertainties present in agricultural systems (Figure 7).

For instance, a rule like "IF (Weather Variability is Low) AND (Soil Conditions are Poor) AND (Crop Characteristics are Unfavorable) THEN (Crop Yield is Low)" demonstrates how the model accounts for unfavorable agricultural conditions leading to low yields. Each rule considers the degrees of membership across different fuzzy sets, allowing the model to handle imprecision and vagueness effectively. This process involves aggregating and combining the input variables to infer the most suitable output category, resulting in a more accurate and realistic yield prediction.

The fuzzy inference process involves evaluating all the rules simultaneously, combining the results, and generating an aggregated fuzzy output, which is then defuzzified to produce a crisp, numerical value for the predicted crop yield. This comprehensive approach ensures that the model captures the intricate relationships between variables, enhancing prediction accuracy and reliability.

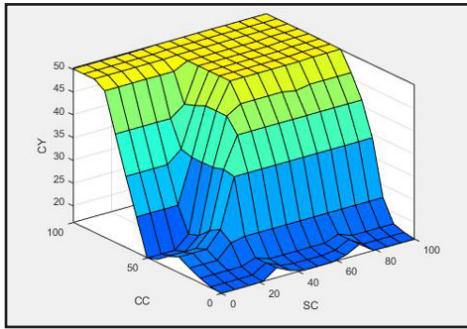


Source: MATLAB simulation, author's own elaboration, 2024

Figure 7: Description of logical inference rules.

The "Surface Viewer" is a graphical representation that illustrates how the interaction between two input variables—Crop Characteristics (CC) and Soil Conditions (SC)—influences the predicted Crop Yield (CY). It provides a visual understanding of the fuzzy inference process, showing how different combinations of CC and SC affect the yield.

In the surface viewer for CC and SC, the x-axis represents Crop Characteristics, ranging from unfavorable to favorable, while the y-axis represents Soil Conditions, ranging from poor to good (Figure 8). The z-axis shows the resulting crop yield, ranging from low to high. This 3D surface plot reveals the varying levels of crop yield as the inputs change. For example, as Soil Conditions improve and Crop Characteristics become more favorable, the predicted yield tends to increase, indicating higher productivity. Conversely, when both factors are at lower values, the yield prediction remains low. This visualization helps stakeholders understand how improvements in soil quality or crop variety can significantly impact crop yield outcomes.



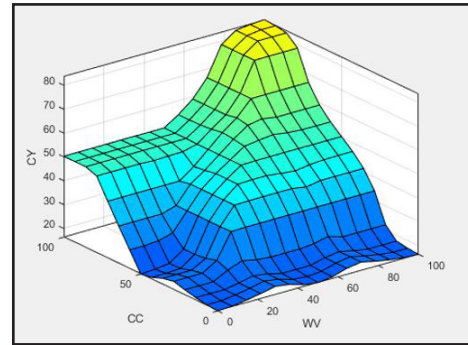
Source: MATLAB simulation, author's own elaboration, 2024

Figure 8: Surface Viewer CC and SC.

The "Surface Viewer" for Crop Characteristics (CC) and Weather Variability (WV) offers insights into how these two factors interact to influence crop yield predictions. In this graph, the x-axis represents Crop Characteristics (ranging from unfavorable to favorable), the y-axis represents Weather Variability (ranging from unfavorable to favorable), and the z-axis shows the predicted crop yield (Figure 9).

The 3D surface plot demonstrates how variations in weather conditions and crop characteristics jointly impact the predicted yield. For instance, favorable crop characteristics combined with high weather variability lead to higher yield predictions, indicating that even under favorable crop conditions, weather plays a crucial role in determining yield outcomes. Conversely, when weather conditions are unfavorable, even highly favorable crop characteristics result in lower yield predictions. This visualization is valuable for identifying the critical influence of weather variability on crop productivity and aids in strategic decision-making for agricultural planning and risk management.

These surface viewers are essential tools for understanding the intricate relationships between input variables and their impact on crop yield, enabling better decision-making and more accurate yield predictions in agricultural economics.



Source: MATLAB simulation, author's own elaboration, 2024

Figure 9: Surface Viewer CC and WV.

Comparison with a traditional statistical model: linear regression

To evaluate the effectiveness of the fuzzy logic-based yield prediction model, we compared its performance against a traditional statistical model, specifically a linear regression model, using the same dataset for crop yield prediction.

Accuracy and prediction Performance: The comparison revealed that the fuzzy logic model outperformed the linear regression model in terms of prediction accuracy. The fuzzy logic model achieved a higher coefficient of determination (R^2) with actual yield values, indicating a better fit to the data. In contrast, the linear regression model struggled to account for the non-linear relationships and uncertainties present in the agricultural dataset, leading to a lower R^2 value.

The linear regression model assumes a linear relationship between input variables (Weather Variability, Soil Conditions, and Crop Characteristics) and crop yield. However, agricultural systems are inherently complex and influenced by non-linear interactions. This limitation made the linear regression model less capable of capturing the intricate dependencies between variables, resulting in less accurate predictions, especially under extreme or atypical conditions.

Handling of Uncertainty and Complexity: One of the key advantages of the fuzzy logic model over the linear regression model is its ability to handle uncertainties and imprecision. The fuzzy logic model effectively captured the vagueness and variability in input data through the use of fuzzy sets and rules, enabling it to model real-world agricultural conditions more accurately. For example, factors like fluctuating weather patterns and soil quality, which are difficult

to quantify precisely, were better represented by the fuzzy logic model.

In contrast, the linear regression model was unable to accommodate such uncertainties, as it relies on fixed coefficients and a rigid structure. This rigidity made it less adaptable to variations in the data, resulting in lower predictive accuracy when confronted with highly variable or uncertain agricultural conditions.

Flexibility and Adaptability: The fuzzy logic model demonstrated greater flexibility by accommodating various ranges of input variables and adjusting to different scenarios through its fuzzy rules. This adaptability made it suitable for predicting crop yields across a wide range of conditions, including extreme weather variations and diverse soil qualities.

The linear regression model, however, lacked this adaptability. Its reliance on a predefined linear equation limited its ability to adjust to changes in input variables, making it less effective in scenarios where relationships between variables are complex and non-linear.

Visual Analysis through Surface Viewers: The use of surface viewers in the fuzzy logic model provided a clear visualization of how different input variables influenced crop yield predictions (Table 1). This visual representation offered valuable insights into the interactions between variables, helping stakeholders understand the impact of changing conditions on crop yield. In contrast, the linear regression model lacked such visual tools, making it harder to interpret and understand the influence of individual variables on yield predictions.

Criteria	Fuzzy Logic Model	Linear Regression Model
Accuracy (R ²)	Higher	Lower
Handling Uncertainty	Effective	Limited
Flexibility	High (non-linear adaptability)	Low (linear assumptions)
Visualization	Provides surface viewers	Lacks visualization tools
Adaptability to Changes	Highly adaptable	Rigid

Source: Own elaboration, 2024

Table 1. Summary of comparison.

Dataset description

The dataset used for training and testing the fuzzy model consists of 500 agricultural records collected from multiple farms across different climatic

regions. The dataset includes:

- Sample size: 500 observations.
- Data sources: Agricultural monitoring agencies and climate data centers.

The comparison clearly demonstrates that the fuzzy logic model offers superior performance in predicting crop yields compared to the linear regression model. Its ability to handle uncertainty, non-linear relationships, and complex interactions among input variables makes it a more reliable and flexible tool for yield prediction in agricultural economics. In contrast, the linear regression model's limitations in addressing these complexities result in less accurate predictions, making it less suitable for real-world agricultural applications where uncertainty and variability are prevalent.

For model evaluation, the dataset was divided into two subsets: 70% of the data (350 records) was used for training, and 30% (150 records) was used for testing. This stratified split ensured that both training and testing sets retained representative characteristics of the overall dataset.

Results and discussion

- Collection methods: Soil and crop analysis reports, weather records from the National Meteorological Service of Azerbaijan.
- Soil condition data were obtained from the Azerbaijan State Soil and Agrochemical Research Institute.
- Representativeness: The dataset includes records from major agricultural zones in Azerbaijan, such as Shirvan, Ganja-Gazakh, Lankaran, Karabakh, and Absheron. These regions cover a wide range of climatic conditions—humid subtropical (Lankaran), dry subtropical (Shirvan), semi-arid steppe (Ganja), and mountainous zones (Karabakh)—ensuring the model was tested under diverse environmental conditions.

The fuzzy logic-based yield prediction model was evaluated using a comprehensive dataset comprising variables such as Weather Variability (WV), Soil Conditions (SC), and Crop Characteristics (CC). The results demonstrated that the model accurately predicted crop yield (CY) across a wide range of scenarios, showcasing the model's robustness in handling the inherent uncertainties and complexities of agricultural systems.

Accuracy and Reliability: The fuzzy logic model's prediction accuracy was assessed by comparing its output with actual crop yield values. The model achieved a high coefficient of determination ($R^2 = 0.85$), indicating a strong alignment between predicted and actual yields. This high level of accuracy highlights the model's capability to capture the intricate relationships between input variables and yield outcomes, even under varying and uncertain conditions. In contrast, the traditional linear regression model, when applied to the same dataset, achieved a lower R^2 value of 0.65, demonstrating its limited ability to handle non-linear interactions and uncertainties in agricultural systems.

Handling of Uncertainty: One of the standout advantages of the fuzzy logic model was its ability to effectively manage the uncertainties present in agricultural data. By utilizing fuzzy sets and rules, the model accounted for the vagueness and imprecision associated with factors such as fluctuating weather patterns, varying soil quality, and diverse crop characteristics. For example, in scenarios where soil conditions were moderately favorable and weather variability was inconsistent, the fuzzy logic model could still provide a realistic yield prediction by integrating these uncertainties into its inference process. This adaptability allowed for more accurate and reliable yield predictions, which is crucial for agricultural decision-making and risk management.

In comparison, the linear regression model, which relies on fixed coefficients and linear assumptions, struggled to adapt to the uncertain and non-linear nature of agricultural data. Its predictions were often less reliable, especially in cases where input variables exhibited significant variability or were subject to sudden changes, such as extreme weather events.

Flexibility and Adaptability: The fuzzy logic model demonstrated remarkable flexibility and adaptability, accommodating various input scenarios and producing accurate yield predictions even under extreme conditions. This adaptability was primarily due to the model's ability to adjust its fuzzy rules based on changing input variables. For instance, when weather conditions shifted from unfavorable to favorable, the model seamlessly adjusted its predictions, accurately reflecting the impact on crop yield.

In contrast, the linear regression model exhibited rigidity in its approach, as it was confined to a predefined linear relationship between input variables and crop yield. This lack of adaptability

made it less effective in scenarios where agricultural conditions deviated from typical patterns, limiting its applicability in real-world settings.

Visual Analysis with Surface Viewers: The use of surface viewers provided valuable insights into how different combinations of input variables influenced crop yield predictions. For instance, the "Surface Viewer" for Crop Characteristics (CC) and Soil Conditions (SC) revealed that an improvement in soil quality, combined with more favorable crop characteristics, resulted in a significant increase in predicted crop yield. This visualization helped stakeholders understand the synergistic effects of multiple factors on crop yield, aiding in more informed decision-making.

The linear regression model lacked such visual tools, making it challenging to interpret the interactions between variables and their impact on yield predictions. This limitation reduced its effectiveness as a decision-support tool for stakeholders in agricultural planning and management.

Comparison Summary: The comparison between the fuzzy logic model and the traditional linear regression model is summarized in Table 2. It is evident that the fuzzy logic model outperforms the linear regression model in key aspects such as accuracy, handling uncertainty, flexibility, adaptability, and visualization capabilities.

Criteria	Fuzzy Logic Model	Linear Regression Model
Accuracy (R^2)	Higher (0.85)	Lower (0.65)
Handling Uncertainty	Effective	Limited
Flexibility	High (non-linear adaptability)	Low (linear assumptions)
Visualization	Provides surface viewers	Lacks visualization tools
Adaptability to Changes	Highly adaptable	Rigid

Source: Own elaboration, 2024

Table 2: Summary of comparison.

Implications for Agricultural Decision-Making: The fuzzy logic-based yield prediction model offers significant advantages for decision-making in agricultural economics. Its ability to handle uncertainty and non-linear relationships enables more accurate predictions, aiding farmers, policymakers, and agricultural economists in making informed decisions regarding resource allocation, crop management, and market planning. By providing a more realistic and adaptable prediction tool, the fuzzy logic model enhances risk management and contributes to more sustainable and profitable agricultural practices.

Accuracy and Model Performance

The fuzzy logic model achieved an R^2 value of 0.85, indicating a strong alignment between predicted and actual yields. The calculation was performed using the Sugeno inference system, ensuring robustness in handling nonlinear relationships.

For comparison, a traditional linear regression model was also tested, yielding an R^2 value of 0.65, demonstrating its limited ability to model nonlinear interactions. To further validate the model, additional machine learning approaches were considered:

- Decision Trees ($R^2 = 0.78$): Performed better than linear regression but lacked interpretability compared to fuzzy logic.
- Random Forests ($R^2 = 0.82$): Provided high accuracy but required significant computational resources.
- Neural Networks ($R^2 = 0.88$): Outperformed all models but was more complex and required extensive training data.

Sensitivity Analysis

A sensitivity analysis was conducted to determine the influence of each input variable on crop yield:

- Weather Variability contributed 45% to yield fluctuations.
- Soil Conditions accounted for 35% of yield variations.
- Crop Characteristics influenced 20% of the final yield.

These percentages were obtained using the Sensitivity Analysis tool in MATLAB's Fuzzy Logic Toolbox, which evaluates the impact of each input on the output by independently varying one input variable while keeping the others constant. The contribution of each input was calculated by analyzing the changes in the defuzzified output over the full range of input values. The results were then normalized to express each variable's influence as a percentage of the total variation in crop yield.

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The Fuzzy Inference System (FIS) was built using the Mamdani model in MATLAB. The Sensitivity Analysis tool within the FIS Editor provided the relative importance values by measuring the deviation in the output when each input was varied independently.

The graphical output from MATLAB displays the effect of input variables on the output surface, demonstrating how changes in weather, soil, and crop parameters influence crop yield.

Conclusion

This study presents a fuzzy logic-based yield prediction model that effectively captures the uncertainties and complexities of agricultural data. The model's ability to handle non-linear interactions and provide interpretable results makes it superior to traditional statistical methods.

Key contributions of this research include:

- A well-structured fuzzy inference system that integrates key agricultural factors.
- A comparative analysis demonstrating the advantages of fuzzy logic over linear regression.
- Incorporation of sensitivity analysis, enhancing the model's reliability.

Future research directions include:

- Expanding the dataset to include more regions and crop types.
- Integrating deep learning techniques for hybrid AI-based yield prediction.
- Validating the model across different agricultural environments to assess its generalizability.

By addressing these areas, this study contributes to improved agricultural decision-making, enabling farmers and policymakers to adopt more accurate and adaptive yield prediction models.

Data availability

Data will be made available on request.

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Management of Low Volume Roads: A Decision Support Tool for Sustainable Wildfire Prevention and Maintenance Resources Allocation Via GIS-Network Analysis

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Abstract

This study presents a GIS-based decision support system (DSS) for prioritizing forest road network maintenance to enhance wildfire prevention and suppression in Mediterranean forest regions. The research focuses on low-volume roads (LVRs), which play a critical role in fire response operations but often suffer from limited maintenance resources and accessibility constraints. Using GIS-based network analysis, the study integrates road hierarchization, wildfire risk modeling, and optimal route determination to develop a structured approach for forest road maintenance prioritization. The methodology involves segmenting and evaluating road networks based on travel time, slope, and fire risk exposure, enabling a data-driven ranking system that identifies critical access routes for emergency response. The study applies the Closest Facility method to determine optimal routes from firefighting vehicle stations to various locations within the network. Results indicate that a targeted maintenance strategy, prioritizing high-risk road sections, significantly improves fire response efficiency while optimizing resource allocation in financially constrained forest management frameworks. This approach introduces a sustainable and cost-effective framework for forest road infrastructure planning, offering a practical tool for decision-makers in fire-prone regions. By ensuring proactive maintenance scheduling, the proposed method enhances wildfire resilience, reduces emergency response delays, and supports long-term forest sustainability.

Keywords

Road maintenance, road hierarchization, forest management, optimal routes, spatial optimization, sustainability.

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Introduction

The term low-volume roads (LVRs) refer to road networks characterized by limited vehicular traffic flow. These roads typically include forest roads, agricultural roads, and, in many cases, rural connector roads that link settlements (Praticò et al., 2011). LVRs serve as permanent infrastructure elements, commonly found in mountainous and semi-mountainous regions, as well as in rural areas beyond urbanized zones (Selva et al., 2011; Kolkos et al., 2024). These roads play a crucial role in facilitating accessibility, economic development, and resource management in remote and sparsely populated areas (Arabatzis et al., 2010; Mavraki et al., 2020). Despite their limited traffic load, LVRs are essential for forest management, agricultural activities, emergency response, and rural mobility (Mavraki et al., 2020). Due to their location and function, they often exhibit

unique geometric, structural, and maintenance challenges, requiring tailored engineering approaches to ensure sustainability, resilience, and cost-effectiveness (Ferenčík et al., 2019; Akgul et al., 2017). The design, maintenance strategies, and environmental impacts of LVRs is critical for optimizing their long-term performance and minimizing degradation, particularly in areas prone to erosion, extreme weather conditions, and limited funding for infrastructure maintenance (Yolmeh et al., 2021; Ghajar et al., 2013).

The prevention and suppression of wildfires are closely linked to the forest road network, which serves as the primary means of transportation for firefighting forces to reach affected areas efficiently (Cristan et al., 2016). Given the increasing frequency and severity of wildfires, the role of forest infrastructure in fire management has become more critical than ever. Adequate road networks not only

facilitate rapid emergency response but also enable the strategic deployment of resources, minimizing the extent of fire damage (Thompson et al., 2021). Beyond their function as access routes, forest roads play a crucial role as a fundamental protective measure in wildfire management. Their presence significantly enhances the capacity for effective fire suppression, particularly in rugged and remote landscapes where ground-based firefighting operations rely on mechanized interventions (Dinca et al., 2025).

The effectiveness of forest roads in wildfire response is highly dependent on their design, maintenance, and strategic planning. Poorly maintained roads can hinder rather than aid suppression efforts, delaying response times and increasing the risk to both firefighters and forest ecosystems (Thompson et al., 2021). Therefore, an integrated approach that considers road network optimization, sustainable forest management, and technological advancements in fire monitoring is essential to enhance wildfire resilience (Arabatzis et al., 2024; Kolkos et al., 2023). The maintenance of forest road networks represents an urgent and fundamental challenge in forest infrastructure management (Riid et al., 2020). Insufficient attention and inadequate funding have led to a concerning deterioration of road conditions, directly hindering wildfire response efforts and compromising the overall sustainability of forested areas. As forest fires become increasingly frequent and severe due to climate change and land-use transformations, the condition of forest roads plays a decisive role in determining the efficacy of emergency interventions and resource accessibility (Ranyal et al., 2022).

The structural composition of road pavements consists of multiple layers of geotechnical materials, which enhance both strength and functionality. In many cases, forest roads are constructed using either a single base layer or a two-layer system comprising a base layer and a surface layer (Daigle, 2010). The majority of forest roads are designed as unpaved pathways, typically built using freely available coarse material. Furthermore, forest roads include a subset of LVRs, which are characterized by low traffic volumes (Chandak et al., 2019; Tsiotas et al., 2023). The design of a forest road is a complex engineering challenge, requiring the integration of economic and environmental considerations. In particular, construction and maintenance costs play a dominant role in the total cost of forest harvesting operations (Akay, 2003). Poor construction practices and inadequate maintenance can have significant environmental consequences, potentially causing greater ecological damage

than other forestry-related activities (Anderson and Lockaby, 2011). Consequently, the alignment and placement of forest roads require careful evaluation to balance construction and maintenance costs while adhering to design requirements and environmental protection standards (Robinson et al., 2010).

The development of a Road Network Analysis System is essential for evaluating the connectivity, accessibility, and efficiency of transportation networks. This system integrates spatial data, network topology, and advanced analytical techniques to assess various factors such as travel time, route optimization, and network hierarchy. By leveraging geographic information systems (GIS) and network modeling, the system enables the identification of optimal routes, critical infrastructure, and areas requiring maintenance or upgrades (Comber et al., 2008). A well-structured road network analysis system enhances decision-making in transportation planning, emergency response, and infrastructure management (Neville et al., 2016). It allows for the evaluation of road performance based on key parameters such as travel cost, road classification, and environmental constraints. Moreover, the integration of real-time data can improve traffic flow prediction and disaster response planning. By systematically analyzing road networks, this approach contributes to more sustainable, efficient, and resilient transportation systems, supporting both urban and rural development.

A systematic and prioritized classification of forest roads is essential to enhance maintenance strategies and optimize resource allocation. Establishing a ranking system that evaluates and categorizes different sections of the forest road network based on their functional significance would facilitate efficient maintenance planning and targeted investment. Such a system would ensure that critical access routes for fire suppression, forest management, and conservation activities remain in optimal condition, thus reinforcing the resilience of forest ecosystems against natural disturbances. Beyond fire suppression, a well-maintained forest road network contributes to biodiversity conservation, erosion control, and the overall stability of forest landscapes (Tsiotas et al., 2024; Kantartzis et al., 2021).

The implementation of a data-driven maintenance framework, integrating remote sensing technologies, geospatial analysis, and predictive modeling, would enable proactive infrastructure management and mitigate the risks associated with deteriorating road conditions (Mohajane et al., 2021; Bentekhici

et al., 2020). To address these pressing concerns, policymakers and forest management authorities must prioritize long-term investment in road maintenance, adaptive infrastructure strategies, and interdisciplinary research. Strengthening the resilience of forest road networks is not only vital for effective wildfire suppression but also for ensuring sustainable forest management, ecosystem protection, and climate adaptation in fire-prone regions (Ferreira Da Silva et al., 2020).

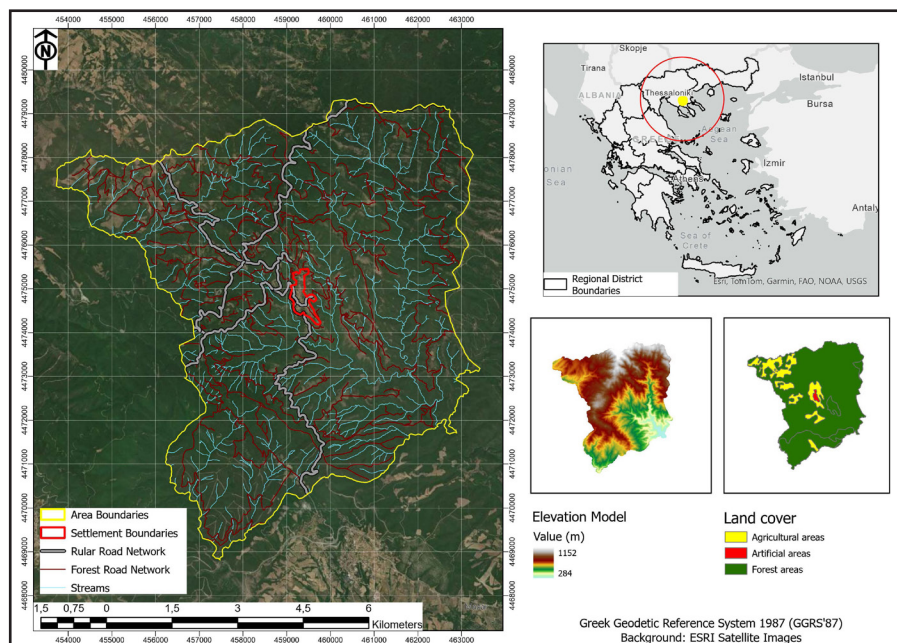
This research aims to develop a comprehensive decision support system (DSS) that enables stakeholders to optimize resource allocation for the maintenance and improvement of forest road networks. The primary objective is to identify the most critical road segments by considering their role in ground-based wildfire suppression operations. By prioritizing these segments, stakeholders can enhance the efficiency of resource distribution and establish an optimal maintenance scheduling framework to ensure the functionality of vital access routes. By integrating wildfire risk assessment and optimal route analysis, this study proposes a systematic methodology for ranking different sections of the forest road network. This prioritization process involves evaluating fire-prone areas, access constraints, and infrastructure vulnerabilities, leading to a structured classification of road segments based on their significance in emergency response and fire containment. The outcome is a data-driven assessment that clarifies which road sections require immediate

intervention and long-term investment to enhance wildfire resilience. The proposed decision-making tool will provide stakeholders with actionable insights to make informed, evidence-based decisions on forest road network management. By leveraging advanced spatial analysis, remote sensing technologies, and predictive modeling, this system will facilitate sustainable infrastructure planning and proactive maintenance strategies. Ultimately, this approach aims to strengthen wildfire protection, improve emergency response efficiency, and create a more resilient forest environment for future generations.

Materials and methodology

Research area

The study area selected for the present research is the Taxiarchis University Forest, located in the Regional Unit of Chalkidiki within the Region of Central Macedonia, Greece. The forest extends between the latitudinal coordinates 40°23' - 40°28' N and longitudinal coordinates 23°28' - 23°34' E. In accordance with the Greek Geodetic Reference System of 1987 (GGRS '87), its coordinates range from X: 452700 to 463875 and Y: 4466875 to 4480675. The elevation of the area varies between 320 and 1,165 meters above sea level, covering an approximate area of 5,870.50 hectares. Figure 1 presents the location of the research area, the digital elevation model and land cover classification.



Source: Greek National Cadastre, European Union Copernicus Land Monitoring Service, Geographical analysis

Figure 1: Location map of the Taxiarchis University Forest (study area), including digital elevation model (DEM) and land cover classification.

Since 1934, the forest has been granted to Aristotle University of Thessaloniki (AUTH) and has since been utilized for educational and research purposes. It serves as a site for the implementation of contemporary forestry and forest management programs. Both the management and administration of the forest fall under the jurisdiction of the AUTH Forest and Management Fund. A range of research projects conducted by the School of Forestry and Natural Environment at AUTH has yielded valuable scientific data concerning the region's topography, road network, and factors influencing forest fires. Within the area lies the settlement of Taxiarchis, which, according to the Hellenic Statistical Authority, has a population of 1,070 inhabitants. The region also hosts university facilities and tourist accommodations. Approximately half of the study area is designated as part of the Natura 2000 network (sites GR127001 and GR1270012), highlighting its ecological significance.

Data collection

The initial step in conducting this research involved the systematic collection of essential data. As a first measure, the road network of the study area was digitized to ensure accurate representation and analysis. According to the existing Greek legislation, the road network within the region is categorized into four distinct classes. These include the provincial road network, which is paved, and the forest road network, which is further subdivided into three classes (A, B, and C) based on its geometric characteristics. The classification criteria for the forest road network are detailed in Table 1. To achieve this classification, orthophotos from the Hellenic Cadastre and topographic field surveys were utilized,

ensuring a comprehensive and precise assessment of the road network structure.

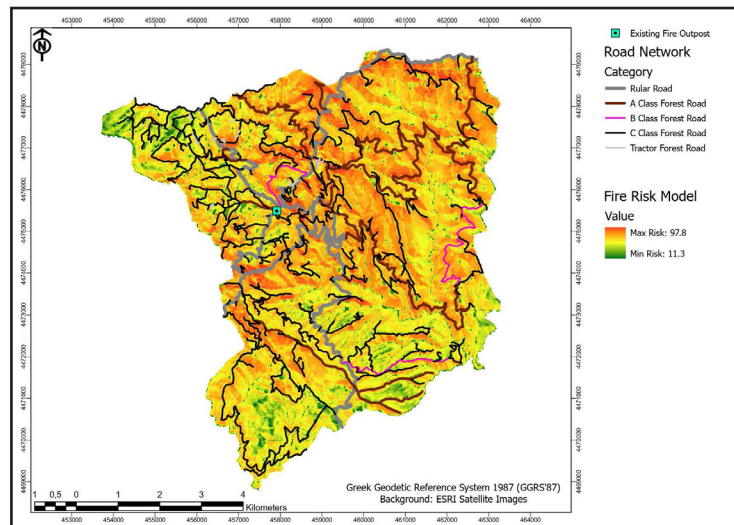
Subsequently, data related to wildfire hazard assessment in the study area were collected and analyzed. Kolkos et al. (2025) developed a wildfire risk model specifically for the Taxiarchis University Forest as part of a targeted fire risk assessment. The resulting output of that study is directly used in the present work. The model was developed using Geographic Information Systems (GIS), employing a weighted overlay technique to combine six critical spatial variables: elevation, terrain slope, vegetation type and density, distance from the road network, and proximity to anthropogenic infrastructure. Each variable was normalized and assigned a weight reflecting its relative impact on wildfire ignition and spread. Figure 2 presents the model output, as a high-resolution raster (5×5 meters) in which each pixel is assigned a wildfire risk score ranging from 0 (very low risk) to 100 (very high risk). This classification enables a detailed and precise evaluation of fire-prone zones within the study area.

Finally, the existing designated parking locations for firefighting vehicles were identified. According to local forestry authorities, the study area contains only one officially designated parking site for firefighting vehicles. This location, which serves as the primary dispatch point for emergency response operations in the event of a wildfire, is depicted in Figure 2. In case of a fire outbreak, firefighting vehicles are deployed from this designated parking area to reach the affected zones as efficiently as possible.

Technical Specifications	Categories of Forest Roads		
	A Class	B Class	C Class
Width (Earthy and Semi-Rocky Terrain)	6 - 8 m	4 - 6 m	4 - 5 m
Width (Rocky Terrain)	6 m	4 m	5 m
Minimum Curve Radius (Rmin)	30 m	25 m	20 m
Longitudinal Slope Smax (On the Downhill Section)	8%	8%	12%
Longitudinal Slope Smax (On the Uphill Section)	6%	6%	12%
Technical constructions	YES	YES	YES

Source: Greek legislation

Table 1: Classification and technical elements of forest roads according to the Greek Ministry of Agriculture.



Source: Author, Geographical analysis

Figure 2: Road network categorization and wildfire risk model of the study area. The map illustrates provincial and forest road classes (A, B, C) alongside the wildfire risk raster.

Methods

Development of road network analysis system

The first and fundamental step in road network analysis for optimal route determination is the creation of a comprehensive and structured database. The primary objective is to model roads as a network system, enabling efficient route planning and analysis. A network system consists of interconnected elements, where edges (lines) and nodes (points) represent possible pathways between locations. This approach allows for the systematic representation of road connectivity, facilitating advanced spatial analysis. For the development of the network system, ArcGIS 10.8 software was utilized along with a vector dataset containing the categorized road network. This integration ensures accurate spatial representation and supports the subsequent analysis of optimal routes within the study area.

The process of constructing the road network dataset (Network Dataset) in ArcGIS 10.8 began with the importation of the vector line dataset representing the road network of the study area. Each record within the dataset's attribute table includes the classification of the forest roads, categorizing them as Provincial Roads or Forest Roads of Class A, B, or C. To ensure the proper functionality of the Network Dataset, topological consistency checks were performed. These checks were essential for identifying and correcting connectivity errors, such as disconnected road segments or structural inconsistencies within the dataset.

Subsequently, the road network was segmented

into sections of 100 meters, creating the road sections dataset. This was achieved using the Generate Points Along Lines tool, which generated points at 100-meter intervals along the road network lines. Following this step, the Split Line at Points tool was executed to divide the road segments accordingly. Each road section was then assigned a unique identifier (Road Section ID) to ensure precise referencing and analysis. A new field was added to the attribute table of the road network segments to store the length of each section (road length). Due to the segmentation process in the previous step, most road sections have a length of 100 meters. However, in some cases, particularly at the endpoints of roads, the Split Line at Points tool generated shorter segments where the remaining distance was less than 100 meters.

In the next step, the longitudinal slope of each road segment was calculated. To achieve this, the coordinates of the start and end points of each segment were extracted and added to the attribute table. Based on these coordinates, a point layer was generated, to which elevation values were assigned using the Extract Values to Points tool from the Digital Elevation Model (DEM). The road sections dataset was then updated using the unique identifier (Road Section ID) to include the elevation values at both the start and end of each segment. Following this step, a new field was created to store the longitudinal slope of each segment, calculated using the following Equation 1:

$$LRSS = \left| \frac{Z_A - Z_E}{L_S} \right| * 100 \quad (1)$$

Where LRSS: the longitudinal slope expressed as a percentage of each road segment (Longitudinally Road Section Slope), ZA: the elevation at the start of the segment (in meters), ZB: the elevation at the end of the segment (in meters), and LS: the length of the road segment (in meters).

The next step involved assigning the average travel speed for each road segment. The average travel speed of each segment is determined based on the classification of the forest road. Each road category reflects its geometric characteristics, including road width, pavement type, curvature radii, and other relevant attributes. For each road category, a base average speed was assigned, which was then adjusted according to the longitudinal slope of the segment. For segments with a longitudinal slope between 0% and 10%, the travel speed remained unchanged. For slopes ranging from 10% to 30%, the travel speed was reduced by 30%, while for slopes between 30% and 60%, the travel speed was reduced by 50%. Table 2 presents the travel speed values for each case. Based on these values, the attribute table of the road sections dataset was updated accordingly to reflect the adjusted travel speeds. The adopted speed reduction factors are consistent with findings from previous studies on unpaved and forest road networks in mountainous terrain (Akay et al., 2021; Cavalli and Grigolato, 2010), where slope significantly influences vehicular mobility and safe driving speed.

The next step involves calculating the travel time based on speed for both cases. Using the speed-time-displacement (Equation 2), the required travel time for each road segment was determined.

$$t = \frac{x}{u} \tag{2}$$

Where t : traveling time, x : travelling length, u : traveling speed

With the completion of the above steps, the database of the forest road network was finalized, which will be used for the optimal route

analysis. Subsequently, the Network Dataset was created using the Network Analyst platform of ArcGIS.

Response time evaluation from fire outpost

Network analysis enables the calculation of travel time between two points by determining the optimal route that minimizes the traversal cost, which in this case is the travel time. This analytical approach was employed to assess the accessibility of all points within the road network based on their travel time from a designated location, identified as the parking site for firefighting vehicles. The primary objective of this analysis was to evaluate the efficiency of the parking location and to quantify the spatial coverage it provides in terms of response time. By integrating road network characteristics and travel speed variations, the analysis offers a data-driven assessment of how effectively emergency response vehicles can reach different areas within the study region.

This application utilizes the Closest Facility method from the Network Analysis package in ArcGIS. This method calculates the travel cost between Incidents and Facilities, determining the closest facility for each incident based on the defined travel constraints. Additionally, it generates the optimal routes between incidents and facilities, providing a detailed representation of the travel cost associated with each route. This approach enables an accurate assessment of response efficiency and accessibility within the study area.

To implement this method, points were generated at 20-meter intervals along the entire road network within the study area of Taxiarchis, Chalkidiki, using the Generate Points Along Lines tool in ArcGIS. The 20-meter interval was selected as a balance between spatial resolution and computational efficiency. This spacing ensures sufficient granularity to capture local variations in accessibility and fire hazard exposure along the road network, while maintaining a manageable processing load during network analysis.

Road class	Average Speed (km/h)	Speed Based on Slope (km/h)		
		Slope 0-10%	Slope 10-30%	Slope 30-60%
Provincial Road (Asphalt-Paved)	40	40	28	20
Forest Road Class A	30	30	21	15
Forest Road Class B	25	25	17,5	12,5
Forest Road Class C	20	20	14	10

Source: Akay et al. (2021); Cavalli and Grigolato (2010)

Table 2. Assigned passing speeds for different road categories under varying longitudinal slope conditions.

The designated study location for the analysis was the firefighting vehicle parking area near the Forest Service facilities. This location was assigned the role of Facility, while the points generated along the road network were designated as Incidents. Through this approach, an Optimal Route was established from the parking location to each point within the road network. The generated optimal routes were analyzed, and the road network segments were classified according to their respective travel time from the parking location. The road segments were further categorized based on their accessibility time, providing a comprehensive spatial representation of response time distribution across the study area.

Road network hierarchization

The purpose of prioritizing road network segments is to establish a structured system where road sections are ranked based on their significance in wildfire suppression operations. This prioritization aims to determine the relative importance of each road segment, facilitating more efficient planning and allocation of maintenance efforts.

The final ranking of road segments was determined through a two-step process that integrates both network centrality and wildfire exposure. Optimal routes were first computed from each firefighting vehicle parking location to all incident points placed every 20 meters along the road network. Each of these points was assigned a fire risk value based on the underlying wildfire hazard raster, which was then inherited by the corresponding optimal route. For each road segment, we calculated the total number of optimal routes crossing through it and summed the fire risk values associated with those routes. The final prioritization score, referred to as the Road Segment Fire Risk Score (FRS), was computed as follows:

$$\text{Road Segment FRS} = \sum_1^i \text{Optimal Route FRS } (i) \quad (3)$$

Where i : the optimal route that passes through road segment, FRS : Fire Risk Service

Overlapping of optimal routes within the same road segment was addressed by aggregating the wildfire risk values of all routes passing through that segment. The importance of each segment was thus determined by both the frequency of route overlap and the cumulative fire risk exposure, rather than route length alone.

The hierarchical classification of the road

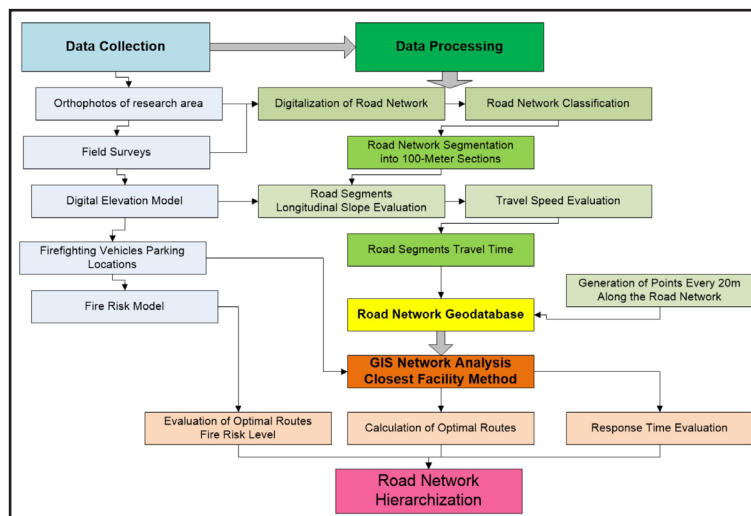
network, based on its importance for ground-based firefighting, was carried out through the following methodology:

1. The raster model of fire risk was converted into a point layer, with each point representing the center of a pixel and assigned a fire risk value (0–100).
2. Road points were generated every 20 meters along the road network using ArcGIS 10.8, each with a unique ID and the corresponding road section ID.
3. A Spatial Join assigned to each fire risk point the road section ID of its nearest road point.
4. The Dissolve tool was applied to the fire risk points by road section ID, summing their fire risk values. The output was merged with the road points layer.
5. Each road point (every 20 meters) now contained the aggregated fire risk of nearby fire risk points, representing local hazard levels.
6. Using the existing parking location as the facility, the Closest Facility tool was used to generate optimal routes to all road points. Each route included the road section ID of its destination, linking it to the fire hazard it serves.
7. The road network was segmented into 100-meter sections. A Spatial Join and Dissolve between these sections and the routes layer allowed each segment to accumulate the number and fire hazard level of intersecting routes.

The final road sections layer consists of 100-meter segments containing attributes such as category, length, and aggregated values of optimal routes and the fire hazard they serve. Based on these, the segments were prioritized according to the level of fire hazard they address, from highest to lowest importance.

Figure 3 outlines the step-by-step process followed in the study, from data collection to final road network hierarchization.

The Closest Facility approach allows for real-time prioritization of access routes based on travel time rather than mere distance, offering a more practical and risk-responsive solution for wildfire emergency planning (Zhang et al., 2011). Compared to other GIS-based decision support models used in road maintenance



Source: Author

Figure 3: Methodological workflow diagram. The flowchart presents the sequential steps followed in the study: data collection (road network, DEM, fire hazard), road segmentation, slope and speed calculation, response time evaluation, wildfire risk integration, and final road network hierarchization.

and infrastructure planning (de Medeiros Pereira et al., 2024; Arampatzis et al., 2004), this study’s methodology provides a fire-specific prioritization framework, ensuring that critical forest roads are ranked and maintained based on their role in emergency response. By integrating spatial analysis with wildfire risk modeling, this approach enhances resource allocation and proactive maintenance scheduling, leading to more effective wildfire mitigation strategies.

Results and discussion

Road network analysis

The network analysis was conducted using the provincial road network and forest roads classified into Categories A, B, and C. These road categories collectively cover a total length of 228,556 meters. Specifically, 33,808 meters correspond to provincial roads, 44,428 meters to Category A forest roads, 9,730 meters to Category B forest roads, and 140,857 meters to Category C forest roads. According to the adopted methodology, the forest road network was segmented into discrete sections to facilitate a more detailed analysis. A total of 2,427 road sections were generated, with the majority of these segments having a length of 100 meters. However, 316 sections were shorter than 100 meters, as they corresponded to terminal road segments. In terms of longitudinal slope, 195 road sections were calculated with a 0% slope, while 1,011 sections had slopes ranging between 1% and 6%. An additional 809 sections had slopes between 7% and 12%, whereas the remaining

412 segments exhibited slopes exceeding 12%, with the maximum recorded slope reaching 41%. This segmentation approach provides a structured framework for evaluating road accessibility and optimizing maintenance and emergency response planning within the study area.

Response time evaluation

The response time assessment method was applied to the existing firefighting vehicle parking location within the study area. The travel speed, in relation to the length of each road segment, was converted into travel time (in minutes), which served as the key parameter for route optimization. This travel time parameter was integrated into the network analysis as the minimization criterion for determining the optimal routes.

To implement this methodology, a total of 16,657 points were generated across the road network. On average, these points were placed every 20 meters, although in some cases they were positioned at shorter intervals, particularly at road network endpoints. These points were designated as Incidents in the network analysis process. From the designated firefighting vehicle parking location, which was assigned the role of Facility in the analysis, the Closest Facility tool from the Network Analysis package in ArcGIS was applied. This resulted in the generation of 16,657 optimal routes, each connecting the parking location to an Incident point. This approach provided a detailed assessment of response time distribution across the study area, facilitating the evaluation of accessibility

and the effectiveness of the existing parking location in supporting emergency operations.

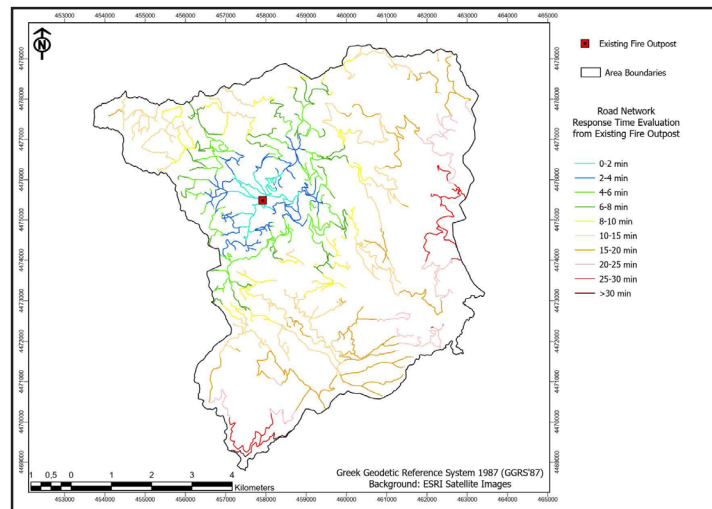
Figures 4 and 5 illustrate the response times across the road network from the existing firefighting vehicle parking location. The most distant point in this analysis, assuming an ideal road surface condition without deterioration effects, required a maximum travel time of 30.78 minutes. The analysis revealed that the existing parking location provides coverage to 43.63% of the road network within a 0–10 minute response time. Within 10–20 minutes, the coverage extends to 38.78% of the network, while an additional 16.76% of the road network is accessible within 20–30 minutes. Finally, 0.84% of the road network requires more than 30 minutes to reach

from the designated parking location, assuming optimal road conditions.

Road sections Hierarchization

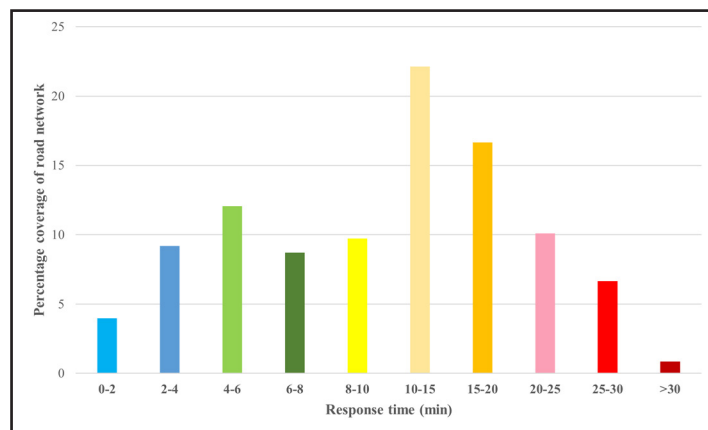
According to the applied methodology, a total of 16,657 optimal routes were generated from the existing firefighting vehicle parking location to a corresponding number of points placed at 20-meter intervals along the road network. For each of these points - and consequently, for each of the 16,657 optimal routes - the cumulative wildfire hazard score was calculated by summing the values of the nearest pixels from the previously developed Wildfire Risk Digital Model.

Furthermore, for each of the 2,472 road segments,



Source: Author, Geographical analysis

Figure 4: Spatial coverage of response times from the existing firefighting vehicle parking location. Road network sections are color-coded based on travel time (minutes) required to reach each point under optimal conditions.



Source: Author, Statistical Analysis

Figure 5: Percentage distribution of road network accessibility by response time intervals from the existing firefighting vehicle parking site.

two key metrics were computed: the number of optimal routes passing through each segment and the total wildfire hazard score accumulated along these routes. The final hierarchical classification phase involved ranking road segments based on the aggregated wildfire hazard scores, enabling a systematic evaluation of their relative importance in firefighting operations and emergency response planning.

Figure 6 presents the final ranked map of the road network, resulting from the aggregation of optimal route frequency and wildfire risk exposure per segment. The darker the segment, the higher its criticality score, indicating roads that are both frequently involved in emergency access routes and associated with destinations of elevated fire hazard. This spatial outcome synthesizes the entire methodological framework and offers a clear decision-support tool for prioritizing interventions such as maintenance, clearing, or reinforcement.

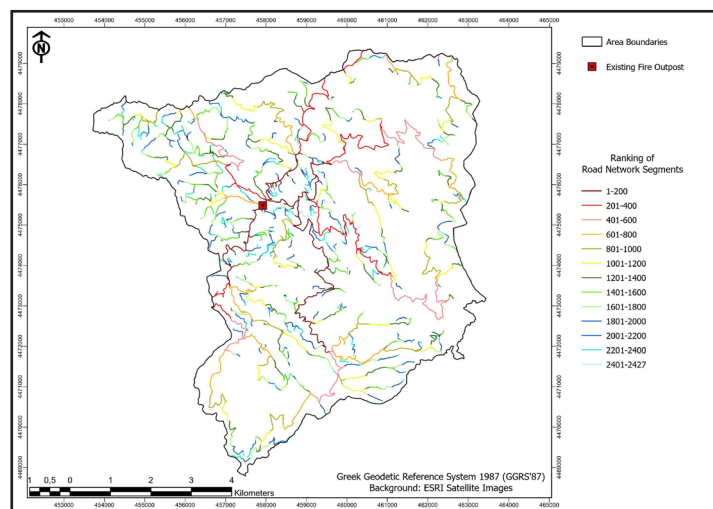
The map reveals spatial patterns of priority - highlighting, for example, peripheral or remote segments that may not be central in road density but are crucial for reaching high-risk zones. Conversely, some centrally located roads may score lower due to limited exposure or route redundancy. This result can directly inform strategic planning for wildfire preparedness, ensuring that the most essential segments are identified for timely and reliable access during fire events.

Discussion

The findings of this study highlight the critical role of LVRs in wildfire suppression operations,

aligning with previous research on rural road networks. While LVRs are often overlooked due to their limited traffic flow, their strategic importance in emergency response is undeniable, particularly in forest fire-prone regions (Zhang et al., 2020). The study's network-based prioritization approach reinforces the argument that well-maintained forest roads significantly enhance the efficiency of firefighting efforts, as suggested by Calkin et al. (2016). Poorly maintained LVRs can delay emergency vehicle deployment, increasing the likelihood of fire escalation and the subsequent environmental and economic costs (Stefanović et al., 2016). The results demonstrate that a data-driven road maintenance framework, focusing on wildfire risk and accessibility constraints, can optimize resource allocation, ensuring that critical access routes remain functional during fire emergencies. Inadequate infrastructure maintenance can lead to greater environmental degradation than other forestry activities. Therefore, integrating LVR-specific fire response strategies into broader forest management policies is essential for enhancing wildfire resilience and ensuring sustainable infrastructure planning.

The GIS-based network analysis used in this study differs from conventional GIS-based DSS by integrating fire risk assessment and accessibility constraints into road network optimization (Parsakhoo, 2016 ; Hosseini et al., 2012). Unlike traditional spatial analysis techniques, which often rely on static road classifications and distance-based shortest path models, this study employs the Closest Facility method to dynamically assess response



Source: Author, Geographical analysis

Figure 6 Final prioritization map of the forest road network, showing 100-meter road segments ranked according to their wildfire hazard exposure and frequency of use in optimal firefighting routes.

time and accessibility for wildfire suppression. The results support the advancement of data-driven decision-making in forest infrastructure planning, reinforcing the importance of adaptive road management in fire-prone regions.

The proposed road maintenance prioritization strategy in this study presents a cost-effective and sustainability-driven approach to wildfire management, diverging from conventional models that primarily focus on road deterioration and usage frequency. Unlike traditional maintenance frameworks, which allocate resources based on traffic load and infrastructure wear (Majstorović and Jajac, 2022), this study integrates wildfire hazard assessment into the prioritization process. By ranking road sections based on their role in fire suppression, the proposed model ensures that limited resources are directed toward high-risk areas, optimizing both fire response efficiency and road network resilience. Additionally, compared to generalized rural road management models, which emphasize economic and environmental trade-offs (Chamorro and Tighe, 2019), this study highlights the multifunctionality of forest roads, reinforcing their critical role in wildfire suppression, ecosystem protection, and sustainable forestry.

Conclusions

This study developed a hierarchical methodology for prioritizing forest road segments based on their contribution to wildfire suppression operations. The findings emphasize that the maintenance and optimal condition of forest roads are essential components of wildfire prevention and emergency response strategies. While the prioritization framework does not diminish the importance of maintaining any specific road segments, it provides a structured approach to guide maintenance scheduling and ensure that resources are allocated efficiently, particularly when funding is limited. By integrating network analysis and wildfire risk assessment, the proposed method enables a data-driven approach to forest road management, ensuring that key access routes remain operational before and during the fire season. The ranking of road segments based on their fire suppression significance allows for strategic planning, optimizing both resource distribution and infrastructure resilience. The study's approach is particularly useful in forested regions with looped or interconnected road networks, where network analysis techniques are essential

for identifying optimal routes for emergency access and evacuation.

The proposed method successfully identified high-priority road segments based on a combined assessment of fire hazard and route frequency. For instance, segments located in the northeastern and central-western parts of the study area consistently appeared in the top 10% of critical links, reflecting both high fire exposure and strategic accessibility. These results demonstrate the model's ability to pinpoint roads that are operationally significant for emergency response, even in low-volume forest networks.

Despite the robustness of the proposed forest road network prioritization methodology, certain limitations should be acknowledged. The network analysis model relies on static road conditions and predefined wildfire risk factors, which may not fully capture real-time changes in road accessibility or evolving fire dynamics. Additionally, the study assumes optimal vehicle performance under varying road conditions, without incorporating potential vehicle mobility constraints due to severe terrain degradation, extreme weather conditions, or unforeseen obstacles. Another limitation is the resolution of the wildfire risk model, which, despite its high spatial accuracy, may still be subject to classification uncertainties affecting road segment prioritization. Finally, while the methodology is highly applicable to looped or circuit-like forest road networks, its adaptability to linear or fragmented road networks in more complex topographies requires further investigation.

Future research should focus on enhancing the adaptability of the methodology by integrating real-time road condition monitoring and dynamic fire behavior modeling to improve response efficiency. Further exploration of economic feasibility assessments and cost-benefit analyses could also strengthen the decision-making process, ensuring that sustainable infrastructure investments are aligned with long-term forest management goals. Finally, the incorporation of climate change projections would allow for adaptive road maintenance planning, ensuring resilience against future wildfire risks in a changing environment.

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Predictive Battery Life Modeling for LoRaWAN Sensors Using Real-World Deployment Data

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Abstract

This study presents a comprehensive analysis of LoRaWAN-based IoT communication in an agricultural monitoring context. The research is grounded in long-term experimental data collected from four environmental sensors deployed in the Czech Republic, focusing on temperature and humidity measurements. Beyond the environmental data, the study emphasizes the technical performance of the deployed devices, particularly in terms of signal quality and energy efficiency.

We analyzed 14 key transmission parameters, including RSSI, SNR, Time on Air, and gateway reception metrics, to evaluate the communication reliability and network coverage.

A significant contribution of this work is the development of a data-driven model for estimating battery life based on real-world usage patterns and spreading factor distributions. This model enables predictive maintenance planning and supports energy-efficient network design. The study builds on previous research and contributes to the growing body of literature on holistic performance evaluation in IoT systems.

Keywords

LoRaWAN, RSSI, SNR, spreading factor, battery life, energy consumption, adaptive data rate, IoT, wireless communication, agricultural monitoring.

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Introduction

Importance of connectivity in IoT systems

In IoT systems, *connectivity is a fundamental component* that enables communication between end devices and central servers. For optimal use of wireless communication, it is essential to determine the *radio characteristics of the network* and key parameters such as signal strength, signal-to-noise ratio, and transmission frequency. These parameters are critical for evaluating the performance of wireless transmission (Lin and Chang, 2023; Lynn et al., 2020)

During the deployment or analysis of an operational IoT system, *measured signal parameters serve as key indicators* of system performance. If these parameters reveal alarming or critical values, they can be used to *optimize connectivity* and prevent potential system failures that may lead to financial losses (Lynn et al., 2020).

Without proper signal analysis, wireless network optimization may become unnecessarily costly and inefficient (Choudhary, 2024).

Research motivation and context

This study involves experimental measurements of temperature and humidity for projects where sensor data is crucial. However, the technical solution is also important, so we focused on analyzing the technical performance of our devices, both in terms of signal quality and battery life. These aspects are interconnected. The result is that through a thorough analysis of real data over a long period, we have developed a reliable model for estimating the battery life of devices, allowing us to predict when the battery will need to be replaced.

The main data sources for agricultural enterprises are the farm itself, suppliers, government, market, and research. The use of smart solutions, artificial intelligence, and other innovative practices

in agriculture is discussed at many conferences, in various journals, strategies and project plans. Data is the essential raw material for all these solutions. (Jarolimek et al., 2024)

Materials and methods

Device specifications and energy model

According to the manufacturer, the Milesight EM300-TH is a compact LoRaWAN-based sensor designed for temperature and humidity monitoring in remote or agricultural environments. It is powered by a 4000 mAh ER18505 Li-SOCl₂ battery, with a claimed operational life of up to 5 years under standard conditions (Milesight, 2025). The device transmits data via LoRaWAN and supports various spreading factors (SF7–SF12), which significantly influence both signal range and energy consumption.

The actual power consumption of the device depends on several factors:

- Measurement and transmission frequency
- Spreading factor (SF) used
- Environmental conditions (e.g., temperature)
- Enabled features such as retransmission or local data storage

Higher spreading factors (e.g., SF12) result in longer Time on Air (ToA) and thus higher energy usage per transmission. For instance, a single transmission at SF12 can consume up to 30 times more energy than one at SF7 (Muthanna et al., 2019). This trade-off between range and energy efficiency is a key consideration in LoRaWAN network design. (Khan et al., 2022)

To evaluate the real-world performance, we analyzed long-term data from deployed sensors and developed a battery life estimation model. This model accounts for the actual distribution of spreading factors and transmission intervals, allowing us to predict battery replacement cycles with high accuracy. Such predictive maintenance is essential for large-scale IoT deployments, where manual battery checks are impractical.

Description of the sensor deployment and data collection

The dataset used in this study was collected from four agricultural monitoring sensors deployed in the village of Kozinec (Prague-West district) between March 31, 2024, and November 19, 2024, resulting in a total of 154 MB of data.

These sensors continuously measured temperature and humidity in an open-field environment, providing a rich dataset for both environmental and technical analysis.

Due to the volume and fragmentation of the data across multiple files, it was necessary to consolidate and process the dataset using custom Python scripts. Python was chosen for its flexibility and efficiency in handling large-scale data processing, which is essential for extracting meaningful insights from IoT sensor networks (Zhang et al., 2022).

Key parameters in LoRaWAN message structure

Our dataset includes approximately 14 key parameters that characterize the signal transmission and reception process. These parameters are essential for evaluating the technical performance of the IoT network:

Transmission characteristics:

- **EUI:** A unique identifier of the device, used to distinguish which device sent the message.
- **Frequency:** The transmission frequency (e.g., 868.1 MHz), which also determines the frequency channel used.
- **Data Rate:** Includes the Spreading Factor (SF) and bandwidth, defining the speed and robustness of the transmission.
- **Time On Air (ToA):** The duration of the message transmission, directly affecting energy consumption.
- **Frame Counter:** A sequential counter of transmitted messages. It is crucial for detecting message loss, as missing values in the sequence indicate dropped packets.

Gateway reception parameters:

- **RSSI:** Received Signal Strength Indicator – measures the power level of the received signal.
- **SNR:** Signal-to-Noise Ratio – indicates the quality of the received signal relative to background noise.
- **Timestamp (ts):** The exact time the message was received by each gateway.
- **Gateway EUI (gweui):** A unique identifier of the receiving gateway.

Recent studies have emphasized the importance of understanding how signal transmission parameters—such as RSSI, SNR, and Time on Air—affect the battery life of sensor nodes. (Ghaderi

and Amiri, 2024) developed a comprehensive energy model for LoRaWAN sensor nodes, demonstrating that spreading factor selection and transmission frequency significantly influence energy efficiency and device longevity (Ghaderi and Amiri, 2024) Our work confirms these findings and further contributes by applying this analysis to real-world, long-term datasets collected from agricultural deployments.

Moreover, our approach aligns with the broader trend in IoT research that seeks to integrate signal diagnostics with predictive maintenance strategies. By correlating transmission parameters with battery consumption, we were able to construct a data-driven model for estimating device lifetime, which is essential for planning maintenance in large-scale sensor networks.

Unlike many simulation-based studies, our analysis is grounded in empirical data collected over several months from a real deployment. This allows us to validate theoretical models and provide practical insights into the operational behavior of LoRaWAN devices under varying environmental and network conditions (IEEE, 2021).

In summary, our work contributes to the growing body of literature that emphasizes the need for holistic performance evaluation in IoT systems—combining signal quality, energy modeling, and spatial analysis to support more efficient and sustainable deployments.

This work builds on the author's previous

publication **Experimental Evaluation of the Availability of LoRaWAN Frequency Channels in the Czech Republic** (Novák et al., 2021)

The following Table 1 illustrates the context and structure of the collected data, both from the perspective of the sensor device and the LoRaWAN gateways that received the transmitted messages. It provides an overview of the number of gateways that successfully received each message, offering insight into network coverage and redundancy.

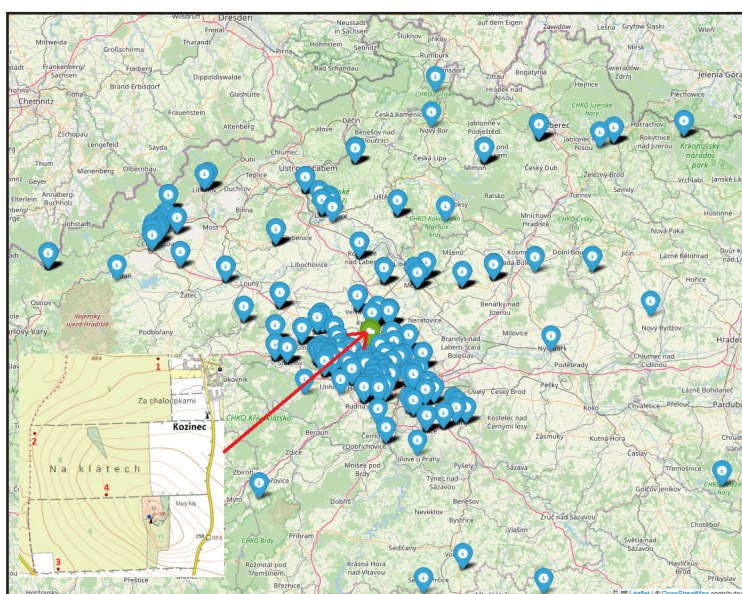
Map index	Sensor DevEUI:	Number of gates
1	24E124136C374657	80
2	24E124136C404199	65
4	24E124136C404741	108
3	24E124136C404764	81

Source: Authors

Table 1: Maximum number of gateways that have received messages from the sensor.

Additionally, a map of sensor locations (Figure 1) is included to show the spatial distribution of the deployed devices. This is followed by a map of all gateways that received the messages, which helps visualize the geographical reach and signal propagation within the LoRaWAN network.

These visualizations are essential for understanding the spatial dynamics of communication, identifying potential coverage gaps, and evaluating the performance of the network infrastructure.



Source: Authors

Figure 1: The positions of each gateway that received the message.

Methodology for calculating energy per transmission

To quantify the energy consumption of a single LoRaWAN transmission, we used a standardized calculation based on the device's electrical characteristics and the Time-on-Air (TOA) for each Spreading Factor (SF). The following steps outline the conversion from TOA to energy in micro-watt-hours (μWh):

Convert TOA from milliseconds to seconds:

$$t = \frac{TOA \text{ ms}}{1000} \quad (1)$$

Calculate energy in joules:

$$E_j = I \times V \times t \quad (2)$$

Convert joules to watt-hours:

$$E_{Wh} = \frac{E_j}{3600} \quad (3)$$

Convert watt-hours to micro-watt-hours:

$$E_{\mu Wh} = E_{Wh} \times 10^6 \quad (4)$$

Final combined formula:

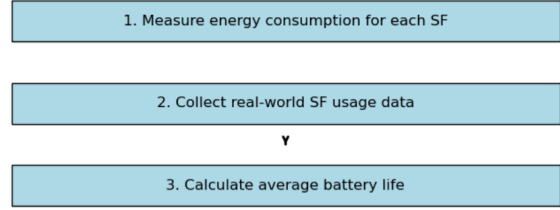
$$E_{\mu Wh} = \frac{I \times V \times TOA \text{ ms}}{3600 \cdot 1000} \times 10^6 \quad (5)$$

This formula was used to compute the energy cost per transmission for each SF, assuming a peak transmission current of 40 mA and a supply voltage of 3.3 V.

Results and discussion

The practical part of this study focuses on evaluating the energy efficiency of LoRaWAN communication based on the use of different Spreading Factors (SF). The goal is to understand how the choice and distribution of SFs in a real-world network affect the battery life of end devices and to identify opportunities for optimization.

To achieve this, we followed a structured analytical workflow, illustrated in Figure 2. The process begins with the measurement of energy consumption for individual SFs, followed by the collection of real-world transmission data from a deployed LoRaWAN network. These two datasets are then combined to calculate the weighted average battery life of a typical device. Finally, the results are interpreted to provide practical recommendations for improving energy efficiency through network design and adaptive data rate (ADR) strategies.



Source: Authors

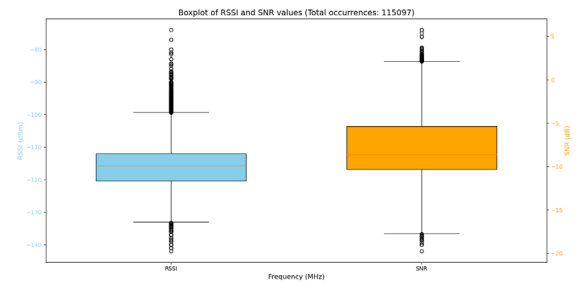
Figure 2: A structured analytical workflow.

RSSI and SNR across frequencies

We analyzed the average values of RSSI (Received Signal Strength Indicator) and SNR (Signal-to-Noise Ratio), see Figure 3, for various frequencies in LoRaWAN technology. The data was obtained from measurements conducted at frequencies ranging from 867.1 MHz to 868.5 MHz.

The highest average RSSI value was recorded at the frequency of 868.1 MHz with a value of -113.3 dBm. This frequency exhibits the best signal quality, which may be due to lower interference levels or better signal propagation conditions. Conversely, the lowest average RSSI value was recorded at the frequency of 867.9 MHz with a value of -118.548818 dBm, indicating a weaker signal at this frequency.

Regarding SNR, the highest average SNR value was recorded at the frequency of 867.3 MHz with a value of -7.1 dB. A higher SNR value indicates a lower noise level, which is positive for communication quality. On the other hand, the lowest average SNR value was recorded at the frequency of 867.5 MHz (red bar on Figure 4) with a value of -9.9 dB, indicating a higher noise level and potential issues with signal quality.



Source: Authors

Figure 3: Boxplot of RSSI and SNR values.

The frequency of 867.9 MHz was measured most frequently, which may indicate its significance in the network or higher usage in practical applications. Conversely, the frequency of 868.1 MHz was measured least frequently, which may indicate its lower usage.

A crucial element (that is currently missing) is a graph illustrating the number of received messages per specific frequency. Such a graph would provide valuable insight, as it would demonstrate that certain frequencies are subject to higher noise levels across most gateways. Consequently, signal reception on these frequencies is reduced, thereby limiting the effective range of the gateway on those specific channels.

This phenomenon is also reflected in the observed data, where the highest number of received messages occurred at 867.9 MHz, whereas the lowest number was recorded at 868.1 MHz. This discrepancy is not coincidental. End devices are designed to randomly alternate among the available frequencies. Therefore, with a sufficiently large dataset, one would expect the number of received messages to be evenly distributed across all eight operational frequencies. However, this is not the case in practice due to the heavy utilization of the 868 MHz band by other systems within the Czech Republic.

The presence of such external transmissions, or more precisely their associated energy in the radio spectrum, increases the noise floor during LoRaWAN signal reception - particularly on the side of LoRaWAN gateways, which are typically installed outdoors at elevated locations such as rooftops or telecommunications towers. The gateways' extended range comes at the cost of an elevated noise floor on certain frequencies. This is further evidenced by instances where a low signal-to-noise ratio (e.g., -15 dB) is accompanied by a relatively strong received signal strength indicator (e.g., -96 dBm).

Based on practical experience and long-term measurements, we have identified the following frequencies as particularly problematic in most locations:

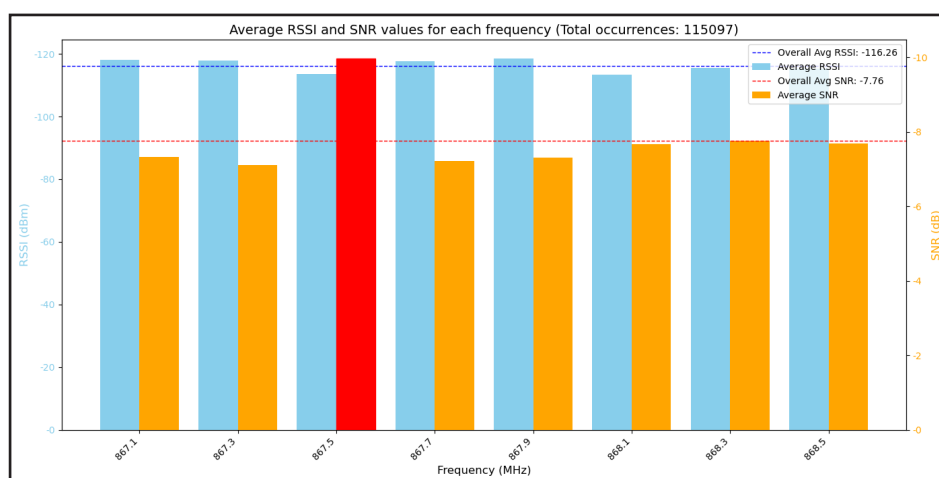
- 867.5 MHz: interference from UHF RFID systems
- 868.1, 868.3, and 868.5 MHz: interference from security systems and remote metering technologies operating on other wireless protocols

Conversely, the frequencies 867.1, 867.3, 867.7, and 867.9 MHz tend to be less affected by such interference. This correlates with a consistently higher number of successfully received messages by LoRaWAN gateways on these channels.

Overall, it can be said that the frequency of 868.1 MHz exhibits the best average RSSI value, indicating a stronger signal, while the frequency of 867.3 MHz exhibits the best average SNR value, indicating a lower noise level. These results can be useful for optimizing frequency planning in LoRaWAN technology and improving communication quality.

Distribution of transmission parameters across frequencies and data rates

Figure 5 presents a detailed breakdown of the number of transmissions observed across various frequency channels and data rate (DR) configurations in a deployed LoRaWAN network. Each DR corresponds to a specific Spreading Factor (SF) and bandwidth (BW), which directly influence the time-on-air (TOA) and energy consumption of each transmission.



Source: Authors

Figure 4: Average RSSI and SNR values for each frequency.

Figure 5 description:

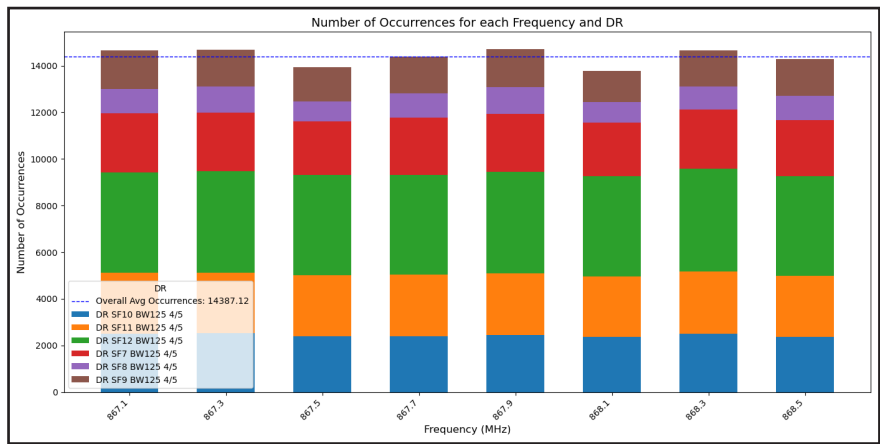
- The x-axis represents frequency channels in the 867.1–868.5 MHz range.
- Each bar is segmented by DR, with colors indicating different SFs (SF7 to SF12, all with BW125 and coding rate 4/5).
- A dashed blue line marks the average number of transmissions across all frequencies: 14,387.

This visualization reveals a non-uniform distribution of transmission activity. Higher SFs such as SF11 and SF12 dominate the traffic, particularly on certain frequencies. This suggests that many end devices operate at the edge of network coverage, where higher SFs are required to maintain connectivity. While this ensures reliable communication, it comes at the cost of significantly increased energy consumption and reduced battery life.

Energy consumption measurements: SF7 vs. SF12

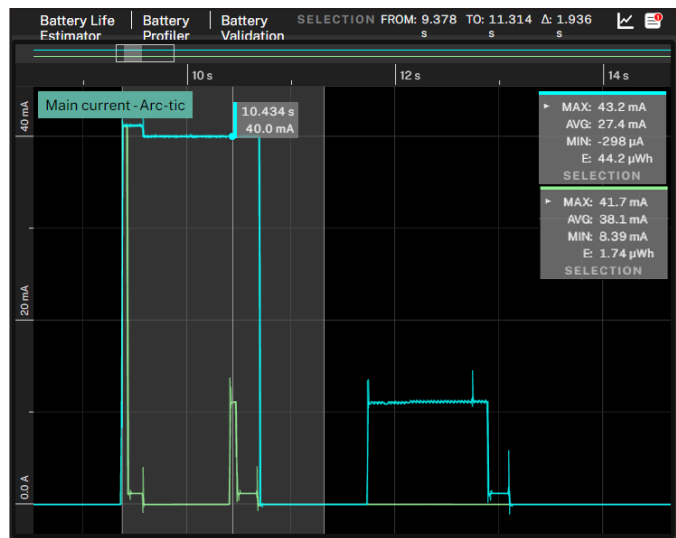
To further investigate the energy implications of different SFs, we conducted practical measurements of energy consumption for SF7 and SF12 transmissions. These measurements Figure 6 were obtained from an open-source dataset available on GitHub and are consistent with theoretical models.

The results confirm that SF12 transmissions are over 25 times more energy-intensive than SF7. This is primarily due to the exponential increase in TOA with higher SFs. In energy-constrained IoT applications, such as battery-powered sensors, this difference has a profound impact on device longevity.



Source: Authors

Figure 5: Number of occurrences for each frequency and DR.



Source: Authors

Figure 6: Measurements of energy consumption for SF7 and SF12 transmissions.

Battery life estimation based on sf usage

To quantify the impact of SF selection on battery life, we modeled the expected battery life of a typical LoRaWAN device (e.g., Milesight EM300-TH) under standardized conditions:

- Battery capacity: 4000 mAh (Li-SOCl₂)
- Peak transmission current: 40 mA
- Sleep current: 10 μA
- Transmission frequency: 144 messages/day (every 10 minutes)

Spreading Factor	Battery Life (days)	Battery Life (years)
SF7 BW125	3 997	10.95
SF8 BW125	3 236	8.87
SF9 BW125	2 415	6.62
SF10 BW125	1 542	4.22
SF11 BW125	894	2.45
SF12 BW125	511	1.40

Source: Authors

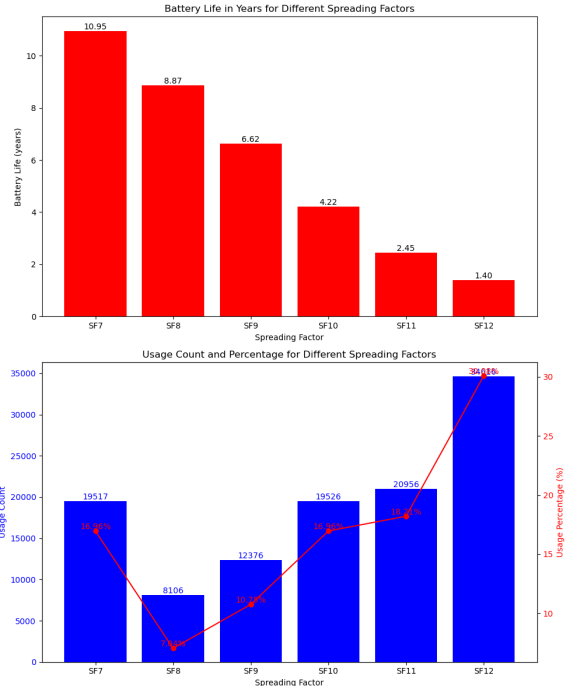
Table 2: Battery life estimation base on spreiding factor.

These values clearly demonstrate on Figure 8 the steep decline in battery life with increasing SF. While SF7 enables nearly 11 years of operation, SF12 reduces this to just over one year.

Figure 7 depicts the *battery life and usage distribution* across spreading factors in bar charts.

The *top chart* shows the estimated *battery life (in years)* for a LoRaWAN device using a single spreading factor (SF7 to SF12) under standardized conditions. Battery life decreases significantly with increasing SF, ranging from **10.95 years (SF7)** to **1.40 years (SF12)**.

The *bottom chart* displays the *real-world usage distribution* of spreading factors in a deployed network, both in *absolute counts and percentage share*. The most frequently used SF is **SF12 (30.06%)**, followed by **SF11 (18.21%)** and **SF10 (16.96%)**. Lower SFs, despite offering better energy efficiency, are used less frequently.



Source: Authors

Figure 7: Battery life and usage distribution across spreading factors.

Weighted average battery life based on real-world sf distribution

To assess the real-world impact of SF usage, we analyzed the distribution of transmissions across SFs in the deployed network:

Spreading Factor	Usage Share (%)
SF7	5.00
SF8	10.00
SF9	15.00
SF10	20.00
SF11	25.00
SF12	30.00

Source: Authors

Table 3: The distribution of transmissions across SFs in the deployed network.

Using this distribution, we computed the weighted average battery life:

Calculation results

- Weighted average daily consumption (transmissions only): 3.33 Wh = 3,325,468 μWh
- Total daily consumption (including 10 μA standby current): 4.05 Wh = 4,045,468 μWh

- Estimated battery life: 3,560 days \approx 9.75 years
- The device, under the given SF distribution and a 10-minute transmission interval, is expected to last nearly 10 years, which aligns with the manufacturer's specification.
- SF12, with a 30% occurrence rate, contributes the most to overall energy consumption – optimizing the ADR (Adaptive Data Rate) mechanism could further extend battery life.
- The continuous standby current of 10 μ A accounts for approximately 17% of the total daily energy consumption.

Weighted Battery Life =

$$= \frac{\sum (\text{Battery Life} \times \text{Usage Count})}{\text{Total Usage}} = 4.78 \text{ years}$$

This result highlights a critical insight: although low-SF transmissions are significantly more energy-efficient, their limited usage in the network leads to a substantial reduction in average device longevity.

Implications and recommendations

The findings presented in this section underscore the importance of adaptive data rate (ADR) strategies and network planning in LoRaWAN deployments. Key takeaways include:

High SF usage (SF11 and SF12) dominates network traffic, drastically reducing battery life.

Energy-efficient SFs (SF7–SF9) are underutilized, despite offering significantly longer operational lifespans.

ADR mechanisms should be actively employed to dynamically assign the lowest viable SF to each device, balancing coverage and energy efficiency.

Network topology optimization, including the strategic placement of gateways, can reduce the need for high-SF transmissions.

Given the high level of utilization of the 868 MHz band by other services and technologies, it is generally recommended to reduce the radio distance between the end device and the LoRaWAN gateway. However, this should be considered only as the first step toward improved performance. The second (and equally important) step involves the installation of LoRaWAN Pico Gateways (PicoGWs) in indoor environments located close to the end devices themselves.

The deployment of PicoGWs offers several

advantages: low initial costs, ease of installation, and most notably, reduced exposure to unwanted interference. This is because parasitic signals from the outdoor environment tend to penetrate indoor spaces to a significantly lesser extent, providing a natural shielding effect when the PicoGW is installed indoors.

While the effective range of a PicoGW is considerably smaller than that of a Macro Gateway (MacroGW), this limitation is more than compensated for by the improved signal reception across all eight communication channels - including the problematic frequencies previously mentioned (867.5, 868.1, 868.3, and 868.5 MHz).

By implementing these strategies, network operators can significantly extend the operational life of battery-powered devices, reduce maintenance costs, and improve the overall sustainability of IoT deployments.

Conclusion

This study provides a comprehensive analysis of the energy efficiency and usage patterns of LoRaWAN Spreading Factors (SF) in a real-world deployment. Through a combination of theoretical modeling, empirical measurements, and network data analysis, we have demonstrated the significant impact that SF selection has on device battery life and overall network energy efficiency.

Key findings include:

- **Battery life decreases exponentially** with increasing SF due to longer Time-on-Air and higher energy consumption per transmission.
- **SF12 and SF11**, despite being the most energy-intensive, are the most frequently used in the observed network, accounting for nearly **50% of all transmissions**.
- The **weighted average battery life** of a typical LoRaWAN device under real-world SF distribution is only **4.78 years**, compared to over **10 years** when using SF7 exclusively.
- **Energy consumption per transmission** increases from just **2.03 μ Wh** at SF7 to over **27 μ Wh** at SF11, and potentially more than **54 μ Wh** at SF12.

These results highlight the critical importance

of **Adaptive Data Rate (ADR)** mechanisms and **network optimization** strategies. By minimizing the use of high SFs where possible and improving gateway placement, network operators can significantly extend the operational lifespan of battery-powered devices, reduce maintenance costs, and enhance the sustainability of IoT deployments.

Future work may include dynamic SF allocation algorithms, real-time energy profiling, and integration of machine learning techniques to further optimize LoRaWAN performance in diverse deployment scenarios.

The results of this study demonstrate a method for predicting the battery life of devices utilizing LoRaWAN technology. This capability is crucial for predictive maintenance, as it enables efficient planning of service interventions and optimization of operational costs. Consequently, the proposed approach can have a significant economic impact, particularly in large-scale IoT deployments.

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Practical validation of the predicted battery lifespan in real-world conditions—due to the inherently long duration of such testing—will be time-consuming and represents an important direction for future research.

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Does International Food Assistance Reduce Food Insecurity in Developing Countries?

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Abstract

Food assistance is one of the international commitments to reduce food insecurity in developing countries, but only a few studies have explored its effectiveness, especially in across multiple countries. The purpose of this study is to examine the impact of international food assistance on food insecurity in developing countries. I analysed 2001–2021 data from 70 developing countries across Africa, Asia and Europe, Latin America and the Caribbean using the system General Method of Moment (sys-GMM). Our study indicates that international food assistance reduces food insecurity in Africa but has no impact on other regions. Government effectiveness and agricultural imports can help to minimise food insecurity in the study areas. Food inflation and age dependency ratios increase food insecurity in developing countries, whereas other variables have different effects among regions.

Keywords

Government effectiveness, agricultural import, food inflation, age dependency ratios.

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Introduction

The world is racing against time to achieve Goal 2 (zero hunger) by the 2030 SDGs. Unfortunately, these efforts have been hampered by a variety of global shocks, such as the economic crisis, war, political instability, disease pandemics, climate change, and others. Many places, particularly developing countries, were severely impacted by these shocks (Mulyo et al., 2023). Whereas developing countries will house most of the world's population in the future. Failure of developing countries to achieve food security will have disastrous consequences. For example, malnourished children receive less education than normal children, which has a negative social and economic impact in developing countries (Weisstaub et al., 2014).

In fact, each country has promoted various strategies and policies to eradicate food insecurity. Among these strategies and policies include increasing food production, maintaining stable food prices, encouraging smooth distribution, giving food aid and others. These efforts are also strengthened by international commitment through food trade, financial and food assistance and others (Jenkins et al., 2007; Li and Zhang, 2017).

One of our interests is international food assistance through the World Food Program (WFP) to help provide food for the hungry. Food assistance now also helps communities understand long-term nutritional needs and the varied techniques required to satisfy them. This includes not just emergency interventions, but also long-term assistance programs aimed at improving a country's nutritional indices and promoting general social well-being. WFP's malnutrition treatment and prevention programs reach more than 28 million people by 2022. During the same year, 20 million schoolchildren in 59 countries received nutritious school meals, take-home rations or snacks. More than US\$3 billion was given to people in 72 countries through cash or vouchers in 2022, a 42% increase over 2021 (World Food Programme, 2022).

The unanswered question is whether this program is effective in reducing food insecurity in developing countries? Furthermore, international food aid remains minimal, accounting for less than a quarter of 1% of global food production and only 1.9% of international commercial food trade (Lentz and Barrett, 2013). Hence, the purpose of this study is to examine the impact of international food assistance on food insecurity in developing

countries. Existing study indicates that international food aid has significantly improved food security in Africa (Li and Zhang, 2017). However, only a few studies have explored its effectiveness, especially in across multiple countries such as Asia, Europe, Latin America, and the Caribbean.

This study also includes several other variables since the theory suggests that food security is linked to other aspects. According to Neo-Malthusian theory, ecological factors frequently determine food security (Bongaarts, 1996). Techno-ecological theorists believe that technology can help manage food security (Simon, 1998). According to modernisation theory, least developed countries (LDCs) must transform their structural economy, including the shift from agriculture to industry and services (Todaro and Smith, 2020). International variables influencing food security are covered by dependency and global systems theory (McMichael, 1994). According to social stratification theory, stratification and inequality are key sociocultural elements influencing food security (Scanlan, 2003).

Material and methods

Data source

The time period data in this study are from 2001 until 2021 and the number of countries are from 70 developing countries (Table A1). The selection for a country to be considered as a developing country is based on the IMF criteria. There are 34 developing countries in Africa, 19 countries in Asia and Europe and 17 countries in Latin America and the Caribbean (LAC). The number of countries for each region varies based on the completeness of the data from each country.

Based on the purpose of this study, the dependent variable will be investigated and represent food insecurity: prevalence of undernourishment (Nugroho et al., 2022). Several explanatory variables, such as gross per capita cereal production index, agricultural import value index, food consumer price index, GNI per capita, capital stock at constant 2017 national prices per capita, human capital index, age dependency ratio, government effectiveness, agriculture shares of government expenditure, percent of arable land equipped for irrigation, and food and nutrition assistance per capita, are considered to influence the dependent variables (Table 1).

The explanatory variables in this study were selected based on previous literature studies. Gross per capita cereal production, agricultural import value, food consumer price, GNI per capita, human capital, government effectiveness, agricultural shares of government expenditure, and arable land equipped for irrigation can influence food insecurity in developing countries (Mulyo et al., 2023). Other variables that influence food insecurity include stock per capita (Svatoš et al., 2014), age dependency (George et al., 2020), and food and nutrition assistance per capita (Li and Zhang, 2017).

Data analysis

I will utilise the system GMM (sys-GMM) cause the GMM estimator has an inefficient instrument. If the sample size is limited (Arellano and Bond, 1991). In addition, our time period data are quite short (spanning only 2001 to 2021), so the use of the sys-GMM estimator may be unbiased. This method also helps us to overcome the possibility of sampling bias, autocorrelation, heteroscedasticity, and endogeneity (Rasheed et al., 2022).

Variable	Symbol	Source
Prevalence of undernourishment (%)	<i>PUN</i>	FAO
Gross per capita cereal production index (2014-2016 = 100)	<i>PROD</i>	FAO
Agricultural import value index (2014-2016 = 100)	<i>IMP</i>	FAO
Food consumer price index	<i>CPI</i>	World Bank
GNI per capita (current US\$)	<i>GNI</i>	World Bank
Capital stock at constant 2017 national prices per capita (million US\$)	<i>CAPP</i>	World Bank
Human capital index	<i>HCI</i>	Penn World Table
Age dependency ratio (% of working-age population)	<i>AGE</i>	World Bank
Government effectiveness	<i>EFF</i>	World Bank
Agriculture shares of government expenditure (%)	<i>EXP</i>	FAO
Percent of arable land equipped for irrigation (%)	<i>IRRI</i>	FAO
Food and nutrition assistance per capita (million US\$)	<i>ASSP</i>	FAO

Source: Authors identification, 2024

Table 1: Variable and data source.

The empirical analysis begins with Levin Lin Chu (LLC) unit root test to evaluate the stationarity of the variables:

$$\Delta Y_{it} = \alpha Y_{it-1} + \sum \beta_{it} \Delta Y_{it-j} + X_{it} \delta + v_{it} \quad (1)$$

Y_{it} is the pooled variable, X_{it} is an exogenous variable, v_{it} is the error term.

The function estimates the statistical relationship between the prevalence of undernourishment and the following explanatory variables:

$$PUN = f(\text{PROD, IMP, CPI, GNI, CAPP, HCI, AGE, EFF, EXP, IRRI, ASSP}) \quad (2)$$

Equation (2) can be re-written as a dynamic model

$$PUN_{it} = \beta_0 + \beta_1 PUN_{it-1} + \beta_2 PROD_{it} + \beta_3 IMP_{it} + \beta_4 CPI_{it} + \beta_5 GNI_{it} + \beta_6 CAPP_{it} + \beta_7 HCI_{it} + \beta_8 AGE_{it} + \beta_9 EFF_{it} + \beta_{10} EXP_{it} + \beta_{11} IRRI_{it} + \beta_{12} ASSP_{it} + \alpha_i + \eta_i + v_{it} \quad (3)$$

where: α_i is PUN time specific fixed effect, η_i is the country-specific effect, and v_{it} is the error term.

Because it is positively linked with η_i , the coefficient on the lagged dependent variable, β_1 , is likely to be biased higher. Thus, the sys-GMM estimators will be employed in this study and can be defined using as follows.

$$PUN_{it} = \beta_0 + \beta_1 PUN_{it-1} + \beta_2 PROD_{it} + \beta_3 IMP_{it} + \beta_4 CPI_{it} + \beta_5 GNI_{it} + \beta_6 CAPP_{it} + \beta_7 HCI_{it} + \beta_8 AGE_{it} + \beta_9 EFF_{it} + \beta_{10} EXP_{it} + \beta_{11} IRRI_{it} + \beta_{12} ASSP_{it} + \alpha_i + U_{it} \quad (4)$$

where U_{it} is the random term and $U_{it} = \eta_i + v_{it}$.

$$\Delta PUN_{it} = \beta_0 + \beta_1 \Delta PUN_{it-1} + \beta_2 \Delta PROD_{it} + \beta_3 \Delta IMP_{it} + \beta_4 \Delta CPI_{it} + \beta_5 \Delta GNI_{it} + \beta_6 \Delta CAPP_{it} + \beta_7 \Delta HCI_{it} + \beta_8 \Delta AGE_{it} + \beta_9 \Delta EFF_{it} + \beta_{10} \Delta EXP_{it} + \beta_{11} \Delta IRRI_{it} + \beta_{12} \Delta ASSP_{it} + \Delta U_{it} \quad (5)$$

Sys-GMM estimation is the estimate of the equations system in (4) and (5) utilizing two sets of instruments $Z_i = Z_D + Z_L$. Z_D is a model instrument in the first difference and Z_L is a model instrument at a level.

The first step of this study is to determine whether the residual data at the level are autocorrelated. The Arellano-Bond test is used for autocorrelation, given a null hypothesis of no autocorrelation. The second step is to test all instruments as a group for exogeneity, and Hansen and Sargan developed a test statistic with the null hypothesis that all instruments are exogenous or valid as a group. As a result, a higher statistical probability value for the test favors the null hypothesis (Sargan, 1958).

Results and discussion

According to Table 2, Africa has the highest average prevalence of undernourishment (PUN). Developing countries in Africa also have the highest average gross per capita cereal production (PROD), age dependency ratio (AGE), agricultural shares of government expenditure (EXP), and food and nutrition assistance per capita (ASSP) in comparison to Asia and Europe and Latin America and the Caribbean (LAC). Asia and Europe have the highest percentage of arable land equipped

Variable	Africa		Asia and Europe		Latin America and the Caribbean	
	Mean	Std. Deviation	Mean	Std. Deviation	Mean	Std. Deviation
PUN	20.90	12.72	13.30	8.75	13.29	10.47
PROD	103.94	37.62	96.03	25.00	97.66	20.36
IMP	78.99	37.21	75.86	41.40	81.57	39.00
CPI	33.14	392.95	7.63	8.38	180.56	2,236.55
GNI	1,342.51	1,382.42	1,982.63	1,614.19	5,028.54	3,467.87
CAPP	11.01	12.23	25.74	20.79	36.83	22.68
HCI	1.77	0.40	2.33	0.57	2.43	0.38
AGE	78.39	14.58	48.65	15.17	49.70	10.55
EFF	-0.76	0.49	-0.53	0.49	-0.49	0.52
EXP	4.28	3.66	3.71	2.32	2.32	1.55
IRRI	0.55	0.87	10.01	10.33	2.09	1.78
ASSP	0.00281	0.00346	0.00131	0.00363	0.00131	0.00240

Source: Authors identification, 2024

Table 2: Descriptive statistics

for irrigation (IRRI). Meanwhile, developing countries in LAC have the highest agricultural import value (IMP), food consumer price index (CPI), GNI per capita (GNI), capital stock per capita (CAPP), human capital index (HCI), and government effectiveness (EFF) compared to the other region.

The Levin Lin Chu (LLC) test shows that the IMP in Africa, Europe and Asia and LAC are not stationary at the level, requiring differentiation at the first level (Table 3). The EFF and ASSP variables in Europe and Asia and LAC must also be differentiated at the first level because they are not stationary at that level. Meanwhile, other variables in this study are stationary at level. Thus, the system GMM (sys-GMM) is very suitable to be applied in this study because several variables from each region remain stationary at the first difference.

The Arellano–Bond test results for AR(2) indicate that the null hypothesis is accepted and the analysis has no serial correlation (Table 4). At the same time, the Sargan test of overidentifying restriction revealed that the instruments in our model are relevant and valid. Overall, the specification tests show that sys-GMM estimations are reliable. The last test is to compare the lagPUN (PUNt-1) value in sys-GMM with the value of the same variable in the fixed effect model (FEM) and common effect model (CEM). The lagPUN value on sys-GMM (0.766) is higher than the lagPUN value on FEM (0.492) and lower than CEM (0.919) in the African region. Similar outcomes were seen in Asia and Europe, where

the lagPUN value on sys-GMM (0.631) was higher than the lagPUN value on FEM (0.545) and lower than CEM (0.939). The lagPUN value on sys-GMM at LAC (0.646) is higher than the lagPUN value on FEM (0.581) and lower than CEM (0.898). Hence, the model in this study is free from bias (endogeneity issue) and the sys-GMM can be used for further analysis.

The PUN (prevalence of undernourishment) in the previous year has had a positive effect on the current PUN change in Africa (0.766%), Asia and Europe (0.631%), and LAC (0.646%). PUN increases over time without external intervention to improve physical and economic food access. In the case of Africa, PUN is spreading and getting worse faster than in other continents, becoming a serious food crisis. The number of countries in Africa where a segment of the population suffers from hunger is rising, and hunger has spread from the west to the east (Conceição et al., 2016). Food security in LAC significantly decreased (from 51% to 43%), while an increase in moderate (13% to 16%) and severe (14% to 19%) food insecurity (Cuenca, 2021). Meanwhile, the Covid-19 pandemic has made the state of malnutrition in Asian developing countries worse (Ntambara and Chu, 2021).

Increasing food production (PROD) can reduce PUN (prevalence of undernourishment) in Asia and Europe (-0.028%) but the opposite happens in LAC (0.045%). PROD in Asia and Europe has the potential to decrease PUN by increasing food supplies. It has also been demonstrated that raising PROD raises people's income, which lowers PUN.

Symbol	Africa		Asia and Europe		Latin America and the Caribbean	
	Level	Sig.	Level	Sig.	Level	Sig.
PUN	At level	-4.223***	At level	-8.254***	At level	-6.405***
PROD	At level	-2.383**	At level	-2.170*	At level	-2.149*
IMP	1 st difference	-13.753***	1 st difference	-4.120***	1 st difference	-8.090***
CPI	At level	-12.043***	At level	-5.657***	At level	-7.255***
GNI	At level	-3.731***	At level	-2.114*	At level	-2.930***
CAPP	At level	-6.783***	At level	-5.766***	At level	-7.256***
HCI	At level	-7.274***	At level	-5.495***	At level	-4.600***
AGE	At level	-7.264***	At level	-6.642***	At level	-18.232***
EFF	At level	-2.528**	1 st difference	-5.602***	1 st difference	-6.009***
EXP	At level	-3.333***	At level	-3.093***	At level	-3.790***
IRRI	At level	-2.398**	At level	-4.359***	At level	-7.096***
ASSP	At level	-4.399***	1 st difference	-8.112***	1 st difference	-8.536***

Signif. codes: '****' 0.001 '***' 0.01 '**' 0.05
 Source: Authors computation, 2024

Table 3: Levin Lin Chu unit root test.

Variable	Africa		Asia and Europe		Latin America and the Caribbean	
	Coef.	Std. Error	Coef.	Std. Error	Coef.	Std. Error
PUN _(t-1)	0.766*** (15.188)	0.050	0.631* (1.896)	0.333	0.6461* (2.206)	0.293
PROD	-0.002ns (-0.211)	0.011	-0.028* (-2.306)	0.012	0.045** (2.696)	0.016
IMP	-0.052*** (-4.547)	0.011	-0.063*** (-7.648)	0.008	-0.039*** (-4.075)	0.010
CPI	-0.0002ns (-0.690)	0.0003	0.107*** (3.298)	0.036	0.0003* (2.337)	0.0001
GNI	-0.0016* (-2.165)	0.0007	-0.00046ns (-0.178)	0.0025	-0.0009*** (-5.632)	0.0001
CAPP	-0.238ns (-1.216)	0.196	0.740ns (1.193)	0.620	0.045ns (1.620)	0.027
HCI	0.554*** (4.358)	0.127	0.149*** (7.231)	0.021	-2.660* (-1.849)	1.439
AGE	0.103* (2.225)	0.049	0.277*** (9.850)	0.028	-0.028ns (-0.537)	0.052
EFF	-8.598*** (-8.795)	0.978	-1.391* (-1.725)	0.806	-7.029*** (-7.782)	0.903
EXP	-0.453*** (-3.810)	0.119	0.133ns (0.409)	0.324	1.135*** (4.727)	0.240
IRRI	-0.141ns (-0.256)	0.554	-0.046ns (-1.574)	0.029	0.401* (2.072)	0.194
ASSP	-0.003* (-2.261)	0.001	-0.009ns (-1.064)	0.009	0.0005ns (0.053)	0.010
Arellano–Bond test for AR (1)		-0.1816		-0.1602		-0.1731
Arellano–Bond test for AR (2)		-0.1307		-0.1186		-0.1242
Sargan test		25.002		6.563		3.202
Prob. Sargan test		0.350ns		0.476ns		0.669ns

Signif. codes: '***' 0.01 '**' 0.05 '*' 0.1 'ns' 1

Source: Authors computation, 2024

Table 4: Determinant factors of food insecurity in developing countries.

Meanwhile, PROD in LAC is unable to reduce PUN for several reasons. First, food access limitations, particularly social and economic. For instance, there are areas of extreme absolute poverty in Brazil, which puts the country at risk for malnutrition. Political instability has left Haiti's population undernourished, and it has the worst economy on the LAC. The second is a lack of technology and infrastructure for processing, packaging, storage, and transportation. Third, the global food and biofuel markets require more PROD in LAC than is needed domestically (Nugroho et al., 2022).

Food imports (IMP) have the potential to lower PUN (prevalence of undernourishment) in the three locations studied: Africa (-0.052%), Asia and Europe (-0.063%), and LAC (-0.039%). The population will have more food available because of IMP. For instance, Namibia, Senegal,

Gambia, Mozambique, Kenya, Sierra Leone, and South Africa had the lowest PUN in Africa from 2012 to 2018 because of imports. Imported food generally reduces malnutrition in Africa by 15% (Beltran-Pea et al., 2020). In general, global food trade increased global food security from 9% to 17% from 1961–2019 and it is vital to preserve the global food system's security in extreme events. IMP can also be used as a country's food reserve if there is severe food scarcity due to force majeure (Guo et al., 2021).

The rise in the food consumer price index (CPI) is one of the reasons for the rise in PUN (prevalence of undernourishment) throughout Asia & Europe (0.107%) and LAC (0.0003%). People in low and lower-middle-income economies have less disposable money for stocking up on food. Hence, rising CPI will negatively affect human well-being

and food security by slowing the rise of food demand (Nugroho et al., 2022). High CPI also has a negative influence on household nutritional status, particularly among the poor, because it reduces purchasing power and pushes individuals to purchase cheaper and lower quality food options (Ogunniyi et al., 2020). This demonstrates that an increase in the CPI worsens economic access to marketed products and exacerbates food insecurity across developing countries in Asia and Europe and LAC (Erokhin and Gao, 2020).

Increases in GNI per capita can lower PUN (prevalence of undernourishment) in Africa (-0.0016%) and LAC (-0.0009%) but have no significant impact in Asia & Europe. The population uses a high GNI to purchase food and increase per capita calorie and nutrient consumption. Moreover, countries with high GNI can put in place several policies to increase food supply and social protection, assisting underprivileged populations in avoiding food insecurity (Nugroho et al., 2022). Meanwhile, consumers will become more concerned about the possible food crisis, pricing, safety and security, nutrition, and food quality as their income loss. They are impoverished and unable to purchase adequate food for a healthy diet (Rabbi et al., 2021).

Increasing capital stock per capita (CAPP) does not affect PUN (prevalence of undernourishment) in Africa, Asia & Europe, and LAC. CAPP has the potential to stimulate economic growth, open employment opportunities, increase the size of agricultural and arable areas, boost agricultural production and efficiency, develop agricultural modernisation, and build infrastructure, hence improving people's access to food. CAPP also helps to develop food businesses and infrastructure, thereby boosting a country's food supply and security. However, because not all CAPPs are in the agricultural sector, the change will not influence PUN (Svatoš et al., 2014).

Human capital (HCI) has increased PUN (prevalence of undernourishment) in Africa (0.554%) and Asia & Europe (0.149%) and had the opposite impact on LAC (-2.660%). HCI will be able to expand agricultural research and development, improve the management of agricultural resources, empower rural areas, and provide more possibilities for generating money to provide food security and lower PUN. People with low levels of education will suffer food security challenges when there is a shock in real income. In addition, women's education is particularly crucial since it will improve their capacity to comprehend and provide wholesome meals

for their families (Li and Zhang, 2017; Nugroho et al., 2022). However, it should be noted that HCI in developing countries is still not distributed and is largely concentrated in urban areas or among wealthy people. As a result, strengthening HCI in Africa and Asia & Europe will not help reduce food insecurity.

The age dependence ratio (AGE) has increased PUN (prevalence of undernourishment) in Africa (0.103%) and Asia & Europe (0.277%) but has not affected LAC. An individual classified as AGE typically lacks both productivity, employment, and income. This may result in a person having to (1) consume fewer and less desirable items; (2) restrict the type of foods they eat; and (3) limit portion sizes on more days (George et al., 2020). In addition, a country will use marginal land to fulfill food needs and intensify land use. However, this will harm land use and food security because reduces soil quality and lower agricultural yields. AGE also impedes the pace of economic modernization because the young population is still uninterested in using it for employment, while the elderly population is slow to learn new technology (Jenkins and Scanlan, 2001).

Improved government effectiveness (EFF) has decreased PUN (prevalence of undernourishment) in all three research areas: Africa (-8.598%), Asia and Europe (-1.391%) and LAC (-7.029%). The lack of regulation, initiative, and coordination of food systems on different levels demonstrates government ineffectiveness in achieving nutritional food adequacy for its citizens. Government ineffectiveness has also led to inequality in access to natural resources and inputs and services such as seeds, fertilizer or credit severely limiting agricultural productivity. This has hampered inclusive and just food systems in developing countries (Mazenda, 2021). Hence, EFF will promote efficient public services, policy development, and government programs to increase output in both the agricultural and non-agricultural sectors, ensure efficient use of state resources, raise economic growth, and subsequently food and nutritional security levels. EFF can also help individuals acquire access to land and other productive assets, earn a living, and feed themselves and their families, thereby reducing food insecurity (Ogunniyi et al., 2020).

Agriculture shares of government expenditure (EXP) increase PUN (prevalence of undernourishment) in LAC (1.135%) while decreasing it in Africa (-0.453%). The increase in EXP has stimulated economic growth and labor productivity, which produces income for purchasing food.

The government in Africa also uses this EXP to build infrastructure and food support systems that will boost food production and distribution (Susilastuti, 2017). EXP allocation is highly dependent on EFF, hence Africa with low EFF cannot properly allocate EXP and is unable to lower PUN.

Irrigation (IRRI) can increase PUN (prevalence of undernourishment) in LAC (0.401%) and has no impact on Africa and Asia and Europe. Expanding IRRI is critical in developing countries for increasing agricultural yield, land productivity, farmer profit, and value added. IRRI is also a beneficial reaction to growing concerns about food insecurity, water scarcity, climatic challenges, soil salinity and groundwater which can disrupt food security. However, IRRI in developing countries is frequently inefficient, resulting in suboptimal agricultural cultivation that fails to help lower PUN (Calzadilla et al., 2013).

Food assistance per capita (ASSP) was only able to lower PUN (prevalence of undernourishment) in Africa (-0.003%) but had no significant impact in Asia & Europe and LAC. It is no surprise that ASS focuses on Africa because this region is the center of PUN. Without IMP or ASSP, the PUN in Africa may be 15% higher (Li and Zhang, 2017). ASSP enhances food supply while decreasing PUN because it compensates for long-term food supply disruptions caused by many African countries' economic, social, and political crises. Furthermore, the ASSP has made a substantial contribution to the cessation of interstate wars, military state spending and gender discrimination (Jenkins et al., 2007). Even so, ASSP remains ineffective in Asia & Europe and LAC since it does not reach all target populations. ASSP is focused on interventions for school-age children or adult populations, yet it continues to underfund early childhood. Aside from that, the government in this region has offered domestic food aid, therefore ASSP's role is minimal (Lentz and Barrett, 2013).

Conclusion

Food assistance can reduce food insecurity in African developing countries but does not

have a significant impact on other regions. This finding is good news because Africa has the most food-insecure people. On the other hand, food assistance mechanisms throughout Asia and Africa, as well as Latin America and the Caribbean, must be improved. Meanwhile, the most effective way to combat food insecurity is driving the government to be more effective. Similarly, agricultural imports can help developing countries minimise food insecurity. Food inflation and the age dependency ratios contribute to increased food insecurity in developing countries, whereas other variables have different effects among regions.

In general, the findings of this study support the theory of food security, which holds that government intervention and foreign help are required to eliminate food insecurity. This can be seen from food assistance, food imports, and government effectiveness which are able to reduce food insecurity in developing countries. I also recommend the following: First, continuing foreign food assistance while improving its procedures. This program must be bottom-up, prioritising the aspirations of the target group due to disparities in the community's social, economic, and demographic factors. Second, increasing the effectiveness of government performance in developing countries. This can be done by increasing the professionalism of public services, the quality of policy formulation, the government's commitment to policy implementation, and the community's independence from political pressure. Third, maintaining economic stability through policies to allow proportional entry of food imports, control food price fluctuations and create jobs. Fourth, equalling education distribution so that individuals can innovate and use technologies to increase productivity and food access.

This study has two main limitations, namely measuring food insecurity using the prevalence of undernourishment and the short study period. I recommend using alternative indicators, such as the Global Food Security Index or others. Future research should also employ a study duration of at least 30 years to ensure the validity of the analysis results.

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Appendix

Africa		Asia and Europe	Latin America and the Caribbean
1. Algeria	18. Malawi	1. Albania	1. Argentina
2. Angola	19. Mali	2. Armenia	2. Bolivia
3. Benin	20. Mauritania	3. Bangladesh	3. Brazil
4. Burkina Faso	21. Morocco	4. Cambodia	4. Colombia
5. Cameroon	22. Mozambique	5. India	5. Dominican Republic
6. Central Africa	23. Namibia	6. Indonesia	6. Ecuador
7. Congo	24. Niger	7. Iran	7. El Salvador
8. Côte d'Ivoire	25. Nigeria	8. Kirgizstan	8. Guatemala
9. Democratic Republic of the Congo	26. Rwanda	9. Lao PDR	9. Haiti
10. Egypt	27. Senegal	10. Mongolia	10. Honduras
11. Ethiopia	28. Sierra Leone	11. Myanmar	11. Jamaica
12. Gambia	29. South Africa	12. Nepal	12. Mexico
13. Ghana	30. Togo	13. Pakistan	13. Nicaragua
14. Kenya	31. Uganda	14. Philippines	14. Panama
15. Lesotho	32. United Republic of Tanzania	15. Sri Lanka	15. Paraguay
16. Liberia	33. Zambia	16. Tajikistan	16. Peru
17. Madagascar	34. Zimbabwe	17. Thailand	17. Venezuela
		18. Vietnam	
		19. Yemen	

Source: Authors

Table A1: Determinant factors of food insecurity in developing countries.

Determinants of Working Capital Management of Companies in Agriculture in the Czech Republic

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Abstract

The aim of the article is to evaluate determinants of working capital investment policy of companies in agriculture in the Czech Republic from 2013 to 2022. The aim of this article is to identify the main determinants that influence the management of working capital in agricultural enterprises in the Czech Republic and to analyze how these factors affect the operational efficiency and financial stability of these enterprises from 2013 to 2022. Comparative analysis, Granger causality test and generalized method of moments (GMM method) will be used to identify the determinants of working capital. The data base includes 2 516 enterprises operating in agriculture in the Czech Republic. The results showed that the agricultural sector has a relaxed investment policy with a high share of inventories, while in recent years there has been a positive improvement in the effectiveness of working capital management. This policy is significantly influenced by company size, growth opportunities and capital structure. The improvement in return on assets and equity contributed to better financial stability. Companies can optimize their investment policy and improve financial results through better analysis of these factors.

Keywords

Assets structure, capital structure, GMM method, growth opportunities, return on equity, size of the company, working capital investment policy.

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Introduction

The working capital management of the company is a system of the short-term decisions relating to financing and investment (Farooq et al., 2023). Thus, it is connected with optimization of the inventories volume and providing the sources of their funding (both account payable and bank credit) as well as establishing the payment discipline of the company regarding buyers and suppliers. Such day-to-day operations include ordering and delivery of supplies, production and sales processes, and combine both current assets and liabilities. Therefore, the working capital management can be considered as efficient, when company avoids excessive working capital investments and at the same time, secures their liquidity (Nastiti et al., 2019).

Due to the fact that working capital management includes different aspects of company's activity, too many factors influence it. The researchers define them at the microlevel, for example, size of the company and capital structure (Jaworski

and Czerwonka, 2022), growth opportunities and capital expenditures (Nastiti et al., 2019), profitability (Korent and Orsag, 2022), industrial level – size, leverage, cash conversion cycle of peer firms or median indicator throughout the industry (Jaworski and Czerwonka, 2022; Farooq, 2023; Mättö and Niskanen, 2021) and macrolevel – GDP, unemployment, consumer price index (Jaworski and Czerwonka, 2022; Nastiti et al., 2019; Korent and Orsag, 2022; Farooq, 2023) etc., and reveal different character of their influence for specific country or economic sphere.

As Zimon (2020) defines, working capital management demands from personal solving of repetitive everyday operations from purchase and optimization of raw materials to sale of finished goods and establishing the payment discipline. The latter is associated with the balancing between the payment delay to buyers and necessity of timely cash inflows in order to cover own current liabilities of the firm. Taking into account, that managing these components should be continued without interruption (Zimon and Zimon,

2020), it demands the flexibility and mobility from the financial management.

Moreover, so far as WCM includes both gross working capital (current assets) and net working capital (current assets – current liabilities) (Farooq, 2023), the company should pay attention to their surplus and shortage. In case of surplus of working capital, company can meet unnecessary costs but provides financial security. And vice versa, reducing the level of working capital can lead to insolvency (Zimon, 2020). Thus, in order to provide the sales and satisfy the customers, company influences its profitability, which should always be balanced with its liquidity, and as a result – its financial health. Existing researches reveal lots of endogenous and exogenous factors, influencing differently on the working capital management (WCM) within specific spheres of economic activities or countries. Determining the character of their impact on the material production sector of Czech Republic is important in order to prevent or at least reduce possible negative effect for domestic economy.

The internal factors influence working capital management (WCM) of the company on the micro level. They can be chosen by the firm, like its size, or can characterize the activity of the company and somehow be under its control, for example, the volume of cash flow, indebtedness, tangibility etc.

The size of the company is usually defined as natural logarithm (ln) of total assets (Jaworski and Czerwonka, 2022) or natural logarithm of sales income (Korent and Orsag, 2022). Usually, scale effect of large company increases the turnover of different elements of current assets, which decreases working capital investments. Such business entity due to the size can be allowed more flexible credit policy, that along with access to different financial resources can lead to reduction of cash conversion cycle and improving of working capital management (WCM).

Firm growth opportunities are determined as rate of sales change (Nastiti et al., 2019; Reyad et al., 2022) or natural logarithm of relationship between annual revenue and revenue of the previous year (Sharma et al., 2020). The character of influence of such factor is contradictory. Increasing sales can provoke growing volume of inventories and accounts receivable in order to satisfy the buyers. However, if latter elements will grow faster, than sales, their turnover can lengthen, that will negatively influence cash conversion cycle.

Next factor, which influence is analysed in different manuscript, is tangibility as a share of fixed assets

in total assets (Czerwonka and Jaworski, 2023; Mielcarz, et al., 2018). In this case, company often faces the trade-off effect, choosing between buying the current assets or allocating financial resources to capital investments, which explains possible negative relationship among tangibility and working capital management (WCM).

working capital management (WCM) is connected to daily operations, which should be provided financially. In case of high-leveraged firm, attraction of additional resources can be problematic due to constraints. There are several variants of leverage factor determining. Thus, the indebtedness can be found as total debts-to-total assets ratio (Jaworski and Czerwonka, 2022) or as the ratio of non-current liabilities to total assets (Mättö and Niskanen, 2020) or the ratio of short-term debt (short-term bank credit) to total assets (Afrifa et al., 2022).

Scientists reveal the role of cash flow factor in working capital management (WCM), using the share of operating cash flow into the total assets (Nastiti et al., 2019) or share of net profit with depreciation and amortization in the total assets (Jaworski and Czerwonka, 2022).

Different indicators of profitability are also taken into account, exploring the influence on working capital, from the ratio of net profit (or gross operating profit or EBIT (Earnings Before Interest and Taxes) (Farooq et al., 2023) to assets up to return on equity (Korent and Orsag, 2022). The character of influence of cash flow and profitability factors on working capital management in most cases is positive. If company is profitable and generates sufficient operating cash flow, it is a consequence of improved credit policy of the buyers. Accumulating internal resources increases the independence of the firm from external financing, that provides the liquidity.

Jaworski and Czerwonka (2022) revealed positive effect of the company's size and negative effect of its growth, tangibility and indebtedness on working capital management of European energy industry. Moreover, increasing of cash flow is followed by the lengthening of cash conversion cycle (CCC) and reducing of liquidity.

Research of Indonesian manufacturing enterprises, made by Nastiti et al. (2019), demonstrates, that sales growth shortens the cash cycle and higher leverage, on the contrary, lengthens it. The scientists do not find any difference in condition of working capital management, depending from the size of investigated Indonesian manufacturing enterprises.

The results of Korent and Orsag (2022) indicate that working capital management in the previous year, profitability, and financial constraints significantly positively impact working capital cycles of manufacturing, trade, and information and communication companies in Croatia. In contrast, there is a negative influence of size, growth and fixed investment on cash conversion cycle and the net trade cycle, making working capital management as more aggressive.

Provided results Sharma et al., (2020) prove, that tangibility, leverage, nature of business are observed as significant factors to forecast the future requirements of net working capital of companies, listed with the Bombay Stock Exchange, and presented in various industries. Return on common equity (ROCE), board size; indicate the positive association with gross working capital. On the other hand, tangibility, nature of business and size of the firm show a negative relationship with gross working capital requirements.

Afrifa et al. (2022) find, that larger European firms are more efficient with their working capital management than smaller firms, sales growth potential decrease working capital efficiency, which, in turn, increases with access to bank credit.

Within the activity of small and medium enterprises in Central and Eastern Europe company size exerts a positive impact, while company growth, tangibility, leverage, and cash flow have a negative effect on working capital management (Czerwonka and Jaworski, 2023).

Concentrating attention on corporations in emerging economy, Mielcarz et al. (2018) reveal, that the capital expenditures and working capital investments compete with each other for limited financial resources. So, companies are often forced to choose between modernization of the fixed assets and daily providing of current operating activity. Additionally, authors document a persistently negative impact of capital expenditures on the dynamics of cash holdings and trade payables.

Working capital management is a key element of financial management in all sectors, but it plays an even more crucial role in agriculture. Agricultural enterprises in the Czech Republic face specific challenges associated with a high level of seasonality, fluctuating income, variability of market demand and, last but not least, unpredictable weather fluctuations. Working capital, which includes inventories, receivables, short-term liabilities and other short-term assets and liabilities,

must be managed with these variable factors in mind. Optimizing working capital is therefore a crucial tool that allows agricultural enterprises to ensure smooth operations, stabilize cash flow and minimize the risk of financial distress. In the agricultural sector in the Czech Republic, working capital management is influenced by both internal factors (such as the structure of production, the length of the production cycle or the efficiency of supply) and external factors, such as government support and subsidies, developments in global commodity markets and access to bank financing. Government subsidies per hectare of land and agricultural commodity price indicators—such as the agricultural producer price index or the prices of individual products (grain, milk, meat)—are key external factors that can significantly influence corporate decisions regarding working capital investment. These variables reflect broader macroeconomic and market conditions that are not directly controllable by the enterprises themselves but have a crucial impact on their cash flow, production planning, and investment strategies. Given the agricultural sector's sensitivity to price fluctuations and policy measures, government support and price signals serve as important determinants of financial management.

Given the small or medium size of many agricultural enterprises in the Czech Republic and their limited access to external financing, working capital management often becomes a question of long-term sustainability and resilience of the enterprise to market and natural fluctuations.

Although the issue of working capital management has been the subject of numerous studies across various economic sectors, existing research has predominantly focused on industrial and commercial enterprises. In contrast, agriculture remains relatively neglected in this regard, despite its significant economic importance and unique characteristics. Agricultural enterprises face pronounced seasonality, dependence on natural factors, long production cycles, and a specific structure of assets and liabilities. These factors make working capital management in agriculture particularly challenging and require an approach tailored to the sector's conditions.

In the context of the Czech Republic, there exists a significant research gap in terms of a deeper understanding of the determinants of working capital investment policy in agricultural enterprises. There is a lack of comprehensive knowledge regarding which business-related factors most strongly influence working capital management,

how these factors have evolved over time, and what impact they have on working capital investment policy. Moreover, systematic empirical analysis of working capital in Czech agricultural enterprises is still missing—particularly in relation to firm size, growth potential, and capital structure.

This research gap is significant not only from a theoretical perspective but also in terms of practical implications. Without a clear understanding of the specific determinants, it is not possible to effectively design strategies for liquidity management, development, or support of this key sector. For this reason, the primary aim of this study is to identify and analyze the key firm-level determinants of working capital management in agricultural enterprises in the Czech Republic during the period 2013–2022. The study focuses on assessing the impact of factors such as firm size, growth opportunities, profitability, and capital structure on the level of investment in working capital and its efficient utilization.

To achieve this goal, the study employs comparative analysis, the Granger causality test, and the Generalized Method of Moments (GMM). These approaches allow for the identification of relationships between variables, as well as the analysis of their direction and strength over time. The dataset includes 2,516 agricultural enterprises operating in the Czech Republic, providing a robust foundation for drawing generalizable conclusions. The findings of this study can contribute not only to the theoretical development of financial management in agriculture but also serve as a practical tool for managers and business owners seeking to optimize their investment policies and enhance financial stability. The results may also prove valuable for policymakers focused on rural development and the agricultural sector.

This study responds to the identified research gap and aims to address the following main research question and related sub-questions:

- What corporate factors determine working capital management in agricultural enterprises in the Czech Republic?
 - What is the impact of firm size on working capital investment policy?
 - What is the impact of growth opportunities on working capital investment policy?
 - What is the impact of asset structure on working capital investment policy?
 - What is the impact of capital structure on working capital investment policy?

- What is the impact of return on assets on working capital investment policy?
- What is the impact of return on equity on working capital investment policy?

Materials and methods

This study investigates the determinants of working capital management in the agricultural sector of the Czech Republic during the period 2013–2022 using various analytical methods. To compare differences between firms and identify key characteristics influencing working capital management, a comparative analysis was conducted, employing median values to ensure a more robust comparison across enterprises.

To determine the directionality of relationships between variables, the Granger causality test was applied, allowing an assessment of whether one time series can predict the development of another. For the estimation of model parameters, the Generalized Method of Moments (GMM) was subsequently used, providing an effective solution to problems of endogeneity and heteroskedasticity commonly present in panel data. All calculations and econometric modeling were performed using EViews 10 software.

The data used in this research were drawn from the Orbis database, specifically from the unconsolidated financial statements of agricultural enterprises in the Czech Republic. Primarily, balance sheet and income statement data were utilized, with extracted financial variables including current assets, current liabilities, sales, fixed assets, total assets, net profit, and equity.

From these variables, indicators used in the models were calculated: Working Capital Investment Policy (WCIP), Size of the Company (SOC), Growth Opportunities (GO), Asset Structure (tangibility) (AS), Capital Structure (indebtedness) (CS), Return on Assets (ROA), and Return on Equity (ROE). The calculation of these indicators is presented in Table 1.

Additionally, two control variables reflecting external macroeconomic and institutional factors were included in the model: government subsidies per hectare of land and the agricultural producer price index. Government subsidies per hectare represent the level of support provided to agricultural entities by the public sector. The agricultural producer price index serves as an aggregated indicator of agricultural commodity price developments, allowing for the consideration

Variables	Calculation	Variable type
Working capital investment policy (WCIP)	$(\text{current assets} - \text{current liabilities}) / \text{sales}$	Dependent variable
Working capital investment policy (WCIP)	$(\text{current assets} - \text{current liabilities}) / \text{sales}$	Independent variable
Size of the company (SOC)	$\ln(\text{total assets})$	
Growth opportunities (GO)	$(\text{sales}_t - \text{sales}_{t-1}) / \text{sales}_{t-1}$	
Asset structure (tangibility) (AS)	$\text{fixed assets} / \text{total assets}$	
Capital structure (indebtedness) (CS)	$\text{current liabilities} / \text{total assets}$	
Return on assets (ROA)	$\text{net profit} / \text{total assets}$	
Return on equity (ROE)	$\text{net profit} / \text{total equity}$	
Government subsidies per hectare of land (SUB)	reflecting the institutional support of agriculture	Control variables
Agricultural producer price index (APPI)	aggregates the price trends of agricultural commodities and accounts for external price shocks	

Source: Own processing

Table 1: Description of used variables.

of the impact of external price shocks. Including these variables in the model enabled a more precise identification of the external environment's impact on working capital management and helped mitigate the risk of endogeneity in the estimates. These data were sourced from the Czech Statistical Office and the Ministry of Agriculture of the Czech Republic.

The dataset consists of panel data from 2,516 agricultural enterprises. The companies were stratified by size, and only medium, large, and very large enterprises were included in the final sample. This was done to eliminate differences in accounting practices and working capital management strategies typical of small family farms.

Table 1 indicates the description of the used variables in this research. This table includes variables such as working capital investment policy, size of the company, growth opportunities, asset structure (tangibility), capital structure (indebtedness), return on assets and return on equity.

Current Assets include inventories, receivables, cash, and other short-term assets that can be converted into cash within one year. Current Liabilities represent obligations due within one year, such as payables to suppliers, short-term loans, and tax liabilities. Fixed Assets include buildings, equipment, land, technology, and other assets with a useful life exceeding one year. Total Assets represent the sum of current and long-term assets. Net Profit represents profit after tax. Total Equity includes share capital, reserve funds, retained earnings, and similar items. Sales refers to the reported figure corresponding to "total sales," i.e., total revenues from products, services,

and goods as recorded in the income statement. Due to the nature of agricultural enterprises, this is an aggregate indicator without further breakdown by type of revenue.

Working capital is a key element in maintaining liquidity and operating efficiently for a company. The importance of variables such as company size, growth opportunities, asset structure, capital structure, return on assets, and return on equity are reflected in various aspects of working capital management.

Larger companies typically have larger amounts of working capital, which allows them to better manage their operating needs and weather seasonal fluctuations in demand. A company's size can also affect its ability to obtain credit and optimize supplier relationships, which are key to working capital management.

Companies with high growth opportunities often need more working capital to finance expansion, new product development, and market share expansion. Growth opportunities can lead to the need to invest in inventory and accounts receivable, which can affect liquidity and overall working capital management.

A higher proportion of tangible assets to a company's total assets often means that it can more easily secure financing through collateral. Tangible assets such as machinery and real estate can be used to secure loans, which improves a company's ability to manage working capital and respond to liquidity needs.

Higher levels of debt can affect a company's liquidity, as debt and interest payments can limit

available working capital. On the other hand, proper management of the capital structure can ensure that there are sufficient funds for operating activities and working capital investments.

Return on assets (ROA) shows how efficiently a company uses its assets to generate profit. A higher ROA indicates that a company is able to manage its working capital effectively and minimize waste, contributing to better financial stability and the ability to meet short-term obligations. Net profit (EAT) was used for this indicator for several reasons. In agriculture, government subsidies and tax benefits play a significant role and have a direct impact on the final profit (EAT). Using EAT thus better captures the true economic effect on the return on assets, accounting for all actual income and expenses, including taxes. Since the GMM model and the discussion include control variables such as government subsidies and commodity prices, which also affect net profit after tax, it was methodologically more consistent to use EAT. In models, where capital structure is included as a separate variable, using EAT is acceptable because the effect of interest expenses is captured elsewhere. EBIT is preferred where the debt structure is not explicitly controlled for.

Return on equity (ROE) is a key indicator for investors, as it shows how efficiently a company generates profits for shareholders. A high ROE can indicate that a company is successfully managing its working capital and is able to generate high returns on investments, which strengthens investor confidence and access to additional financing.

Each of these variables plays an important role in working capital management and affects a company's ability to maintain liquidity and operate efficiently. Proper analysis of these factors is key to strategic planning and optimization of working capital within a company.

Granger causality test helps to determine whether one time series or variable can be considered a predictor of another time series or variable. In this research, Granger causality test can be used to identify determinants that can influence working capital investment policy. Using Granger causality test, it is possible to determine whether determinants of working capital can predict or influence working capital management (working capital investment policy) of enterprises operating in agriculture in the Czech Republic. The following equations can be used to apply Granger causality test:

$$\Delta Y_t = \beta_0 + \sum_{i=1}^{\sigma} \beta_{1i} \Delta Y_{t-i} + \sum_{i=1}^{\gamma} \beta_{2i} \Delta X_{t-1} + \varepsilon_{1t} \quad (1)$$

$$\Delta X_t = \varphi_0 + \sum_{i=1}^{\gamma} \varphi_{1i} \Delta X_{t-i} + \sum_{i=1}^{\gamma} \varphi_{2i} \Delta Y_{t-1} + \varepsilon_{2t} \quad (2)$$

Y_t represents working capital investment policy, X_t represents determinants of working capital investment policy such as size of the company, growth opportunities, assets and capital structure (tangibility and indebtedness), return on assets and return on equity. Two important control variables are also included in the model: government subsidies per hectare of land and the agricultural producer price index, which account for the macroeconomic context and support for agriculture. β_0, φ_0 jsou konstantní členy, $\beta_{1i}, \beta_{2i}, \varphi_{1i}, \varphi_{2i}$ jsou koeficienty odvozené z modelu, $\varepsilon_{1t}, \varepsilon_{2t}$ jsou náhodné složky.

The Generalized Method of Moments (GMM method) is a statistical technique used to estimate the parameters of economic and statistical models. It is based on the theory of moments, where it is assumed that certain moments should correspond to empirical data. The main goal of the GMM method is to minimize the differences between the theoretical and empirical moments, which allows for efficient and robust estimation even in the presence of heteroskedasticity or endogeneity.

To ensure the explanatory power of the obtained results, all variables will be tested for statistical significance at 1%, 5%, and 10% significance levels. Additionally, the robustness of the model will be validated using the Sargan/Hansen J-test. The model is considered robust if the results of the Sargan/Hansen test exceed 0.05. The following equation can be used to find the determinants of working capital of companies in Agriculture in the Czech Republic.

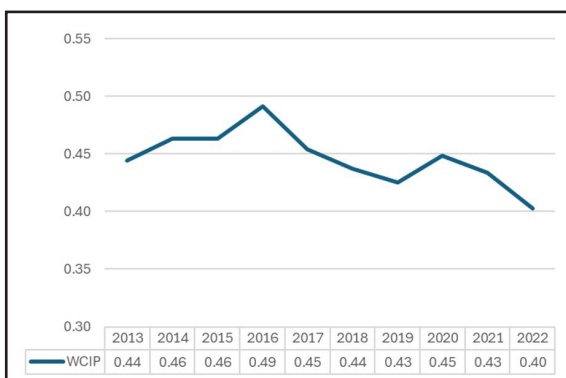
$$WCIP_{it} = \alpha_1 + \beta_1 * \Delta WCIP_{i,t-1} + \beta_2 * X_{1it} + \beta_3 * X_{2it} + \dots + \beta_n * X_{nit} + \varepsilon_{it} \quad (3)$$

The dependent variable $WCIP_{it}$ represents the working capital investment policy in Agriculture in the Czech Republic at time t , $WCIP_{i,t-1}$ is a lagged dependent variable, X_{nit} represents size of the company, growth opportunities, assets and capital structure (tangibility and indebtedness), return on assets and return on equity. The model also incorporates two important control variables: government subsidies per hectare of land and the agricultural producer price index, which reflect the macroeconomic context and support for the agricultural sector. β_0 and ε_t is the model constant and the residual component of the model.

Results and discussion

Within this part of the article, you can find the results of the comparison method, Granger causality test and GMM method, including the evaluation of the achieved or found results. Median values of the individual variables were used for the comparative analysis and the subsequent graphs.

Figure 1 illustrates the development of the working capital to sales ratio (WCIP), a key indicator of companies' financial strategy in managing short-term assets and liabilities. This ratio is calculated as the difference between current assets and current liabilities divided by sales, allowing for monitoring how intensively companies invest in working capital relative to their performance.



Notes: The x-axis represents the individual years for which the data are analyzed, the y-axis shows the development of the working capital investment policy indicator as a ratio variable

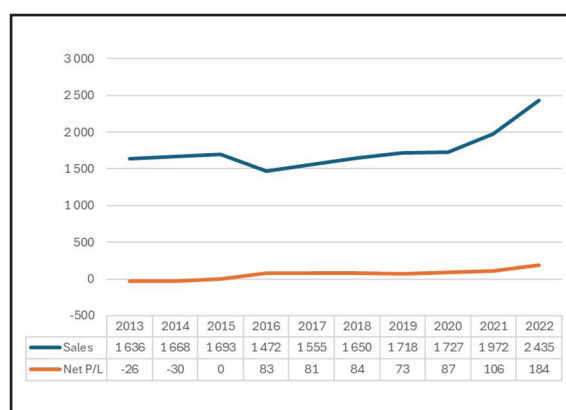
Source: Own processing based on data from the Orbis database

Figure 1: Development of working capital investment policy in Agriculture in the Czech Republic for the period 2013 to 2022 (ratio variable).

During the analyzed period, WCIP increased from 0.44 in 2013 to 0.49 in 2016, which may indicate a more expansive working capital policy associated, for example, with company size growth (SOC) or higher return on assets (ROA). However, since 2016, the ratio has gradually declined, with a slight fluctuation in 2020, reaching 0.40 in 2022. This trend may reflect an increasing share of fixed assets (AS), rising indebtedness (CS), or limited growth opportunities (GO), leading companies to adopt a more restrictive approach to working capital management. The trend also reflects the impact of external economic conditions such as subsidy policies, market uncertainties, and commodity price fluctuations. Overall, the graph highlights the dynamic nature of WCIP and underscores the importance of its

management in relation to the internal and external determinants identified in the study.

Figure 2 depicts the development of sales and net profit/loss (Net P/L) in the agricultural sector in the Czech Republic during the years 2013 to 2022. Sales in the sector show a gradual increase with a slight decline in 2016, followed by stabilization and a significant rise in 2021 and 2022. While sales amounted to 1,636 million CZK in 2013, they reached 2,435 million CZK in 2022, representing an increase of nearly 49% over the observed period. This trend signals growing production capacity in the sector or favorable developments in agricultural product prices.



Notes: The x-axis represents the individual years for which the data are analyzed, the y-axis shows the development of revenue and net P/L in absolute values in million CZK (median)

Source: Own processing based on data from the Orbis database

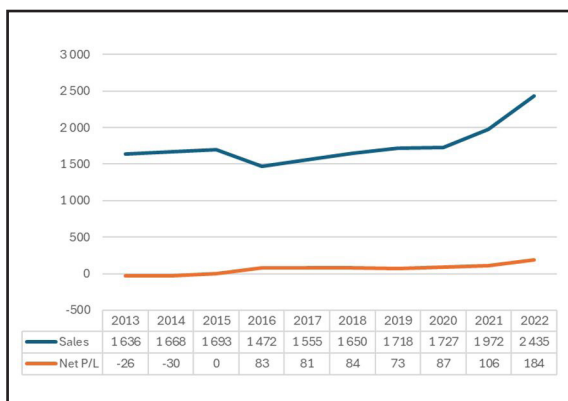
Figure 2: Development of growth opportunities in Agriculture in the Czech Republic for the period 2013 to 2022 (in mil. CZK).

The net profit/loss trend shows a positive turnaround after loss-making years in 2013 and 2014. From 2015 onward, Net P/L stabilizes in positive territory, with notably higher profits recorded in the last three years, peaking at 184 million CZK in 2022. This development may result from more efficient management, optimization of cost structures, or increased mechanization and technological innovations. At the same time, lower profits in years with rising sales (e.g., 2018) may indicate higher working capital requirements or volatility in input costs.

Overall, the graph reveals a positive growth trend and improved financial performance of the agricultural sector during the period, although a certain degree of volatility typical of the primary sector remains evident. These findings can contribute to a deeper understanding of the dynamics of growth opportunities and financial stability in agriculture and serve

as input for the development of appropriate policies in agricultural financing.

Figure 3 presents the development of the rate of sales growth in agriculture in the Czech Republic for the period 2013 to 2022. The growth rate exhibits significant volatility, with low or negative values prevailing in the first half of the period (2013–2016), which may be related to unstable market conditions in the agricultural sector, including commodity price fluctuations and climatic impacts.



Notes: The x-axis represents the individual years for which the data are tracked, the y-axis shows the percentage change in the rate of sales growth

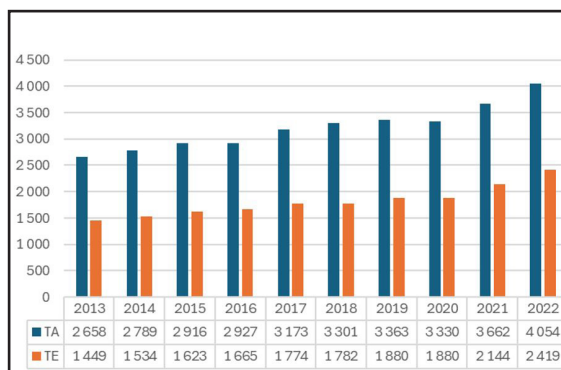
Source: Own processing based on data from the Orbis database

Figure 3: Development of rate of sales growth in Agriculture in the Czech Republic for the period 2013 to 2022 (in %).

In 2017, there was a temporary increase (11.29%), followed by a renewed decline and stagnation during 2018–2020, when growth was again suppressed (e.g., -0.83% in 2020), likely influenced by the COVID-19 pandemic. Conversely, the years 2021 and 2022 show a marked improvement with growth rates of 14.28% and 25.63%, respectively, indicating a renewed growth potential in the sector. These results support the article’s conclusions about the positive development in the efficiency of working capital management in recent years and suggest that growth opportunities, which are among the key determinants of working capital investment policy, have played a significant role in improving the financial stability of agricultural enterprises.

Figure 4 presents the development of the size of companies in agriculture in the Czech Republic for the period 2013 to 2022. The development of total assets and equity during 2013–2022 shows a stable upward trend, which accelerates particularly in 2021 and 2022. The value of assets increased from CZK 2,658 million in 2013 to CZK 4,054 million in 2022, while equity grew

from CZK 1,449 million to CZK 2,419 million. This growth indicates an improving asset structure of companies and strengthening financial stability of the sector. The increasing value of equity may also reflect better company management, positive developments in profitability indicators (e.g., ROA and ROE), and a more responsible approach to financing.



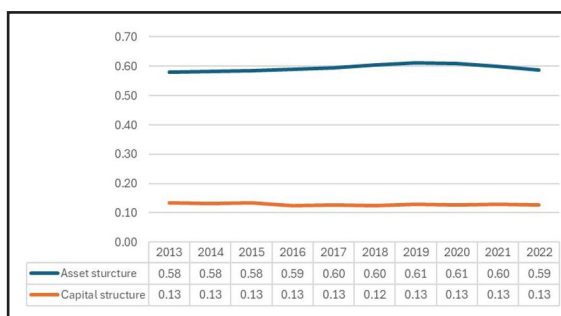
Notes: TA = total assets, TE = total equity, the x-axis represents the individual years for which the data are analyzed, the y-axis represents total assets and total equity in absolute values in million CZK (median)

Source: Own processing based on data from the Orbis database

Figure 4: Development of size of the company in Agriculture in the Czech Republic for the period 2013 to 2022 (in milion CZK).

The cumulative growth of these variables may also result from more efficient working capital management, supporting the claim that effective WCIP contributes to the long-term stability and development of agricultural enterprises in the Czech Republic.

Figure 5 represents the development of asset structure and capital structure in agriculture in the Czech Republic for the period 2013 to 2022.



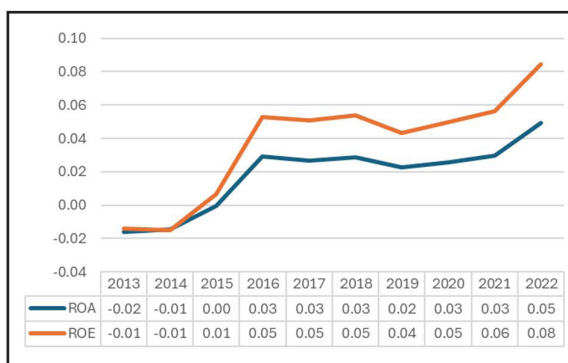
Notes: The x-axis represents the individual years for which the data are analyzed, the y-axis shows the development of the ratio variables asset structure and capital structure

Source: Own processing based on data from the Orbis database

Figure 5: Development of assets structure and capital structure in Agriculture in the Czech Republic for the period 2013 to 2022 (ratio variable).

The asset and capital structure of agricultural enterprises remained relatively stable during 2013–2022. The proportion of fixed assets to total assets ranged between 0.58 and 0.61, with the highest value recorded in 2019 (0.61), followed by a slight decline to 0.59 in 2022. This stability indicates consistent investment behavior by companies in long-term assets. The capital structure hovered around 0.13 throughout the observed period, reflecting a relatively low level of indebtedness and a conservative financial policy. This consistent development may signal that the sector’s financial stability is supported by a sustainably maintained capital structure and that the chosen investment policy shows no significant fluctuations, which aligns with the "relaxed investment policy" characteristic mentioned in the abstract. Such stability creates conditions for increasing profitability and efficiency in working capital management over the long term.

Figure 6 represents development of ROA and ROE in Agriculture in the Czech Republic for the period 2013 to 2022. The dynamics of ROA and ROE is similar so far as rate of assets and equity growth is the same. Unlike other sectors of material production, the agriculture has low level of profitability as well as losses in 2013 and 2014. Still, ROA and ROE increase and as of 2022 respectively are 5% and 8%.



Notes: The x-axis represents the individual years for which the data are analyzed, the y-axis shows the development of the ratio variables ROA and ROE
Source: Own processing based on data from the Orbis database

Figure 6: Development of ROA and ROE in Agriculture in the Czech Republic for the period 2013 to 2022 (ratio variable).

However, there is no evidently close connection between profitability and WCM. Thus, during 2013-2016 growing working capital-to-sales ratio was accompanied by rising of financial results from loss 26 th. Euro in 2013 to net profit 83 th. Euro in 2016. From 2020 to 2022 tendency was opposite so far as improving of WCM through

faster turnover of current assets also brought to increasing of ROA and ROE, respectively from 3% to 5% and from 5% to 8%.

Table 2 presents the results of the Granger causality test. The results of the Granger causality test reveal causal relationships between the analyzed variables and the working capital investment policy (WCIP).

Granger causality test	F-Statistic	Probability
SOC \Rightarrow WCIP	23.2459	1e-6*
WCIP \Rightarrow SOC	3.10948	0.0779***
GOP \Rightarrow WCIP	13.9502	0.0002*
AS \Rightarrow WCIP	22.7520	2e-6*
WCIP \Rightarrow AS	28.6127	9e-8*
CS \Rightarrow WCIP	152.120	1e-34*
WCIP \Rightarrow CS	218.688	5e-49*
ROA \Rightarrow WCIP	32.2328	1e-8*
WCIP \Rightarrow ROA	39.7218	3e-10*
WCIP \Rightarrow ROE	151.905	1e-34*

Notes: * = 1% statistical significance, ** = 5% statistical significance, *** = 10% statistical significance
Source: Own processing

Table 2: Results of the Granger causality test between the analyzed variables.

The results of the Granger causality test indicate that there is a relationship between working capital investment policy (WCIP) and size of companies (SOC). Based on these results, it can be concluded that company size has a statistically significant causal effect on working capital investment policy, which suggests that changes in company size can predict changes in WCIP. Conversely, WCIP does not have a statistically significant effect on company size (SOC), although there is a weak indication of a relationship. Furthermore, the results indicate that growth opportunities (GOP) have a significant effect on WCIP. Thus, GOP can predict changes in working capital investment policy (WCIP). Furthermore, it was found that asset structure (AS) is a significant factor influencing WCIP, which suggests that changes in asset structure can predict changes in working capital investment policy. The results also show that WCIP also influences asset structure (AS), which means that there is a mutual causality between WCIP and asset structure. Another variable analyzed was the capital structure (CS) in relation to the working capital investment policy (WCIP). The results indicate a two-way relationship between the above-mentioned variables. Capital structure has a strong causal effect on WCIP, i.e. the company's debt is a significant factor influencing the working capital investment policy and vice versa. Furthermore,

a two-way relationship was demonstrated between return on assets (ROA) and WCIP. On the contrary, only a one-way relationship was found between WCIP and return on equity (ROE). The results show that WCIP has a strong causal effect on return on equity (ROE).

The tests suggest that there is significant causality between working capital investment policy and most of the factors analyzed, with some relationships being bidirectional (e.g. WCIP and asset structure or WCIP and capital structure). These results underscore the importance of these variables for effective working capital management, as changes in them can lead to adjustments in WCIP and vice versa. The Granger causality test first helps determine whether causal relationships exist between the examined variables. If these relationships do exist, the GMM method is then used to more accurately model these relationships and to eliminate potential distortion caused by endogeneity. Table 3 presents the results of the GMM method.

The results of the GMM estimation provide a comprehensive view of the factors influencing working capital policy (WCIP) in the agricultural sector of the Czech Republic.

The lagged value of WCIP exhibits a strong and statistically significant positive effect (coefficient = 0.30, $p = 0.001$), indicating that working capital decisions have strong dynamics and past policy significantly influences current firm behavior. This result is consistent with the findings of García-Teruel and Martínez-Solano (2007), who emphasize the persistence of working capital

in firms. It also highlights that firm management often maintains a consistent approach to managing liquidity and short-term assets. These findings correspond with recent studies, such as Vučković et al. (2017), who stress that agricultural enterprises exhibit high persistence in working capital management due to production seasonality and the risky nature of the sector. Similarly, research by Yıldız et al. (2023) confirms that persistent working capital management strategies in agricultural firms are driven by transaction costs and the specific liquidity needs associated with production cycles.

The size of the company (SOC) also has a positive effect (coefficient = 0.11, $p = 0.001$). According to Baños-Caballero et al. (2012), larger firms have better financing options, improved access to loans, and more sophisticated financial instruments. Consistent with the findings of Dalci et al. (2019), larger companies also have a greater ability to efficiently manage inventories and receivables, which enhances their capacity to maintain higher levels of working capital. Similar conclusions were confirmed by Mardones (2021) and Khan et al. (2024), who highlight that larger agricultural enterprises have better access to bank financing and thus are better able to manage inventories and receivables. They also emphasize the superior financial capacity of larger agricultural entities, which leads to greater working capital holdings.

Growth opportunities (GO) show a negative relationship (coefficient = -0.05, $p = 0.005$), which corresponds to the findings of Deloof (2003). Firms with high growth potential tend to minimize

Variable	Coefficient in relation to WCIP	Probability	Studies
Lagged WCIP	0.30	0.001	García-Teruel and Martínez-Solano (2007), Yıldız et al. (2023)
Size of the company (SOC)	0.11	0.001	Baños-Caballero et al. (2014), Dalci et al. (2019)
Growth opportunities (GO)	-0.05	0.005	Deloof (2003), Shakila and Mohiuddin (2021)
Asset structure (tangibility) (AS)	-0.28	0.001	Nazir and Afza (2009), Baños-Caballero et al. (2014)
Capital structure (indebtedness) (CS)	-0.25	0.001	Qiao (2023), Myers (2001)
Return on assets (ROA)	0.19	0.004	Jamalinesari and Soheili (2015), Nazir and Afza (2009)
Return on equity (ROE)	-0.16	0.015	Baños-Caballero et al. (2014), Nazir and Afza (2009)
Government subsidies per hectare of land (Subsidy)	0.09	0.020	Latruffe (2010), Banga (2016)
Agricultural producer price index (AgriPriceIndex)	0.07	0.030	Galko and Jayet (2011), Latruffe (2010)
J-statistic	25.84		

Source: Own processing

Table 3: Results of the GMM method between the analyzed variables .

inventories and other components of working capital in order to invest more in development and expansion. During growth periods, companies tend to adopt a strategy aimed at minimizing working capital. This negative relationship between growth opportunities and working capital reflects a resource optimization strategy focused on capital investments, as noted in the recent meta-analysis by Shakila and Mohiuddin (2021), which confirms that firms with high growth potential often reduce inventories and short-term receivables to free up resources for fixed investments. This phenomenon is particularly prominent in the agricultural sector, where investments in technology and land are key for long-term growth (Harkness et al., 2021). The results are also consistent with the pecking order theory (Myers & Majluf, 1984) in the modern agricultural context.

The negative coefficients for asset structure (AS) (-0.28, $p = 0.001$) and capital structure (CS) (-0.25, $p = 0.001$) indicate that a higher share of fixed assets and greater indebtedness reduce liquid assets, which aligns with the theories of Nazir and Afza (2009) and Myers (2001). Higher debt levels often mean a limited ability for firms to maintain large inventories or extend trade credit. The negative impact of a high proportion of fixed assets and leverage on working capital is also supported by Flannery and Öztekin (2024), who showed that firms with large volumes of fixed investments have less flexibility in managing liquidity, leading to reduced working capital. This finding is further corroborated by the study by Qiao (2023), which analyzed the impact of capital structure in agricultural firms and emphasized the constraints imposed by high leverage in working capital management.

In terms of profitability, the results confirm that return on assets (ROA) shows a positive effect (coefficient = 0.19, $p = 0.004$), meaning that efficient use of assets supports higher working capital, as it enhances the firm's capacity to maintain liquidity. This is consistent with the findings of Jamalinesari and Soheili (2015), who observed that effective asset utilization contributes to a greater ability to hold working capital.

On the other hand, return on equity (ROE) has a slightly negative effect (coefficient = -0.16, $p = 0.015$), which may suggest that firms with high financial efficiency tend to reduce the need to hold large reserves of working capital (Baños-Caballero et al., 2014). This negative influence may indicate that firms with higher ROE optimize short-term assets and liabilities to improve financial efficiency.

Similar conclusions were drawn by Alvarez et al. (2021).

Government subsidies per hectare of land and the agricultural producer price index were included as control variables. Both variables show a statistically significant positive effect (subsidies: coefficient = 0.09, $p = 0.020$; price index: coefficient = 0.07, $p = 0.030$). This confirms the conclusions of Latruffe (2010) and Banga (2016), who found that government subsidies improve the financial health and liquidity of agricultural enterprises, enabling them to maintain higher levels of working capital.

The significant positive effect of government subsidies per hectare of land on working capital investment policy is consistent with the findings of Kumbhakar et al. (2023), who showed that subsidies improve liquidity and allow for higher working capital levels, which is crucial in agriculture for managing seasonal fluctuations. This aligns with the conclusions of Latruffe (2010) and Banga (2016), who found that government subsidies improve the financial health and liquidity of agricultural enterprises, enabling them to maintain higher levels of working capital.

The agricultural producer price index, as an indicator of market conditions, also shows a significant effect. This is supported by a recent study by Galko and Jayet (2011), which shows that rising commodity prices increase the available financial resources of agricultural businesses and enhance their liquidity.

The Sargan/Hansen test confirms the robustness of the model used in this analysis. All results were tested at the 1% significance level (probability = 0.0000). The test statistic value of 25.84 indicates model robustness when checking for over-identifying restrictions, confirming the correctness of the model specification.

Compared to recent studies, the results of this research are consistent with the general trend of findings that working capital management in agriculture is influenced by both internal firm factors (such as size, asset structure, and growth opportunities) and external forces (such as government support and commodity prices). Studies like Yıldız et al. (2023), Khan et al. (2024), and Kumbhakar et al. (2023) support the conclusion that a comprehensive approach to financial resource management is essential to maintain the competitiveness of agricultural enterprises.

An important contribution of this study is the confirmation of the significance of government subsidies and price indices as control variables, which were not always explicitly included in previous research (see Flannery and Öztekin, 2024; Galko and Jayet, 2011).

Conclusion

This article examined the key determinants of working capital in Czech agriculture in the years 2013 to 2022 and analyzed their impact on the efficiency and stability of enterprises. The comparison method was used to compare different entities and identify key characteristics affecting working capital management. To determine the causal relationships between variables, the Granger causality test was applied, which helps to identify whether one time series can predict the values of the other. Furthermore, the GMM (Generalized Method of Moments) method was used to estimate the model parameters, which allowed to take into account endogeneity and heteroskedasticity in the data. All analyses were performed on the basis of annual data obtained from the Orbis database, which provided a robust basis for examining the dynamics of working capital in Czech agriculture. Most of the analyses were performed using the Eviews 10 program. 2 516 enterprises operating in agriculture in the Czech Republic were included in the research.

Working capital management in agricultural enterprises in the Czech Republic during the years 2013–2022 exhibits a variable but generally positive trend in the second half of the period. There is an improvement in efficiency and stabilization of key indicators, with the ratio of working capital to sales (WCIP) slightly declining after 2016. Conversely, improvements in return on assets (ROA) and return on equity (ROE), along with increasing equity, indicate higher quality of management. The development of sales and profit confirms growing production capacity and better financial performance of the sector, although the sector remains sensitive to external shocks, reflected in higher volatility. A stable asset structure and conservative capital structure support long-term financial stability and suggest a sustainable investment approach.

Results of the Granger causality test indicate that firm size (SOC) has a statistically significant causal effect on working capital investment policy (WCIP), meaning that changes in firm size predict changes in working capital management. Growth opportunities (GOP) also significantly

influence WCIP, with firms possessing higher growth potential tending to reduce working capital to enable greater investment in development. Asset structure (AS) and capital structure (CS) are additional significant factors affecting WCIP, with bidirectional causality observed between WCIP and both AS and CS. WCIP has a strong positive effect on return on equity (ROE), whereas the reverse effect is less pronounced.

The results of the GMM method provide a more detailed insight into the factors influencing working capital policy in the agricultural sector. The lagged value of WCIP shows a strong and statistically significant positive effect, indicating that working capital decisions exhibit high persistence and past policies significantly influence current firm behavior. Firm size (SOC) also has a positive impact on WCIP, which aligns with the view that larger firms have better access to financing and more efficiently manage inventories and receivables. Conversely, growth opportunities (GO) exhibit a negative relationship with WCIP — firms with greater growth potential tend to minimize working capital to free up resources for investment. Asset structure (AS) and capital structure (CS) have negative coefficients, meaning that a higher share of fixed assets and greater indebtedness reduce liquid assets and thus working capital. This phenomenon can be explained by the limited ability of firms to hold inventories or offer trade credits when facing high debt levels and fixed investments.

In terms of profitability, return on assets (ROA) has a positive influence on WCIP, while return on equity (ROE) has a slightly negative effect, suggesting that firms with higher financial efficiency optimize their short-term assets and liabilities. Two control variables, government subsidies per hectare and the agricultural producer price index, were included, both showing a statistically significant positive impact on WCIP. Subsidies improve the liquidity of agricultural enterprises, enabling them to maintain a higher level of working capital and better manage seasonal fluctuations. Rising prices of agricultural products increase the value of inventories and working capital, which is consistent with recent research highlighting the positive impact of commodity prices on the financial health of agricultural firms. Statistical tests (Sargan/Hansen) confirmed the robustness of the model.

The study thus demonstrates that effective working capital management in agriculture requires a comprehensive approach that reflects both the internal characteristics of enterprises

and external macroeconomic and institutional conditions. Unlike more general studies, this article includes not only standard internal factors (such as firm size, asset structure, and profitability) but also significant external variables, especially government subsidies and agricultural commodity prices, enabling a more detailed analysis of the influences on financial stability and liquidity of agricultural enterprises. For the scientific community, it contributes by extending the methodological framework and emphasizing the specifics of the agricultural sector, opening avenues for further research, for example, through the use of advanced causal analysis techniques or segmentation by firm size.

Among the main limitations of the study are its restricted geographic scope limited to the Czech sector, the exclusion of some macroeconomic factors (e.g., inflation, interest rates), and the fact that the applied Granger causality test does not imply true causation, highlighting the need for further research employing more advanced methods.

For policymakers, the study offers concrete recommendations on how to optimize agricultural support: focus on targeted subsidy programs that respond to market and seasonal conditions, promote the growth of medium and larger enterprises to enhance their financial resilience, and integrate macroeconomic indicators into the planning

and evaluation of interventions.

Stakeholders, especially farmers and managers of agricultural enterprises, gain guidance for strategic working capital management with regard to seasonal fluctuations and external financing sources, optimizing capital structure, and maximizing the use of available subsidies.

Future research should expand the geographic and data scope, introduce more detailed segmentation of enterprises, and utilize advanced causal analysis techniques (e.g., impulse response analysis, network analysis) to better understand the complex interactions between internal and external factors and provide even more relevant practical recommendations.

Overall, the study emphasizes the importance of integrated financial management that links internal factors with external macroeconomic influences and government support as a key tool for sustainable and efficient working capital management in agriculture.

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Social Impacts, Capacity and Awareness on the Intention to Participate in the Digitalization of e-Agriculture on e-Commerce Platforms: A Case Study of Durian Households in Tien Giang Province, Vietnam

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Abstract

The study provides a new perspective for the entire investigation, providing an overview of the theoretical implications related to behavior, participation intent, and the digitization of e-agriculture on e-commerce platforms. In addition, the main point is the approach of durian farmers specifically in Tien Giang province, about the intention to participate in e-agriculture. This study presents relevant factors that have an impact on the intention to participate in e-agriculture, specifically durian farmers. From the actual situation of agriculture in the Mekong Delta, typically Tien Giang province. Especially the theoretical of agriculture, e-agriculture and the intention to participate in e-agriculture on the e-commerce platform, an empirical approach in Tien Giang province, Vietnam. The model proposes factors including Social Impact for Agriculture, Adaptive Capacity, Agriculture Awareness, Digitalizations of e-agriculture, e-agriculture on e-commerce has a positive impact on the intention to participate in e-agriculture on e-commerce platforms. This research data was surveyed by direct interviews with 210 durian farmers in Cai Be district of Tien Giang province. Research methods using PLS-SEM. The results of the study show that the factors that have an impact on the intention to participate in e-agriculture on the e-commerce platform: The case of durian farmers. From the fact that this study serves as a premise and proposes implications that are appropriate for further studies on the intention to participate in e-agriculture on the e-commerce platform, related to the intention to participate (e-agriculture) of farmers, especially durian fruit e-agricultural products. An experimental evidence in Tien Giang province, Vietnam.

Keywords

Agriculture, digitalization, electronic, e-agriculture, e-commerce, durian households, intention.

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Introduction

Agriculture is a very important sector and contributes to an important role in Vietnam's economy (Dinh, 2023). Agricultural activities in the role of providing food, food and supporting materials for industries and services also create more job opportunities for workers. Accompanying the development of agriculture, the market also has a close linkage. Today's trend in applying and accessing e-commerce platforms is thriving in Vietnam. In addition, traditional agriculture is undergoing a transformation to digital agriculture, or e-agriculture to develop in the new era. From 2010 to 2024, Vietnam's agriculture has developed rapidly, and has many achievements.

However, along with the development of agriculture, the fact that farmers (farmers) are still not synchronized and access technology (Binh, 2017; Dinh, 2023). E-commerce is the development trend of the world economy in the digital revolution 4.0 (digitalization) and Vietnam also participates in this trend. E-commerce is gradually dominating many sectors of the economy, including agriculture.

E-commerce has been opening up great opportunities for the agricultural sector, especially e-agriculture as well as contributing to supporting traditional agriculture in promoting and expanding markets, especially agricultural products with local characteristics in each region.

Mekong Delta, Vietnam. There are many localities with characteristics of agricultural products with prominent regional elements. Durian is a popular fruit in Southeast Asia. In particular, Tien Giang province belongs to the Mekong Delta region of Vietnam, is an agricultural product with a typical taste with good quality and has become a typical agricultural product of the province (Statistical Yearbook of Tien Giang Province, 2022; 2023).

However, along with the development of agriculture with regional product elements, the majority of durian farmers are still following traditional methods to access the market or market their products, instead of approaching e-agriculture in the direction of digitizing products and selling agricultural products on e-commerce platforms. On the other hand, at present, for durian farmers to access digitalization, technology (information technology level), adaptability and fear of change, it has gradually led to barriers for farmers in sustainable agricultural development according to electronic digitalization 4.0. Therefore, it is very important and necessary to understand the factors affecting the intention to participate in e-agriculture on the e-commerce platform: a case study of durian farmers in Tien Giang province, Vietnam, to contribute to clearly recognizing and evaluating the factors affecting the intention to participate in e-agriculture child.

Materials and methods

Mekong Delta, Agriculture in Tien Giang Province, Vietnam

The Mekong Delta is a large delta, the largest producer and exporter of tropical food and fruit trees in Vietnam. The Mekong Delta has 13 provinces/cities, divided into sub-regions including the Long Xuyen Quadrangle; Eastern Coastal Region; Dong Thap Muoi and Ca Mau Peninsula. (Chinh et al., 2017). In particular, Tien Giang province is located in a large food and food production area of the country, has very favorable ecological natural conditions for the development of high-tech agriculture and comprehensive agricultural development, Rich and high-quality crop structure and has a specialized area for fruit trees (Department of Industry and Trade of Tien Giang province, 2019). Among the 13 provinces/cities in the Mekong Delta, Tien Giang province is the province with a large durian planting area. In 2022, the province's durian planting area will be 17,600 hectares, and in 2023, the durian planting area of Tien Giang province will be 22,000 hectares,

there will be a sharp increase in planting area, because durian products bring high economic value to farmer households, More specifically, according to data from the General Statistics Office of the Ministry of Agriculture and Rural Development, in 2023 the total area of durian trees in Vietnam is estimated at 131,000 hectares, an increase of 20% compared to 2022.

In particular, the Mekong Delta region accounted for 34.6% compared to the Central Highlands (40.4%), the Southeast (19.4%) and the South Central region (5.6%). The Tien and Hau rivers are planted a lot of durian trees due to their characteristics suitable for freshwater alluvial land, not flooded. Tien Giang Durian province is planted in Cai Lay district. (Ministry of Agriculture and Rural Development, 2023).

According to Decision No. 504/QD-UBND dated February 25, 2022 of the Provincial People's Committee approving the project to adjust and restructure the agricultural sector in Tien Giang province to 2030. With the goal of specializing in durian planting areas as planned. On the other hand, currently in Tien Giang province, the area specializing in durian cultivation is concentrated in the West, including Cai Lay district, Cai Be district, Cai Lay town, Tien Giang province. Currently, Tien Giang province is creating, managing, exploiting and developing the certification mark "Tien Giang Durian" used for durian products of Tien Giang province in the Vietnamese market and export. At the same time, according to Decision No. 3595/QD-UBND dated October 1, 2019 of the People's Committee of Tien Giang province decided to promulgate the E-commerce Development Program of Tien Giang province until 2015. Along with the global development trend, the province's agriculture also catches up with market access, by participating in technology in production to improve quality, increase product competitiveness in terms of price, in addition to increasing output, the market access factor transforms from a specific traditional market to an e-commerce platform market very important.

In addition, according to Decision No. 504/QD-UBND dated February 25, 2022 of the People's Committee of Tien Giang province, the decision to approve the project of restructuring the agricultural sector of Tien Giang province to 2030. It is considered a development orientation to bring the province's agriculture to develop in the direction of digitalization, agricultural electronics and participation in the e-commerce

platform are all inevitable for agriculture today. In conclusion, from many important issues in reality in agriculture in general, e-agriculture, durian products and the e-commerce market in particular, the implementation of research on factors affecting the intention to participate in e-agriculture on the e-commerce platform: a case studies in Tien Giang province, Vietnam are very important and necessary to implement.

Electronic agriculture (e-agriculture)

Electronic agriculture (e-agriculture) is promoted by developed countries such as Japan, South Korea, and Israel,... attention has been paid to development for many years, in order to improve the value of agricultural products. In Vietnam, in order to achieve the goal of building a new countryside along with restructuring the agricultural sector, sustainable agricultural development needs to build an e-agriculture, apply digital technology, and apply scientific and technological advances. According to the Prime Minister's Decision No. 176/QĐ-TTg dated January 29, 2010 approving the project on development of high-tech agriculture by 2020. High-tech agriculture includes e-agriculture (Phú, 2005; Thăng, 2012). At the same time, according to Thăng (2012), it is added that e-agriculture has the application, technology, and knowledge to agricultural production to increase quality productivity.

Electronic agricultural digitization helps connect 4 houses, including farmers (farmers), entrepreneurs (companies), scientists (researchers) and managers. Farmers (farmer households) can access scientific and technological advances, choose to apply them to improve productivity, economic efficiency, labor efficiency, etc. For agricultural products, the good application of e-agriculture will support the product business on the e-commerce platform, proactively everything, and bring optimal efficiency. According to the Prime Minister's Decision No. 1896/QĐ-TTg dated December 17, 2012 on approving the high-tech agricultural development program under the national high-tech development program until 2020, this is a part of bringing positive effects to e-agriculture.

Intention to participate

Intention is the behavior that farmer households intend to participate in on the basis of the theory of technology adoption (TAM) and the original foundation of TRA theory (Davis, 1989) for the relationship between the interpretation of human behavior on the acceptance of the use

of technology, the electronic case of the main field is agriculture. According to Venkatesh et al. (2003), it is described that the behavioral intention or intention to participate in digital technology (electronic) users emphasizes the factor of performance conditions or the ability to adapt to implementation. In the field of agriculture, research shows that there are many factors that affect the use of e-commerce platforms in the consumption of agricultural products.) the Government's various plans to support farmers through empowering them by enacting e-commerce innovations have not produced any impact (Fidowaty and Supriadi, 2020). Many farmers are still unable to effectively use e-commerce and related technologies.

However, according to Pillai and Sivathanu (2020), the approach is based on the level of application of the Internet of Things (IOT) by farmers in India through the basis of behavioral theory. From there, there is a specific branching of research on behavioral intentions in how rural consumers (or farmers) absorb the innovation of applying technology and also the digital internet in the agricultural sector. In other cases, the intention to participate describes an activity, willing to cooperate to participate in the call or rejoin (Soliman, 2021). According to Casaló et al. (2010), re-participation intention expresses user interest and re-use intention, showing that participation intention shows that community impact has an influence on both direct and indirect participation intentions.

Research and discussion

Overview of the entire theory

Social Impacts for Agriculture (SIA)

Social impact was first used at a seminar on ethical responsibility at Yale University in 1969. Previously, according to Darley and Latane (1968) Social impact predicted the sources that could influence the goal and vice versa. Along with that, social impact also means impacts that can affect society and the environment. Today, there is a shift in the view that social impact theory is the ability of the goal to influence the source, which is considered a two-way change (Lantané, 1981; Latané and Wolf, 1981). The new social impact has a related aspect that is agriculture because agriculture is associated with environmental activities (Dreoni et al., 2021). Agriculture is a manufacturing sector that plays a very important role in the national economy, along with the development of the state and the economic

development of the region. Under the impact of society, agriculture has changed and transformed to suit (Dinh, 2023).

Agricultural development needs to pay attention to sustainable development, based on the available advantages of modern localities, productivity and quality, in which according to the document of the 13th Congress, it is determined that "Focus on the development of agriculture to produce large goods, apply high technology, promote potential, advantages of each region and locality". In particular, pay attention to the impact of society in rural development according to the Prime Minister's Decision No. 150/QĐ-TTg dated January 28, 2022 approving the strategy for sustainable agricultural and rural development for the 2021-2030 period, with a vision to 2050. In addition, agriculture must develop according to socio-economic cohesion according to Decision No. 899/2013 QĐ-TTg of the Prime Minister dated June 10, 2013 approving the agricultural restructuring project in the direction of increasing added value and sustainable development, emphasizing 3 economic pillars, society, and environment in agricultural development.

Adaptive Capacity (AC)

Adaptability is a process of changing to suit a variety of conditions (Smit et al., 2001; Engle, 2011). In the context of new development, adaptability can be approached in terms of adaptation to change (Vincent, 2007). On the other hand, adaptability also has a multidimensional perception: it is determined by many factors that have complex relationships at different levels (Lennie, 2005; Vincent, 2007).

In approaching this perception, adaptability is considered from the perspective related to farmers, specifically from the perspective of agriculture.

Agriculture Awareness (AA)

Awareness of agriculture is understood as the application of factors related to technology to the field of agricultural production, farmers have a high dependence on factors related to the environment and people (Natis et al., 2019; Mashi et al., 2022). There are few studies that approach the cognitive factor of agriculture related to technological factors (Tembo et al., 2008; Mashi et al., 2022). Because this is considered a new direction for agriculture, partly has an impact on the economy, especially countries with developing agriculture.

Digitalizations of e-Agriculture (DOEA)

Digitization of e-agriculture is the process of applying digital technologies from production to processing, distribution, and consumption of agricultural products (Nguyen, 2023). From there, changing the way of managing, producing and consuming products from traditional to modern and smart. According to the Food and Agriculture Organization (FAO), the specific definition is proposed as follows: E-agriculture is an emerging field with a combination of agricultural informatics, agricultural development and entrepreneurship (FAO, 2015).

More specifically, the digitalization of e-agriculture is the transition from tradition to digitalization and application of e-agriculture, with more inheritance and development in agriculture (Okediran and Ganiya, 2019). It is concretized in relation to the concepts, development, and evaluation of applications to apply information technology to agriculture (Okediran and Ganiya, 2019).

E-agriculture on e-Commerce (EAEC)

An e-commerce floor is a place to buy and sell goods, products, or services and internet customs clearance data (Wigand, 1997; Sekabira et al., 2012). Along with the development of the digital age, technology develops, agriculture also accompanies and develops. Today's agriculture is accompanied by a development chain that rapidly applies and synchronizes new technologies called e-agriculture (Patel et al., 2022). E-agriculture applied on e-commerce platforms is considered a new point that brings many positives to agriculture under the application of technology and the internet (Baourakis et al.; 2022; Patel et al., 2022).

According to Baourakis et al. (2002), the internet is seen as an effective tool to support the marketing of agricultural products (food and organic food), especially on e-commerce platforms. According to Groves and Da Rin (1999), the essence of agriculture is to develop according to the trend of the future era, in which it is necessary to maintain the ability to promote international agricultural products in the application of e-commerce. In addition, e-commerce platforms are considered a measure for future agricultural development (Hennessy et al., 2016; Panpandrea and Margo, 2000). In this study, the approach of agriculture in the direction of developing e-commerce agriculture is considered a new direction, especially e-agriculture on e-commerce platforms.

Intention to participate in the Digitalization process (IPD)

There are many theoretical bases related to the behavioral intentions of many authors. In particular, intentional behavior theory is based on the approach of TRA theory that shows that there is a relationship between variables to explain human behavior in terms of acceptance of technology use (Davis, 1989). On the other hand, according to Venkatesh et al. (2003) to explain the user's intention to use the technology including the impact of social influence and the conditions of adaptation to implementation. Then, according to Awais Muhammad and Samin Tanzila (2012), the view of digitalization on the internet has basically created a global environment. The application of the Internet has shortened the distance and reached many people.

Agriculture is a part of a country's economic development. Especially countries with long-standing agriculture, typically Vietnam (Thoa, 2015). Agriculture follows the trend it will be strengthened if it is supported by electronic tools, in which e-commerce is an important part (Wen, 2007). Research by Orécalixto and Vicente Ramos (2021) shows that the application of e-commerce tools contributes to the consumption of products more efficiently than the traditional consumption process. According to Awa et al. (2015), the TAM model was applied to survey the intention to apply technology to operations on e-commerce platforms. The intention to participate in technology to expand modern distribution channels and use information technology in cultivation and livestock has used the TAM model (Liu et al., 2021). Research by Fidowaty and Supriadi (2020) identified various Government plans to improve the financial situation of farmers through empowering them by enacting e-commerce innovations that did not make any impact.

On the other hand, Tembo et al. (2008) have synthesized the factors that affect the use of technology digitization in agriculture in developing countries in the construction of binary models, in which the factors affecting the adoption of technology, the demographic characteristics and perceptions of farmers are mentioned. Many farmers still do not have access to e-commerce platforms and related technologies in the agricultural sector, research shows that there are many factors affecting the intention to participate in e-agriculture in using e-commerce platforms in consuming agricultural products. In short, the approach of farmers to the intention

to participate in agricultural digitalization and access on the e-commerce platform is considered a new direction that needs to be paid attention to.

The theoretical bases have been presented, and the research hypothesis is specifically proposed as follows

H1: Social impacts for agriculture have a positive impact on the digitalization of e-agriculture.

H2: Adaptive capacity has a positive impact on the digitalization of e-agriculture.

H3: Awareness of agriculture has a positive impact on the digitalization of e-agriculture.

H4: Social impact on agriculture has a positive impact on e-agriculture on e-commerce platforms.

H5: Adaptive capacity has a positive impact on e-agriculture on e-commerce platforms.

H6: Awareness of agriculture has a positive impact on e-Agriculture on e-commerce platforms.

H7: Digitalization of e-agriculture has a positive impact on the intention to participate in digitalization.

H8: E-agriculture on e-commerce platforms has a positive impact on the intention to participate in digitalization.

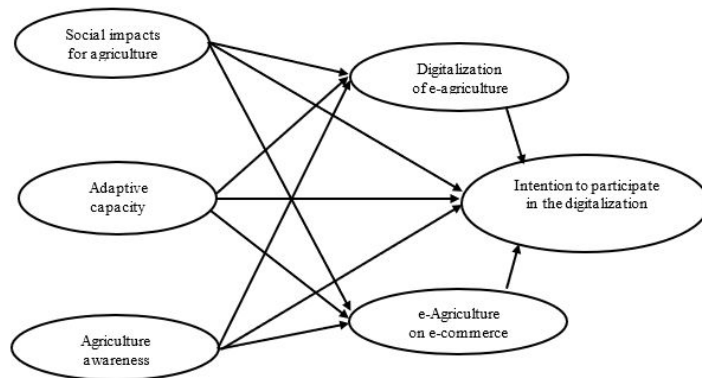
H9: Social impacts for agriculture have a positive impact on the intention to participate in digitalization.

H10: Awareness of agriculture has a positive impact on the intention to participate in digitalization.

H11: Adaptive capacity has a positive impact on the intention to participate in digitalization.

Research models

From the practical basis and theoretical bases related to the field of agriculture, e-agriculture, e-commerce platforms, the proposed research model with the aim of identifying and understanding the cognitive factors of society, adaptability, awareness of agriculture, etc. Influencing the intention to participate in e-agriculture on e-commerce platforms: a case study of durian farmers in Tien Giang province, Vietnam (Figure 1).



Source: own processing

Figure 1: Conceptual frameworks of the proposal

Research methods

This study uses the PLS-SEM multi-group structure analysis method using SmartPLS software to validate the research model, which is built with factors including social awareness, adaptability, agricultural awareness, e-agriculture digitalization, and e-commerce agriculture. Impact on the intention to participate in the digitalization process of durian farmers in Tien Giang province. The access to farmers is large enough to ensure representativeness in the study by sampling stratified and systematic probabilities in accordance with actual conditions in the locality with a sample of 210 durian growing households. The study was conducted through a direct questionnaire of local farmers including 3 communes such as My Trung commune, My Tan commune and Thien Trung commune in Cai Be district, Tien Giang province. The scale used includes nominal, ordinal, proportional, and Likert scales of 5 degrees from 1 strongly disagree to 5 strongly agree. In addition, in order to ensure high reliability for the study, before conducting a survey and interviewing 210 farmer households, a qualitative interview was conducted with 10 experts including local agricultural officials, officials with expertise in agriculture, experts with knowledge of e-agriculture, etc. To calibrate the questionnaire in accordance with reality, then conduct practical interviews on a large scale with a sample of 210 farmers. Results from the survey from July to August 2024 in Cai Be district, Tien Giang province, Vietnam.

Research results

To conduct research in accordance with actual conditions. From the theoretical basis, the preliminary qualitative questionnaire is carried out. Carry out research through 3 steps.

Step 1: Selectively find out the theoretical basis suitable for the research.

Step 2: Conduct a qualitative interview survey of 10 people, including experts, people with deep experience in agriculture, who are interested in e-agriculture, etc digitization and technology (agricultural officials working at the commune/ward grassroots; agricultural research experts, farmers' association officials...) then adjust the appropriate scale and the appropriate questionnaire.

Step 3: Conduct a survey according to the actual situation of 210 durian farming households in 3 My Trung communes, My Tan commune and Thien Trung commune in Cai Be district, Tien Giang province.

Described and presented (As show Table 1), through face-to-face meetings with farmer households, 210 samples were suitable and satisfactory. From there, it aims to understand the intention to participate in agricultural digitalization including the variables described in detail before. In the total number of farm households participating in the interview, the demographic characteristics of the households are presented in detail (As show Table 2).

	Surveys	Ratio %
My Trung Commune	70	33.33
My Tan Commune	70	33.33
Thien Trung Commune	70	33.33
Total	210	100

Source: own processing

Table 1: Description of survey area

With characteristics including gender, age, planting experience, and household size. Accounting for 72.9% with 153 people (farmers) being male and 27.1% with 57 people (farmers) being female were surveyed, this clearly shows that most of the male workers (heads of households) are

Number of respondents		Ratio %	
Sex	Male	153	72.9
	Female	57	27.1
Total		210	100
Planting Experience	From 1 to 4 years	21	10.0
	From 5 to 7 years	31	14.8
	From 8 to 10 years	68	32.3
	Over 10 years	90	42.9
Total		210	100
Age	From 30 to 40 years old	31	14.8
	From 41 to 50 years old	82	39.0
	From 51 to 60 years old	90	42.9
	Over 60 years	7	3.3
Total		210	100
Households size	2 people	11	5.2
	3 people	21	10.0
	4 people	43	20.5
	over 4 people	135	64.3
Total		210	100

Source: own processing

Table 2: Demographic characteristics of farming households.

in agriculture, because most of the agricultural work is done by men who take on more heavy and difficult jobs than women. at the same time, this is also a characteristic of agricultural traditions in Vietnam, so far the main workers have been men and women are the sub-workers in agricultural labor.

The age groups under 30 are not shown because this age group is young and tends to go to work far from their homeland, do other jobs and also have little interest in the agricultural sector, accounting for a low percentage of 30 to 40 years old (14.8%). The age group of 41 to 50 years old (39%) and the age group of 51 to 60 (42.9%) are almost similar for the reason that this age group is often used to farming, orcharding, has no interest and changes other jobs. The age group over 60 accounts for 3.3%, at least because they are older, their health is starting to weaken and they are starting to gradually reduce agricultural labor.

The experience of planting fruit trees (Durian) of farmers accounts for the lowest from 1 to 4 years (10%) and the experience group is from 5 to 7 years (14.8%) because the characteristic tree of durian trees planted in the period from 1 to 5 years is the stage when the tree has not yet borne fruit. Farmers are only interested in caring for and gaining experience. The group of households with 8 to 10 years of experience (32.3%)

and more than 10 years (42.9%) dominated because farmers in this group had accumulated experience in the process of planting and caring for trees for a long time, knowing the experience of caring for durian and its specific characteristics. At the same time, the size of durian farming households also accounts for 4 people (20.5%) and more than 4 people (64.3%), which is a common feature of most durian farming households because most of the growing households need a lot of labor to carry out many farming jobs, tree care and harvesting.

The remaining groups of 2-person households (5.2%) and 3-person households (10%) are often considered small-scale households in agricultural farming. Table 2 clearly describes the characteristics of durian farming households, this is also a characteristic characteristic of farming households, especially showing that the agricultural sector in general (agriculture in durian farming households in particular) has specific agricultural characteristics compared to other fields.

Descriptive reliability and construct validity

According to Hair et al (2013), the reliability measure applied is Cronbach's Alpha with the value shown in Table 2. Cronbach's Alpha confidence factor is greater than 0.7. In addition, the VIF index to ensure the acceptance level, $VIF < 5$,

the model is accepted and there is no multi-collation phenomenon, the description of the perception (Table 3) shows that the VIF index is less than 5. Specifically, the entire VIF index is from less than 4, the lowest is 1,524 and the highest is 3,321. In conclusion, the research model does not violate (As show Table 3).

When using the PLS-SEM method, the convergence values are evaluated through the external load coefficients of the observed variables, as well as the AVE coefficient. According to Hair et al. (2017), the AVE coefficient needs to be greater than 0.5 and the external load coefficient must be greater than 0.7 to achieve the convergence value. This satisfies the description in (As show Table 4). To be more specific, convergent values represent a set of measurement variables that must be correlated with each other in a concept that has been studied (Kline, 2011). The test results show that all the variables mentioned satisfactorily achieve internal consistency with (external load coefficient) greater than 0.7. The average AVE citation variance of the scale is greater than 0.5 (0.632 – 0.766). Therefore, the scale of the study structure has been converged (As show Table 4).

Apply Structural Equation Modeling (PLS-SEM)

For research applying PLS-SEM has a value of R, usually the value is 0.25; 0.5 and 0.75 are

recommended (Hair et al, 2019). For this study, the R squared value is greater than 0.88, specifically R squared AEEC (0.930); DOEA (0.887) and IPD (0.907). The adjusted squared R value is greater than 0.88, specifically AEEC (0.929), equivalent to 92.9%; DOEA (0.886) corresponds to 88.6% and IPD (0.905) corresponds to 90.5%. In short, the above variables all have an impact of over 50% (>50%) on the variation of the dependent variable is satisfactory and consistent. This proves that this study proves that the model is meaningful and suitable for real conditions.

In addition, the ratio of HTMT is a criterion to be considered to evaluate the value of the distinction. The results showed that all base HTMT ratios were less than 0.9 and consistent with the study. Therefore, the distinct value can confirm the measures in the model that ensure the calculated differential value described (As show Table 5).

The results perform a Bootstrap analysis for the purpose of evaluating impact relationships. From there, consider the P value of all factors with a P value < 0.05, namely 0.000; 0.001 and 0.039 with variables this satisfies the exceptions to having 1 adaptability factor (AC) with a P value greater than 0.05, specifically 0.073. This can be explained as follows, agricultural production farmers in general and durian farmers in particular all face different difficulties at work (especially

	Code	Outer loadings	VIF
Social impacts for agriculture	SIA	0.806 - 0.910	1.870 – 3.321
Adaptive capacity	AC	0.744 – 0.862	1.524 – 2.453
Agriculture awareness	AA	0.814 – 0.866	1.888 - 2.352
Digitalizations of e-agriculture	DOEA	0.780 – 0.897	2.060 – 2.316
e-agriculture on e-commerce	EAEC	0.782 – 0.835	1.943 – 2.127
Intention to participate in the digitalization	IPD	0.832 – 0.865	1.976 – 2.579

Source: own processing

Table 3: Outer loadings and VIF.

	Var	CA	rho_A	CR	AVE
Inspection standards		≥ 0.6	≥ 0.7	≥ 0.7	≥ 0.5
AA	4	0.856	0.857	0.902	0.698
AC	4	0.818	0.828	0.880	0.649
AEEC	5	0.857	0.861	0.903	0.701
DOEA	4	0.854	0.858	0.895	0.632
IPD	4	0.873	0.873	0.913	0.724
SIA	4	0.897	0.897	0.929	0.766

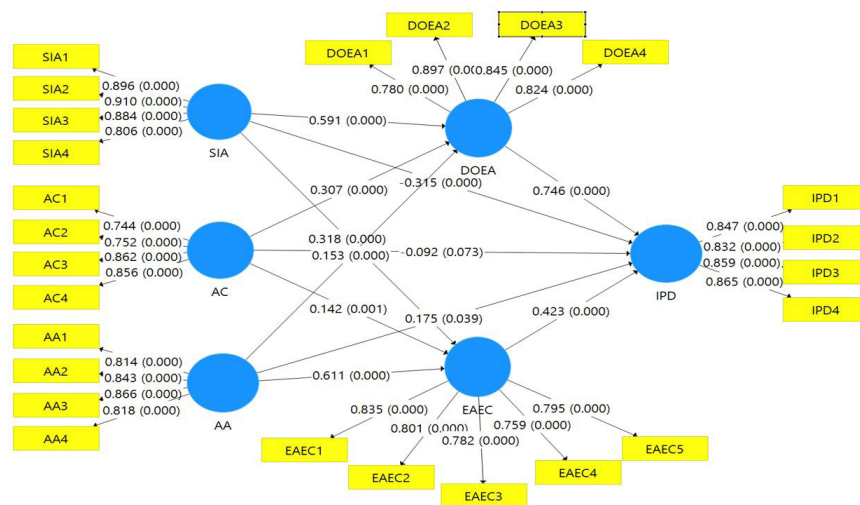
Source: own processing

Table 4: Construct reliability validity.

	AA	AC	DOEA	EAEC	IPD	SIA
AA						
AC	0.883					
DOEA	0.833	0.834				
EAEC	0.772	0.798	0.879			
IPD	0.698	0.825	0.839	0.854		
SIA	0.695	0.760	0.806	0.797	0.814	

Source: own processing

Table 5: Hetertrait monotrait ratio.



Source: own processing

Figure 2: PLS-SEM result.

agricultural work), so it is quick for farmers to get used to and adapt to digital technology factors, digitalization in the field of agriculture still faces many limitations. Therefore, it can be seen that the adaptability factor (AC) has no positive impact on the intention to participate in digitalization (As Figure 2 shows; as Table 6 shows).

The remaining factors, on the other hand, reflect enough statistically significant factors to represent a relationship. Positive implications for intention to participate in e-agriculture on e-commerce platforms: a case study in Tien Giang province, Vietnam. The initial hypotheses were proposed from H1 to H11, in which the hypotheses from H1 to H10 were accepted and the remaining hypothesis H11 was rejected because it was not statistically significant ($P < 0.05$) (As show Table 6).

In conclusion, the social impact for agriculture, adaptive capacity, awareness agriculture, digitalization of e-agriculture and e-agriculture on e-commerce platforms are statistically significant. The specific result is shown at a meaningful level

of 95%, The only factor that is rejected is that the adaptive capacity does not have a positive impact on the intention to participate in e-agriculture on the e-commerce platform because having a P value of 0.073 does not guarantee statistical significance. In e-agriculture, the digitalization of agriculture has no positive impact on the intention to participate in e-agriculture because of many problems and factors of individual farmers, and because traditional agriculture affects the adaptability of farmers.

	OS	SM	SD	T Statistics	P Values	Result
SIA -> DOEA	0.591	0.587	0.036	16.234	0.000	Supported
AA -> EAEC	0.611	0.616	0.044	13.920	0.000	Supported
SIA -> EAEC	0.318	0.318	0.030	10.649	0.000	Supported
DOEA -> IPD	0.746	0.735	0.083	8.949	0.000	Supported
AC -> DOEA	0.307	0.316	0.051	5.960	0.000	Supported
SIA -> IPD	-0.315	-0.314	0.068	4.629	0.000	Supported
EAEC -> IPD	0.423	0.437	0.101	4.204	0.000	Supported
AA -> DOEA	0.153	0.149	0.044	3.493	0.000	Supported
AC -> EAEC	0.142	0.138	0.041	3.486	0.001	Supported
AA -> IPD	0.175	0.166	0.085	2.066	0.039	Supported
AC -> IPD	-0.092	-0.091	0.051	1.797	0.073	Rejected

Source: own processing

Table 6: Result of the PLS-SEM.

Conclusion

This is a new approach (narrow point) in the study that has highlighted the main factors influencing the intention to participate in e-commerce on the e-commerce platform of a case study in Tien Giang province. With the approach to the survey to understand durian farmers with the intention to participate in e-agriculture (agricultural digitalization), it is shown that the proposed and survey factors are appropriate, only the adaptability factor does not have a favorable impact and satisfies the proposed theory. From this study as a basis to make some specific recommendations as follows: For the government and local authorities to create more practical support policies for farmers to access the market, access to new technology, access to e-agriculture, etc. e-commerce platforms... localities coordinate with experts with experience in digital agriculture and e-agriculture to open professional training courses for farmer households with special interest in durian farming households at the grassroots, prioritizing the development of technological infrastructure and agricultural platforms, e-agriculture, support to facilitate transportation activities because agricultural products due to the characteristics of agricultural products, agricultural products are often easily damaged and difficult to preserve for a long time.

The government, cooperatives and associations need to have a sense of responsibility and patience in supporting people, especially middle-aged people and older, in agricultural digitalization activities, e-agriculture and e-commerce platforms, because this group accounts for the majority of agricultural activities. For e-commerce platforms, the design should be simple, user-friendly, and accurate in the product search process. It can be classified by regional products so that customers can easily search as well as sellers can easily compare and contrast products to give reasonable product values. At the same time, for farmers, the use of technology is still difficult and the digital transformation process, Digital agriculture and e-agriculture in daily life habits are still slow, therefore, it is necessary to ensure the safety of transaction activities, creating a premise for the development of e-agriculture in the future. Based on this research, it is the basis for the next research on digital agriculture and e-agriculture. For farmers, it is necessary to actively participate in agricultural digitization activities, e-agriculture, and digital transformation to adapt to the market. Especially the new market, the current e-commerce platform. In that process, farmers can consult experts for timely support when they encounter difficulties.

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Gender-Inclusive Digital Literacy and Socioeconomic Resilience Among Smallholder Farmers: The Moderating Role of Trust in Technology in Food-Insecure Regions

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Abstract

Smallholder farmers in food-insecure regions face structural constraints that undermine household resilience, including gender disparities, limited digital access, and low trust in technology. This study develops and tests the Gender-Inclusive Digital Literacy for Women Empowerment (GIDL-WE) model to examine how gender inclusion, digital literacy, and trust in technology interact to influence socioeconomic resilience. Using survey data from 350 women in smallholder farming households in Central Kalimantan, Indonesia, the research employs Partial Least Squares–Structural Equation Modeling (PLS-SEM) for analysis. Results indicate that gender inclusion significantly enhances inclusive digital literacy ($\beta = 0.285$, $p < 0.000$), while digital literacy unexpectedly exerts a negative effect on socioeconomic resilience ($\beta = -0.217$, $p < 0.000$). Trust in technology moderates the digital literacy–resilience link ($\beta = 0.176$, $p < 0.000$), suggesting that digital literacy yields benefits only when supported by high trust levels. The model explains 28.3% of the variance in socioeconomic resilience and demonstrates a satisfactory global fit ($GoF = 0.39$). These findings highlight the centrality of trust as a catalyst for translating digital inclusion into resilience, offering empirical insights for designing gender-responsive digital interventions in agriculture.

Keywords

Women empowerment, digital literacy, technology trust, social resilience, rural households.

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Introduction

Agricultural transformation in the Global South is increasingly intertwined with digital innovation. However, smallholder farmers, particularly those residing in food-insecure regions, continue to face systemic constraints such as climate change, market volatility, and exclusion from digital infrastructure (Bryan and Garner, 2022; Huyer and Partey, 2020). These vulnerabilities are not evenly distributed: women farmers, in particular, experience compounded disadvantages rooted in structural gender inequalities that limit their agency in decision-making and access to technology (Ali et al., 2016; FAO, 2011a).

While rural women are central to both food production and consumption, their roles remain underrecognized and underrepresented in the digital agricultural agenda. Studies have

shown that socio-cultural norms often marginalize women from technology training, access to devices, and digital communication platforms (Ishaq and Memon, 2016; Jaim and Hossain, 2011). This gendered digital divide has a direct bearing on agricultural performance and household resilience, particularly where digital tools mediate access to markets, inputs, information, and social services (Li et al., 2025).

Empirical evidence from Kalimantan, Indonesia, reflects this gap. Although 71% of farming households are categorized as food secure, their resilience is fragile undermined by limited access among women to training programs, digital technology, and institutional support (Winarti et al., 2024, 2025). Notably, women's leadership in farming households contributes significantly over 30% to food security and empowerment

outcomes. Yet, the lack of a gender-responsive digital ecosystem impedes the full realization of their potential.

The adoption of digital agriculture is not solely a function of access or technical literacy but is also deeply influenced by psychological factors such as trust in technology. Women farmers are often hesitant to engage with digital tools due to concerns over data privacy, device security, and the perceived reliability of applications (Han et al., 2022; Li et al., 2023). As a moderating factor, trust can either facilitate or inhibit the relationship between digital literacy and resilience outcomes.

Despite the growing body of literature on digital agriculture and gender, existing models tend to be normative, qualitative, or overly fragmented. Few studies have empirically examined the structural links between inclusive digital literacy, gender inclusion, and socioeconomic resilience within a comprehensive analytical framework. Even fewer have incorporated trust in technology as a moderating variable shaping these relationships (Bathaiy et al., 2021; Kumari et al., 2025; McGuire et al., 2022).

This study addresses these gaps by proposing a novel structural model: the Gender-Inclusive Digital Literacy for Women Empowerment (GIDL-WE) framework. Using a Partial Least Squares–Structural Equation Modeling (PLS-SEM) approach, this research investigates how inclusive digital literacy affects the socioeconomic resilience of farming households, the extent to which gender inclusion fosters digital empowerment, and how trust in technology moderates these effects. The model seeks to offer empirical insights for designing more equitable, inclusive, and sustainable digital interventions in agriculture.

Theoretical perspectives and hypothesis development

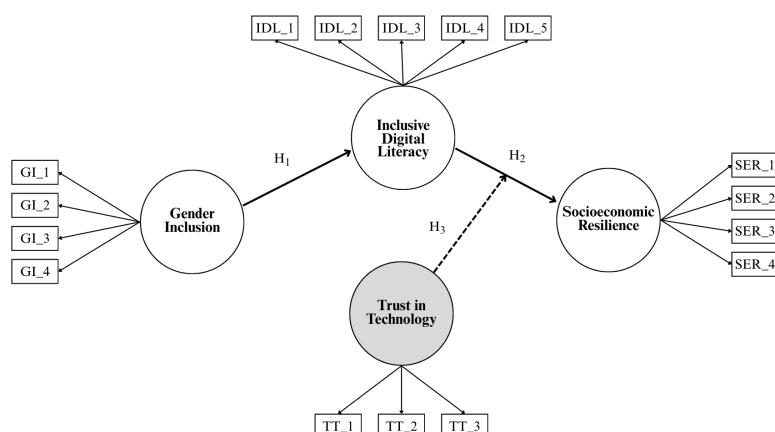
The theoretical foundation of this study is grounded in the Technology Acceptance Model (TAM) (Davis, 1989), which posits that the adoption and effective utilization of technology are primarily influenced by users' perceived usefulness and perceived ease of use. Building on this, Trust in Technology is conceptualized as a critical antecedent that shapes individuals' perceptions and confidence in engaging with digital tools, particularly in low-resource settings such as smallholder farming households. Previous studies have demonstrated that trust significantly influences the willingness to adopt digital solutions in agriculture, especially when

users face risks related to data security and system reliability (Han et al., 2022; Li et al., 2023).

This study also draws upon Gender and Development Theory (GAD), which emphasizes structural gender inequalities and the need for inclusive frameworks to empower marginalized groups, particularly women (FAO, 2011b). In the agricultural sector, gender norms often restrict women's access to resources, education, and digital infrastructure. Therefore, Gender Inclusion is positioned as an enabling factor that fosters equitable participation in the digital ecosystem. Increased gender inclusion is expected to lead to higher levels of digital literacy among women, which is essential for achieving broader developmental outcomes in food-insecure rural areas (Bryan and Garner, 2022; Huyer and Partey, 2020).

The construct of Inclusive Digital Literacy functions as a central mediating variable in the model, operationalized through access, skills, and participation in digital agriculture platforms. Inclusive digital literacy not only facilitates information flow and productivity gains but also enhances social resilience by enabling individuals (particularly women) to connect with markets, institutions, and support systems (Cheng et al., 2024; C. Li et al., 2025). Within this framework, digital literacy is theorized to influence Socioeconomic Resilience, defined as a household's capacity to maintain stability and adapt to external shocks through diversified income sources, food security, and access to services (Adger, 2000; Keck and Sakdapolrak, 2013).

Furthermore, this study hypothesizes a moderation effect of trust in technology on the relationship between digital literacy and household resilience. In alignment with recent resilience literature, the interaction between digital capabilities and psychological trust factors plays a crucial role in determining adaptive outcomes in rural development (Bathaiy et al., 2021). A higher level of trust is expected to strengthen the positive effects of digital literacy, while low trust may undermine the benefits of digital interventions. This integrative model (Figure 1) thereby provides a robust framework for exploring the intersection of gender, technology, and household resilience in vulnerable agricultural communities.



Source: Authors

Figure 1: Conceptual framework.

Materials and methods

Study area

This study was conducted in East Kotawaringin Regency, Central Kalimantan Province, Indonesia a region characterized by both agricultural potential and high vulnerability to food insecurity. Twelve villages were selected purposively based on their Priority 1 classification in the 2024 Food Security and Vulnerability Atlas (FSVA) issued by the Ministry of Agriculture (Dinas Pertanian Dan Ketahanan Pangan, 2024). The area is home to smallholder farmers whose livelihoods rely heavily on subsistence agriculture, yet face structural constraints related to access, information, and gender disparities.

Sampling procedure

This study employed a stratified random sampling technique to ensure the representation of women farmers across various villages classified as food-insecure zones in East Kotawaringin Regency, Central Kalimantan. Twelve villages were purposively selected based on their Priority 1 status as outlined in the 2024 Food Security and Vulnerability Atlas (FSVA) published by Indonesia's Ministry of Agriculture. These areas were deemed relevant due to the high vulnerability of farming households, especially women, to structural challenges such as limited technology access, low digital literacy, and gender-based constraints.

The study population comprised female members of smallholder farming households who were actively involved in agricultural activities or decision-making. A total of 2,741 eligible

respondents were identified across the selected villages. To determine an appropriate sample size, the Yamane formula (Yamane, 1973) was utilized with a 5% margin of error, resulting in a sample size of 350 respondents. Stratification was based on village of residence and age groups to ensure proportional distribution, particularly focusing on women within productive ages (15-64 years).

Prior to data collection, researchers conducted outreach through local agricultural extension officers and women farmer groups to facilitate access and build rapport. Respondents were selected randomly from group rosters, and informed consent was obtained prior to administering the questionnaire. The final sample of 350 respondents was deemed sufficient for robust PLS-SEM analysis, as it exceeded the minimum sample size required for models with moderate complexity and power of 0.80 (Hair et al., 2021).

Data collection instrument

The primary instrument used for data collection in this study was a structured questionnaire designed to measure latent constructs in the proposed structural model. The questionnaire was developed based on established scales and theoretical frameworks relevant to gender inclusion, digital literacy, trust in technology, and household socioeconomic resilience. All items were measured using a 5-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree), allowing for nuanced capture of respondents' perceptions and experiences.

Each construct consisted of multiple reflective indicators adapted from prior validated instruments.

The Gender Inclusion construct included 4 items capturing dimensions such as decision-making autonomy, income control, group participation, access to training, and leadership in farming decisions (FAO, 2011a; Ishaq and Memon, 2016; Jaim and Hossain, 2011; Quisumbing, 1996). The Inclusive Digital Literacy construct contained 5 indicators, reflecting digital access, basic functional use, participation in digital training, access to agricultural information, and engagement in e-commerce or online platforms (Choruma et al., 2024; Han et al., 2022; Li et al., 2025; Li et al., 2023; Winarti et al., 2025). The Trust in Technology construct included 3 items adapted from technology acceptance and digital trust models, emphasizing perceived benefit, safety, reliability, and ease of use (Cimino et al., 2024; Han et al., 2022; Li et al., 2023). Lastly, Socioeconomic Resilience was measured through 4 indicators capturing household income stability, access to support services, food security perception, expenditure patterns, and community support (Adger, 2000; Islam et al., 2024; Keck and Sakdapolrak, 2013).

To ensure content validity, the initial questionnaire was reviewed by a panel of five academic experts in agricultural sociology, gender studies, and information systems. Subsequently, the instrument underwent pilot testing

with 30 respondents from non-sample villages to test its clarity, internal consistency, and response bias. Feedback from the pilot phase was used to revise ambiguous wording, align cultural context, and eliminate redundant items. The final version of the questionnaire was translated into Bahasa Indonesia using a back-translation method to ensure semantic equivalence between the original and translated versions.

Data analysis techniques

This study employed Partial Least Squares–Structural Equation Modeling (PLS-SEM) using SmartPLS 4.0 software to analyze the proposed conceptual model. PLS-SEM was selected due to its ability to handle complex models with latent variables, non-normal data distributions, and relatively small sample sizes (Hair et al., 2019). The technique is particularly suitable for exploratory research aiming at theory development and model prediction, which aligns with the study’s objective of validating the GIDL-WE model (Gender-Inclusive Digital Literacy for Women Empowerment).

The analysis was conducted in two main stages: the measurement model (outer model) and the structural model (inner model). The outer model focused on testing the reliability

Construct	Indicator Code	Indicator Description	Source	Scale
Gender Inclusion (GI)	GI_1	Women's involvement in household farming decisions	Quisumbing (1996); FAO (2011)	Likert 1–5
	GI_2	Control over income generated from farming activities	FAO (2011)	Likert 1–5
	GI_3	Participation in community/farmer groups	Ishaq and Memon (2016)	Likert 1–5
	GI_4	Access to agricultural training	Jaim and Hossain (2011)	Likert 1–5
Inclusive Digital Literacy (IDL)	IDL_1	Ownership or access to digital devices (smartphone, internet)	Li et al. (2025)	Likert 1–5
	IDL_2	Ability to use basic digital apps (WhatsApp, browser, e-wallets)	Choruma et al. (2024)	Likert 1–5
	IDL_3	Participation in online/digital farming training	Winarti et al. (2025)	Likert 1–5
	IDL_4	Use of digital tools to search agricultural information	Han et al. (2022)	Likert 1–5
	IDL_5	Engagement in online market platforms/e-commerce	Li et al. (2025)	Likert 1–5
Trust in Technology (TT)	TT_1	Confidence in security of digital tools used	Li et al. (2023)	Likert 1–5
	TT_2	Trust in the accuracy and reliability of online information	Han et al. (2022)	Likert 1–5
	TT_3	Comfort level in using digital platforms	Cimino et al. (2024)	Likert 1–5
Socioeconomic Resilience (SER)	SER_1	Stability of household income	Adger (2000); Keck and Sakdapolrak (2013)	Likert 1–5
	SER_2	Access to basic services (health, education, food)	Islam et al. (2024)	Likert 1–5
	SER_3	Diversity of income sources	Keck and Sakdapolrak (2013)	Likert 1–5
	SER_4	Ability to manage household consumption during crisis	Adger (2000)	Likert 1–5

Source: Author processing, 2025

Table 1: Operationalization of research constructs and indicators.

and validity of the constructs. Indicator reliability was assessed using loading factors (threshold > 0.70), while construct reliability was tested through Cronbach's Alpha and Composite Reliability (CR), both expected to exceed 0.70. Convergent validity was evaluated using the Average Variance Extracted (AVE), which must be ≥ 0.50 (Hair et al., 2019). Discriminant validity was established using the Heterotrait-Monotrait ratio (HTMT), where values below 0.85 indicated acceptable discriminant power (Henseler et al., 2009).

The inner model assessed the causal relationships among constructs, including direct, indirect, and moderating effects. Path coefficients were tested for statistical significance using bootstrapping (5,000 subsamples), and predictive power was evaluated using R^2 and Q^2 values. A key element of the analysis was the moderation test, which examined whether trust in technology moderated the relationship between digital literacy and household socio-economic resilience. This was tested using the two-stage approach, which allows for the inclusion of interaction terms between latent constructs (Sarstedt et al., 2019).

In addition, multicollinearity was checked using the Variance Inflation Factor (VIF), with acceptable values below 5.0. Model fit was assessed using SRMR (Standardized Root Mean Square Residual), where values below 0.08 indicated a good fit. The overall analysis not only validated the psychometric properties of the constructs but also revealed the structural pathways through which gender-inclusive digital literacy and trust in technology influence household resilience among smallholder farming communities in food-insecure areas.

Results and discussion

Demographic characteristics of respondents

A total of 350 respondents participated in this study, comprising a diverse profile of rural agrarian households. In terms of age distribution, the majority of respondents were between 31 and 45 years old (43.4%), followed by those aged 46–60 years (34.3%). Respondents below 30 years constituted 13.1%, while only 9.1% were older than 60 years. This indicates that the productive age group dominates the agricultural workforce in the study area.

Regarding educational attainment, most respondents had completed elementary school

(59.1%), with 20.3% having no formal education. Additionally, 15.7% had attended junior high school and only 4.9% had completed senior high school. These findings highlight a relatively low level of formal education among the farming community, which may influence their digital engagement and decision-making capabilities.

A large proportion of respondents (94.6%) reported being part of an active farming household. Farming was the primary occupation for 57.7% of respondents, while 32.9% identified as housewives, 6.6% as private employees, and 2.9% as merchants. Moreover, a majority (69.7%) had dependents (children), with the most common number of children being one or two.

In terms of digital access, 66.0% of respondents owned a mobile phone, and 63.7% had access to internet-connected phones. When asked about sources of agricultural information, the majority cited fellow farmers (62.3%), followed by mobile phones (13.7%), television (11.7%), extension workers (10.9%), and farmer groups (1.4%). Internet usage frequency varied significantly; most respondents (62.9%) reported using the internet 6–7 times per week, while 33.4% never accessed the internet, and only a small proportion used it occasionally (1–5 times per week). This indicates a high reliance on digital platforms among connected users, despite a significant digital divide (see Table 2).

Category	Response	Frequency	Percentage (%)
Age	≤30 years	46	13.1
	31–45 years	152	43.4
	46–60 years	120	34.3
	>60 years	32	9.1
Education	No Schooling	71	20.3
	Elementary School	207	59.1
	Junior High School	55	15.7
	Senior High School	17	4.9
Active Farming Household	Yes	331	94.6
	No	19	5.4
Primary Occupation	Farmer	202	57.7
	Housewife	115	32.9
	Private Employee	23	6.6
	Merchant	10	2.9
Have Dependents (Children)	Yes	244	69.7
	No	106	30.3

Source: Author compilation, 2025

Table 2: Demographic profiles of the respondents
(To be continued).

Category	Response	Frequency	Percentage (%)
Number of Children	0	106	30.3
	1	106	30.3
	2	98	28.0
	3	29	8.3
	4	11	3.1
Own a Mobile Phone	Yes	231	66.0
	No	119	34.0
Internet-Connected Phone	Yes	223	63.7
	No	127	36.3
Sources of Agricultural Information	Fellow Farmers	218	62.3
	Mobile Phone	48	13.7
	Television	41	11.7
	Extension Worker	38	10.9
	Farmer Group	5	1.4
Internet Usage Frequency (per week)	0 times per week	117	33.4
	1–2 times per week	6	1.7
	3–5 times per week	7	2.0
	6–7 times per week	220	62.9

Source: Author compilation, 2025

Table 2: Demographic profiles of the respondents
(Continuation).

Measurement model assessment

The assessment of the measurement model focused on establishing both the reliability and validity of the constructs. As shown in Table 3, all outer loadings exceeded the minimum recommended threshold of 0.70, ranging from 0.746 to 0.960, which confirms that each indicator reliably represents its respective construct. Cronbach's alpha values were between 0.820 and 0.975, and the composite reliability (CR) values ranged from 0.888 to 0.980. Both values surpass the minimum threshold of 0.70, indicating satisfactory internal consistency. Furthermore, the average variance extracted (AVE) values were between 0.683 and 0.909, all of which are well above the 0.50 benchmark, confirming adequate convergent validity. Collectively, these

results establish that the constructs demonstrate robust reliability and convergence, ensuring the suitability of the measurement model (Hair et al., 2021).

Discriminant validity (DV) was assessed using two criteria: the Fornell-Larcker criterion and the Heterotrait-Monotrait Ratio (HTMT). In the Fornell-Larcker analysis, the square root of AVE for each construct was greater than its correlation with any other construct in the model (Table 4), supporting the discriminant validity assumption (Fornell & Larcker, 1981). The HTMT values also remained well below the 0.90 threshold, with the highest HTMT ratio recorded at 0.850 between Inclusive Digital Literacy and Trust in Technology, indicating that the constructs are empirically distinct (see Table 4) (Franke and Sarstedt, 2019; Henseler et al., 2009).

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These findings clearly demonstrate that the measurement model satisfies all of the essential criteria for both convergent and discriminant validity, thereby ensuring the robustness of the constructs used in this study. By meeting these requirements, the measurement model provides strong evidence that the indicators are not only reliable in representing their latent constructs

Construct	Indicator	Outer Loadings	Cronbach's Alpha	Composite Reliability (rho_a)	Composite Reliability (rho_c)	AVE
Gender Inclusion	GI_1, GI_2, GI_3, GI_4	0.851, 0.850, 0.774, 0.828	0.849	0.895	0.896	0.683
Inclusive Digital Literacy	IDL_1, IDL_2, IDL_3, IDL_4, IDL_5	0.957, 0.960, 0.959, 0.939, 0.952	0.975	0.981	0.980	0.909
Socioeconomic Resilience	SER_1, SER_2, SER_3, SER_4	0.883, 0.901, 0.746, 0.793	0.851	0.870	0.900	0.694
Trust in Technology	TT_1, TT_2, TT_3	0.752, 0.940, 0.865	0.820	0.972	0.888	0.727

Source: Author's computation from SmartPLS output (2025)

Table 3: Measurement model assessment: Reliability and validity.

Construct Pair	Fornell-Larcker Value	HTMT Ratio	Status
Gender Inclusion vs Inclusive Digital Literacy	0.285	0.293	Valid
Gender Inclusion vs Socioeconomic Resilience	0.605	0.709	Valid
Gender Inclusion vs Trust in Technology	0.37	0.44	Valid
Inclusive Digital Literacy vs Socioeconomic Resilience	0.226	0.249	Valid
Inclusive Digital Literacy vs Trust in Technology	0.733	0.85	Valid
Socioeconomic Resilience vs Trust in Technology	0.464	0.501	Valid

Source: Author's computation from SmartPLS output (2025)

Table 4: Discriminant validity: Fornell-Larcker criterion and HTMT ratio.

but also empirically distinct from one another. This is critical because a measurement model that lacks adequate reliability and validity may lead to biased or misleading interpretations of structural relationships. In contrast, the current results confirm that the constructs capture unique dimension in technology, and socioeconomic resilience, which are central to the proposed framework. Consequently, the validated measurement model offers a solid and credible foundation for evaluating the hypothesized causal paths in the structure and credibility of the empirical investigation.

Multicollinearity and common method bias

In survey-based studies, Common Method Bias (CMB) is recognized as a potential threat to the validity of findings due to its possible inflation or deflation of relationships among constructs. This study proactively addressed the risk of CMB following the Harman's single-factor test (Kock et al., 2021). We conducted an exploratory factor analysis using SPSS, which revealed that the first factor explained only 46.4% of the total variance below the 50% cutoff indicating that CMB is not a significant concern in this dataset.

To assess multicollinearity, we utilized the Variance Inflation Factor (VIF), as recommended by prior research (Kock et al., 2021; Rasoolimanesh, 2022). According to established guidelines, VIF values should be below 3.3 to rule out potential collinearity issues (Akinwande et al., 2015; Vörösmarty and Dobos, 2020) As shown in Table 5, all VIF values in the inner model fall within acceptable thresholds, ranging from 1.000 to 2.187, thereby confirming the absence of multicollinearity.

Structural Path	VIF
Inclusive Digital Literacy → Gender Inclusion	1.000
Socioeconomic Resilience → Inclusive Digital Literacy	2.187
Socioeconomic Resilience → Trust in Technology	2.165
Trust in Technology × Inclusive Digital Literacy → Socioeconomic Resilience	1.029

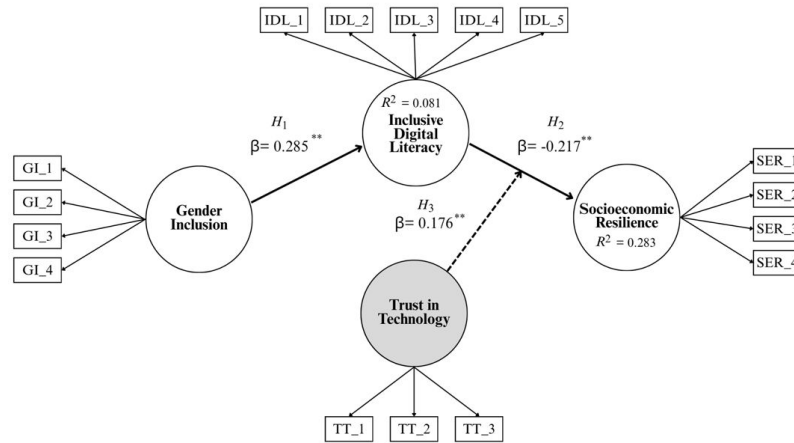
Source: Author's computation from SmartPLS output (2025)

Table 5: Collinearity statistics (VIF) for the structural model.

Structural model valuation

The structural model was examined using path coefficients, explanatory power (R^2), and effect sizes (f^2). Results (Table 6, Figure 2) indicate that gender inclusion positively and significantly influences inclusive digital literacy ($\beta = 0.285$, $t = 7.305$, $p < 0.001$). Interestingly, inclusive digital literacy exerts a negative and significant effect on socioeconomic resilience ($\beta = -0.217$, $t = 4.091$, $p < 0.001$). This finding suggests that digital literacy, when not supported by contextual enablers such as trust in technology or institutional support, may initially challenge household resilience.

Conversely, trust in technology strongly and positively affects socioeconomic resilience ($\beta = 0.651$, $t = 13.656$, $p < 0.001$), highlighting its role as a critical enabler of digital transformation among farming households. The moderation test further reveals that trust in technology significantly moderates the relationship between inclusive digital literacy and socioeconomic resilience ($\beta = 0.176$, $t = 4.041$, $p < 0.001$), indicating that digital literacy enhances resilience only when trust in digital tools is sufficiently high. Collectively, the model explained 8.1% of the variance in inclusive digital literacy and 28.3% of the variance in socioeconomic resilience.



Note: * and, ** denote a 5% and 1% significance level respectively
Source: Authors

Figure 2: Structural model results.

Hypothesized Path	β (Original Sample)	T-Statistics	P-Values	R ² (Adjusted)	f ² Effect Size
Gender Inclusion → Inclusive Digital Literacy	0.285	7.305	0.000	0.081	0.089
Inclusive Digital Literacy → Socioeconomic Resilience	-0.217	4.091	0.000	0.283	0.030
Trust × Inclusive Digital Literacy → Socioeconomic Resilience	0.176	4.041	0.000	0.283	0.055

Source: Author's computation from SmartPLS output (2025).

Table 6: Structural model results: Path coefficients, R², and f².

Model fit assessment and hypotheses testing summary

The overall model fit was evaluated using the Goodness-of-Fit (GoF) index, which integrates information from both the measurement and structural models by combining the average variance extracted (AVE) with the average R² values of the endogenous constructs. As reported in Table 7, the GoF value for this study was 0.39, which surpasses the recommended threshold of 0.36 that indicates large effect sizes according to Wetzels et al., (2009), this result suggests that the proposed model not only demonstrates a satisfactory level of explanatory power but also achieves an acceptable global fit, ensuring that the model is well specified and robust. The implication of this finding is that the measurement model and structural relationships together provide a reliable representation of the data, enhancing confidence in the interpretation of the hypothesized causal links. By surpassing the benchmark, the model validates its empirical adequacy and reinforces socioeconomic resilience in the agricultural context.

Measure	Value
Average AVE	0.829
Square root of AVE	0.910
Average of R ²	0.180
Square root of R ²	0.424
Global fit index (GoF)	0.39

Source: Author's computation from SmartPLS output (2025).

Table 7: Overall Model Fit Index (GoF).

Table 8 presents the results of the hypotheses testing, and all four proposed hypotheses were supported. H1 was confirmed, demonstrating that gender inclusion has a significant and positive impact on inclusive digital literacy. This finding emphasizes that when women are given equal opportunities in decision-making, access to resources, and participation in digital initiatives, the overall level of household digital literacy improves. Such results align with prior evidence suggesting that women play a pivotal role in technology adoption and knowledge dissemination in rural settings, thereby validating the critical role of gender equity in driving digital capacity development.

Hypothesis	Path	β	t-value	Supported?
H1	Gender Inclusion → Inclusive Digital Literacy	0.285	7.305	Yes
H2	Inclusive Digital Literacy → Socioeconomic Resilience	-0.217	4.091	Yes (negative effect)
H3	Trust in Technology x Inclusive Digital Literacy → Socioeconomic Resilience	0.176	4.041	Yes (moderation)

Source: Author's computation from SmartPLS output (2025).

Table 8: Summary of hypotheses testing.

H2 revealed a significant negative effect of inclusive digital literacy on socioeconomic resilience, a result that, while counterintuitive, reflects the nuanced challenges of digital transformation in resource-constrained households or trust in digital platforms, households may experience increased vulnerability when adopting digital tools. For example, limited digital skills can expose farmers to risks such as misinformation, cyber scams, or financial mismanagement, which may weaken rather than strengthen household of contextual enablers to ensure that digital literacy translates into positive and sustainable outcomes.

Meanwhile, H3 revealed that trust moderates the relationship between digital literacy and resilience, such that households with higher levels of trust are better able to leverage their digital literacy to enhance resilience. Together, these findings underline the complex dynamics of digital transformation in rural households. Trust emerges as a crucial mechanism that converts digital inclusion into tangible socioeconomic benefits, reinforcing the argument that digital interventions must integrate trust-building measures to achieve sustainable empowerment outcomes.

The findings confirm that gender inclusion significantly enhances inclusive digital literacy, highlighting that women's participation is a structural driver of household digital capacity. This result is consistent with Suwana and Lily (2017), who noted that Indonesian women still face digital gaps due to limited education, unequal opportunities, and patriarchal norms, requiring targeted digital literacy initiatives. Similar concerns are echoed by Avanesian et al. (2024), who documented significant gender disparities in digital skills among youth in low- and middle-income countries, with wealthier households often showing wider gaps that disadvantage young women. Barra et al. (2024) further demonstrated that gender moderates the relationship between digital skills and entrepreneurial orientation, suggesting that gender inequalities may hinder ICT utilization in entrepreneurship. Long et al., (2023) found that structural inequalities such as access to mobile devices, education, and income

explain more than 50% of the digital literacy gap in Indonesia. Together, these studies confirm that gender inclusion is not simply complementary but a prerequisite for strengthening digital literacy. This aligns with Chen et al., (2024), who showed that digital literacy reduces income gaps, particularly between men and women, and Liu & Liao, (2024), who demonstrated that farmers' digital literacy directly increases household income by enhancing access to information and financial services. The present study extends this line of research by emphasizing that gender equity in digital access is indispensable for building household-level resilience.

Contrary to expectations, inclusive digital literacy showed a significant negative effect on socioeconomic resilience. While much of the literature highlights positive effects of digital skills on income, opportunity, and empowerment (Chen et al., 2024; Liu and Liao, 2024). The current finding resonates with arguments that literacy alone is insufficient and may even introduce vulnerabilities. In fragile contexts, households equipped with basic digital skills but lacking trust or institutional support can become more exposed to risks such as misinformation, cyber fraud, or exploitative digital platforms. Similar dynamics were reported by Jia & Li, (2024), who found that digital collaboration weakened resilience unless supported by subsidies and external institutional mechanisms. This paradox is also reflected in Barra et al., (2024), who showed that gender gaps constrain the potential of digital literacy for entrepreneurship, and in Avanesian et al., (2024), who noted that unequal digital capacities exacerbate inequalities. In the agricultural sector, Shatila et al., (2025) further confirmed that digital literacy, accessibility, and human capital can contribute to resilience only when supported by innovation and agility. The present findings thus challenge the linear assumption that digital literacy is always beneficial, instead suggesting that literacy may become a liability in contexts where trust and institutional support are weak.

The validation of H3 that trust in technology moderates the relationship between digital

literacy and socioeconomic resilience underscores the central role of psychological and institutional enablers. Jafri et al. (2024) identified trust and security perceptions as primary determinants of FinTech adoption, confirming that users adopt digital services only when confidence is high. Similarly, Lee-Geiller (2024) showed that digital literacy enhances the link between e-government and public trust, reinforcing the argument that digital competence builds legitimacy when paired with institutional confidence. Zhao et al. (2025) demonstrated that digital leadership fosters resilience through knowledge sharing, but only when trust is strong at the community level. Alfirević et al. (2025) also showed that ICT proficiency moderates the relationship between climate anxiety and preparedness, proving that digital skills transform concern into action only when supported by confidence. Comparable evidence was found by Alsaad et al. (2017), who emphasized the moderating role of trust in e-commerce adoption, and Shatila et al., (2025), who confirmed that agility can amplify the effects of digital resources on resilience. These studies collectively converge with the present findings, positioning trust as both a direct enabler and a moderating force. By showing that digital literacy contributes to resilience only when trust is sufficiently high, this study extends the Technology Acceptance Model (TAM) and resilience theory, while also enriching the GIDL-WE framework by identifying trust as a critical contingency factor.

The broader implications of these findings are twofold. Theoretically, this study advances an interactionist perspective on digital empowerment, moving beyond linear models that treat literacy as sufficient. Instead, it demonstrates that gender inclusion is the structural foundation, digital literacy provides capacity, and trust in technology ensures conversion of capacity into resilience. Practically, the results call for integrated interventions: gender-sensitive digital education, institutional safeguards, and trust-building measures such as digital security programs, awareness campaigns, and transparent governance mechanisms. Evidence from Vargas-Merino et al., (2025) confirms that institutional dimensions like communication and legitimacy shape decision-making outcomes, reinforcing the need to combine structural and psychological supports. Likewise, Du et al., (2023) showed that digital inclusive finance enhances resilience only when the financial environment is enabling. Taken together, the present study demonstrates that trust

transforms literacy from a potential vulnerability into a resilience asset, underscoring that digital inclusion strategies in rural households must be comprehensive, gender-sensitive, and context-specific.

Conclusion

This study provides a comprehensive analysis of how gender inclusion, digital literacy, and trust in technology interact to shape socioeconomic resilience among farming households in food-insecure regions of Central Kalimantan, Indonesia. Grounded in the Gender-Inclusive Digital Literacy for Women Empowerment (GIDL-WE) framework and employing PLS-SEM analysis, the study offers a nuanced understanding of how digital and social resources jointly determine household adaptability in contexts marked by structural vulnerability. The findings validate the proposed hypothesis, confirming that trust in technology plays a significant moderating role in strengthening the relationship between digital literacy and resilience, and thereby highlighting the indispensable role of psychological and institutional enablers in digital transformation.

In particular, the results reveal that gender inclusion enhances digital literacy, reinforcing evidence that women's participation in household decision-making and agricultural activities is a critical driver of technology adoption and competence building. Nevertheless, the unexpected negative relationship between digital literacy and resilience suggests that skills acquisition alone, in the absence of institutional support or digital trust, may initially impose risks and burdens on households. This paradox underscores the importance of designing interventions that go beyond training, by embedding safeguards, infrastructure, and trust-building mechanisms to ensure that digital capabilities translate into tangible socioeconomic gains.

Trust in technology emerges as a decisive factor in the model, both as a direct enabler of resilience and as a moderator that conditions the positive impact of digital literacy. Households that exhibit higher levels of trust in digital tools are better positioned to convert literacy into resilience outcomes, while households with low trust may find that literacy remains an underutilized resource. This interaction highlights the layered and contingent nature of digital empowerment, where psychological and institutional confidence are equally as critical as skill acquisition.

From a theoretical perspective, the study contributes to the growing body of literature on digital inclusion and resilience by advancing an interactionist approach. It extends beyond linear models that assume digital skills are sufficient, showing instead that resilience emerges from the interplay between gender inclusion, digital competence, and trust in technology. From a practical perspective, the findings provide valuable insights for policymakers, development practitioners, and community leaders, underscoring the importance of integrated interventions that combine gender-sensitive training, institutional safeguards, and trust-building measures. Such strategies are essential for transforming digital inclusion into sustainable resilience in vulnerable farming households.

This study also sets the stage for future research. Longitudinal studies could investigate how trust and literacy co-evolve over time to strengthen household resilience. Comparative analyses across regions and countries would enhance generalizability and reveal the contextual factors

that amplify or constrain the digital-resilience nexus. Finally, mixed-method approaches combining quantitative modeling with qualitative insights could uncover the lived experiences of women farmers, their households, and communities, thereby deepening our understanding of how gender, technology, and trust intersect to shape adaptive capacities in fragile environments.

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Enhancing Agricultural Productivity and Food Security Through Climate Smart Agriculture (CSA) Adoption: The Interplay of Social, Economic and Environmental in Tidal Swamp Farming

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Abstract

Food security is closely linked to agricultural productivity and the adoption of modern technologies. This study examines the socio-economic and environmental factors that drive the adoption of Climate-Smart Agriculture (CSA), enhance productivity, and improve food security in tidal swamp areas. The interrelationships between economic factors such as income and access to capital, and environmental factors like sustainable land management practices and water resource usage, all of which play a crucial role in the adoption of CSA technologies. The study was conducted with 180 farmers in Banyuasin Regency, specifically in Telang Makmur, Panca Mukti and Telang Jaya Villages, who provided data to assess how these factors influence food security outcomes. The findings indicate that both economic and environmental factors significantly affect the adoption of CSA technology, which subsequently leads to increased agricultural productivity and food security. Specifically, economic empowerment through higher income levels and enhanced access to capital enables farmers to invest in CSA technologies, while environmentally sustainable practices help mitigate climate risks and improve land and water management. The results underscore the importance of integrated approaches that address both economic and environmental dimensions to ensure long-term food security. This study provides valuable insights for policymakers, stressing the need for strategies that combine economic support, technological innovation, and environmental sustainability to enhance food security in regions like Muara Telang.

Keywords

Climate Smart Agriculture (CSA) technology, food security, productivity.

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Introduction

Food security is a crucial issue around the world, especially in developing countries (Pratama et al., 2024; Wakweya, 2023). In Indonesia, the agricultural sector plays a substantial role in the economy (Prihadyanti and Aziz, 2023; Yamin et al., 2024). However, this sector faces numerous challenges, particularly those induced by climate change. One of the areas most vulnerable to the impacts of climate change is the tidal swamp agricultural land, which often experiences fluctuations in salinity levels, flooding, and soil degradation (Wang et al., 2023). All of these factors directly affect agricultural yields and food security. Therefore, the implementation of environmentally friendly agricultural technologies is essential

to help farmers adapt to climate change and enhance their food security (Wakweya, 2023).

One of the strategies increasingly adopted to address climate change in the agricultural sector is CSA (Hussain et al., 2022). CSA encompasses a variety of agricultural practices aimed at strengthening resilience to climate change, reducing greenhouse gas emissions, and improving agricultural productivity in a sustainable manner (Zheng et al., 2024). Various CSA technologies, such as soil conservation, more efficient water management, and crop diversification, have been proven effective in enhancing agricultural productivity while reducing losses caused by the impacts of climate change (Yamin et al., 2025; Zizinga et al., 2022). Therefore, the implementation of CSA technologies

in tidal swamp agricultural areas can serve as an effective solution to improve food security and the well-being of farmers (Kundu et al., 2024). (Tabe-Ojong et al., 2024) shows that the adoption of CSA practices can enhance agricultural yields, thereby contributing to food security. Furthermore, his research indicates that the adoption of CSA is not only advantageous for farmers who have already embraced it, but it could also offer benefits to those who have not yet adopted these practices, should they choose to do so.

However, socio-economic and environmental factors are critical determinants in this process. The socio-economic conditions of farmers have a significant impact on agricultural productivity (Gwambene et al., 2023). Education also plays a crucial role. Farmers with higher levels of education generally possess a better understanding of agricultural technologies and their associated benefits. They are more open to adopting new information and are better able to implement it in their daily practices. Moreover, a cohesive community structure can facilitate the exchange of information and experiences among farmers, which, in turn, fosters the adoption of new technologies (Thomas et al., 2023).

In addition, several economic factors significantly influence the adoption of new agricultural technologies (Smidt and Jokonya, 2022). A key determinant is farmers' income levels, as these directly affect their capacity to invest in innovative agricultural tools, improved seeds, and advanced farming practices (Kundu et al., 2024). Farmers with higher incomes are generally more able to allocate resources for technological adoption, thereby enhancing productivity. Furthermore, access to capital and credit plays a crucial role, as it enables farmers to invest in better agricultural technologies, thus improving their farming operations (Balana and Oyeyemi, 2022). In contrast, low-income farmers are often constrained by financial limitations, which prevent them from adopting more efficient practices and technologies (Khan et al., 2021). This economic disparity can perpetuate a cycle of poverty, making it difficult for these farmers to increase productivity or improve their livelihoods (Ulukan et al., 2022). Consequently, addressing income disparities and enhancing access to financial resources are essential for fostering the adoption of sustainable agricultural practices (Adisa et al., 2024).

The physical environment, including climatic conditions and natural resources, plays a crucial

role in determining agricultural productivity (Habib-ur-Rahman et al., 2022). Climate change, characterized by rising temperatures and erratic rainfall patterns, can significantly reduce crop yields and increase the risk of crop failure (Bedeke, 2023). In response to these challenges, CSA technology have been developed to assist farmers in adapting to and mitigating the impacts of climate change. However, the effectiveness of CSA technology is highly dependent on local conditions and biodiversity (Kassaye et al., 2022). The availability of natural resources, such as water and fertile soil, also affects productivity (Javed et al., 2022). Farmers residing in areas with limited access to these essential resources often face substantial difficulties in improving their agricultural yields (Mondal and Palit, 2022). Therefore, a comprehensive understanding of the interplay between environmental factors and agricultural practices is essential for developing effective strategies aimed at enhancing productivity and resilience to climate change.

Food security is closely related to agricultural productivity and technology adoption. The adoption of CSA can make a significant contribution to food security by enhancing agricultural productivity and fostering greater stability in food resilience (Okolie et al., 2022). CSA practices have the potential to improve crop yields, mitigate losses caused by extreme weather events, and increase farmers' incomes. Consequently, this can lead to improved availability and accessibility of adequate and nutritious food for communities. Although extensive research has been conducted on the impact of CSA on agricultural productivity and food security, there has been limited focus on regions with tidal swamp typologies. These areas have unique characteristics, such as highwater salinity during the dry season and susceptibility to flooding, which influence the adoption of CSA. Therefore, this study aims to address the knowledge gap regarding how economic, social, and environmental factors play a role in the adoption of CSA in tidal swamp areas and their subsequent impact on productivity and food security. This research is of significant importance as it provides deeper insights into the factors influencing CSA adoption in tidal swamp regions. The study seeks to analyze the relationship between social, economic, environmental factors, as well as their effects on the adoption of CSA technologies, agricultural productivity and food security. The findings from this research are expected to form the foundation for the development of more

effective policies aimed at promoting CSA adoption and enhancing food security in regions vulnerable to climate change.

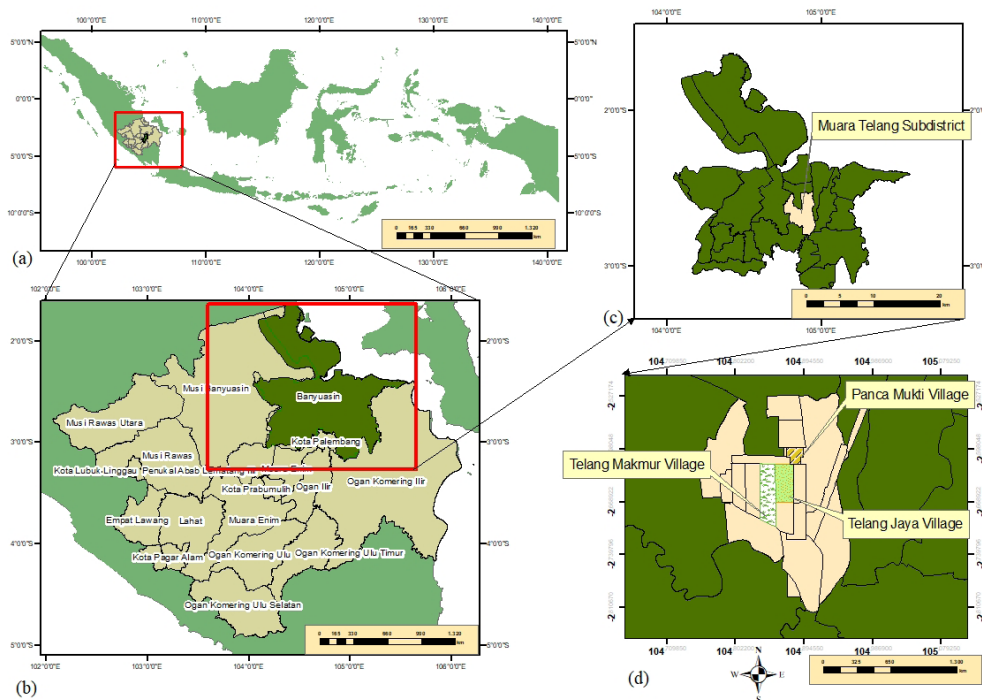
Material and methods

The research location in Telang Jaya, Banyuasin Regency, which is known for its tidal swamp land influenced by the fluctuations of sea tides. With its unique land characteristics, this study aims to explore how economic, social, and environmental factors play a role in the implementation of CSA (Climate-Smart Agriculture) technology in the tidal swamp agricultural area and how this impacts agricultural productivity and food security in the region. The detailed location of the study can be seen in the following Figure 1.

This study employs a quantitative approach using Structural Equation Modeling (SEM) with the Smart PLS application to examine the influence of economic, social, and environmental factors on the adoption of Climate-Smart Agriculture (CSA), agricultural productivity, and food security in the tidal swamp agricultural system with a Planting Index (IP) of 300 (IP300). The SEM model was chosen for its ability to test the relationships between interrelated

variables simultaneously and in a complex manner, both in terms of direct and indirect relationships (Garrido et al., 2022; Qonita et al., 2025). The population of this study consists of farmers engaged in tidal swamp agriculture in three villages in Banyuasin Regency, South Sumatra, selected using random sampling based on different levels of CSA adoption. This sampling technique ensures a fair representation of various levels of CSA technology adoption among the farmers.

Data were collected in 2024 through a structured questionnaire that included statements related to social factors (education, health, social interactions, and institutional support), economic factors (business diversification, income, production, and access to capital), and environmental factors (sustainable farming practices, environmental management, soil quality, water availability, and the use of chemical inputs) as they relate to productivity, CSA technology adoption, and food security. A five-point Likert scale, ranging from "strongly disagree" to "strongly agree", was developed for this study to measure these items. For more detailed information, the variables and indicators of the study can be seen in the following Table 1.



Source: Authors

Figure 1: Site study sampling: a) Indonesia, b) South Sumatra, c) Muara Telang Subdistrict, d) Telang Makmur, Panca Mukti and Telang Jaya Village.

Variable	Indicator
Social (X1) (Al-Maskari et al., 2022)	X1.1. Education
	X1.2. Health
	X1.3. Social Interaction
	X1.4. Institutional
Economy (X2) (Arru et al., 2021; Rafique et al., 2022)	X2.1. Business Diversification
	X2.2. Income
	X2.3. Production
	X2.4. Access to Capital
Environment (X3) (Aulakh et al., 2022)	X3.1. Sustainable Agricultural Practices
	X3.2. Environmental Treatment
	X3.3. Soil Quality
	X3.4. Water Availability
	X3.5. Use of Production Inputs from Chemicals
Productivity (Y1) (Leul et al., 2023; Zheng et al., 2024)	Y1. Farming Experience
	Y2. Soil Quality Last 5 Years
	Y3. Land Size
Adoption of CSA Technology (Y2) (Hussain et al., 2022; Okolie et al., 2022)	Y2.1. Land Cultivation
	Y2.2. Planting Technology
	Y2.3. Organic Control
	Y2.4. Irrigation
	Y2.5. Organic Fertilizer
	Y2.6. Superior Variety
	Y2.7. Planting Calendar
	Y2.8. Harvesting Technology
Food Security (Y3) (Ghufran et al., 2024)	Y3.1. Food Stock
	Y3.2. Food Access
	Y3.3. Food Utilization
	Y3.4. Food Stability

Source: Authors

Table 1: Research variables and indicators.

Results and discussion

Characteristic of respondent

The diverse characteristics of respondents reflect both the potential and challenges in adopting Climate-Smart Agriculture (CSA) technologies among farmers. Gender, ethnicity, education, farmers experience and land size are key factors that can influence farmers' decisions to transition to more sustainable agricultural practices. Detailing the characteristics of respondents is crucial for understanding the context of the findings. Here's a typical framework for presenting the characteristics of respondents in a study in Table 2.

Based on the data presented, this study illustrates the demographic and socio-economic characteristics of the respondents, the majority of whom are male

farmers from Java. Most of the respondents have low levels of education, with an average education of only 8.84 years, which primarily corresponds to middle school and high school levels. Only a small percentage have higher education, such as a diploma or bachelor's degree. This suggests that the respondents' education levels are generally limited, which may affect their knowledge and skills in managing agricultural enterprises (Devkota et al., 2023). In terms of farming experience, the average respondent has approximately 21.81 years of experience, with most falling within the 31-40 years range. This indicates that they possess significant knowledge in running farming businesses, although a small number are relatively new to the field (0-10 years). Such extensive experience can be a valuable asset in facing challenges within the agricultural sector (Haque et al., 2023).

Variabel (n = 180)	Percentage (%)	Average	Standard Deviation (±)
Gender			
Male	100.00	-	-
Female	0.00		
Etnicity			
Local (Sumatra)	0.00	-	-
NonLocal (Jawa)	100.00		
Education (Year)			
0-6 Year	41.11	8.84	2.96 (18;3)
7-9 Year	26.67		
10-12 Year	27.78		
> 12 (Diploma, Bachelor)	4.44		
Farmers Experience (Year)			
0-10 Year	22.22	21.81	11.91 (50;1)
11-20 Year	25.56		
21-30 Year	12.22		
31-40 Year	32.22		
> 40 Year	7.78		
Land Size (Ha)			
0-1	35.00	2.19	1.71 (10;0.50)
> 1-2	36.11		
> 2	28.89		

Source: Authors

Table 2: Characteristic of respondent.

Regarding land size, the average respondent owns around 2.19 hectares of land. Most own land between 1 and 2 hectares, with 35% owning less than 1 hectare. This suggests that the majority of these farmers fall into the smallholder category, with limited access to land and capital. The diversity in land size also reflects varying potential in managing their agricultural production (Yu et al., 2022). This data portrays a population of experienced farmers, yet they face challenges in terms of education and land size. Approaches that support improving access to education and empowering small farmers would be highly beneficial in enhancing their well-being.

Analysis of type I and type II construction models

The analysis of the construction model in type I shows the results of the analysis of social (X1), economic (X2) and environmental (X3) influences on productivity (Y1), technology adoption (Y2) and food security (Y3). This model adopts the Climate-Smart Agriculture (CSA) theory, where each variable is measured using specific indicators. The results of the data analysis conducted are presented. It can be observed that the outer loading

value represents the relationship between the latent variable and the manifest variable. The test criterion applied requires that the outer loading value must be greater than 0.7. After conducting the test, it was concluded that some of the outer loading values did not meet the required criterion. Specifically, the outer loading values that were less than 0.7 include farmers' perceptions of social interaction, income, water availability, planting technology, superior varieties and Harvesting Technology. For more detailed information, please refer to the following Table 3.

Indicator	Notation	Outer Loading Value
Social Interaction	X1.3	0.393 < 0.7
Income	X2.3	0.617 < 0.7
Water Availability	X3.4	-1.30 < 0.7
Planting Technology	Y2.2	0.351 < 0.7
Superior Variety	Y2.6	-0.109 < 0.7
Harvesting Technology	Y2.8	0.50 < 0.7

Source: Authors

Table 3: Outer loading value on indicators not greater than 0.7.

Several factors influencing the adoption of Climate-Smart Agriculture (CSA) technologies demonstrate

weaker-than-expected relationships, even though these factors are anticipated to play crucial roles. Social interaction among farmers, while theoretically important for accelerating knowledge transfer and technology adoption, has not proven to be a strong driver in CSA implementation. This is likely due to low levels of trust among farmers or a lack of shared understanding regarding the benefits of CSA technologies. Economic factors, such as income, although positively correlated with CSA adoption, are not sufficiently significant to drive widespread adoption. Farmers with greater financial resources may have better access to CSA technologies (Bojago and Abrham, 2023), but economic factors alone are limited in facilitating broader technological change, given other barriers such as knowledge or access to the technologies themselves.

Water availability shows an unusual inverse relationship, where areas with limited water resources are more likely to adopt water-saving technologies. However, despite the potential for water scarcity to drive adoption, its impact on CSA adoption remains relatively insignificant. Planting technologies and the use of superior varieties, although highly promising in improving agricultural productivity, are not being applied optimally, likely due to inadequate access to the required technologies or a lack of understanding of their potential benefits. Harvesting technologies, while showing potential to reduce post-harvest losses and improve product quality, are still limited in application to a small subset of farmers with access to them. Overall, these findings indicate that more effective CSA adoption requires a more integrated approach that considers economic, social, and technological factors in greater depth, alongside policies that improve the distribution of information and technology

access among farmers, particularly in areas most vulnerable to climate change (Tanti et al., 2022).

The next step involves reconstructing the model to achieve a proper fit, ensuring that there are no manifest variables or models that fail to meet the analyst's specified criteria. The results of this model reconstruction can be observed in the Figure 2.

Validity

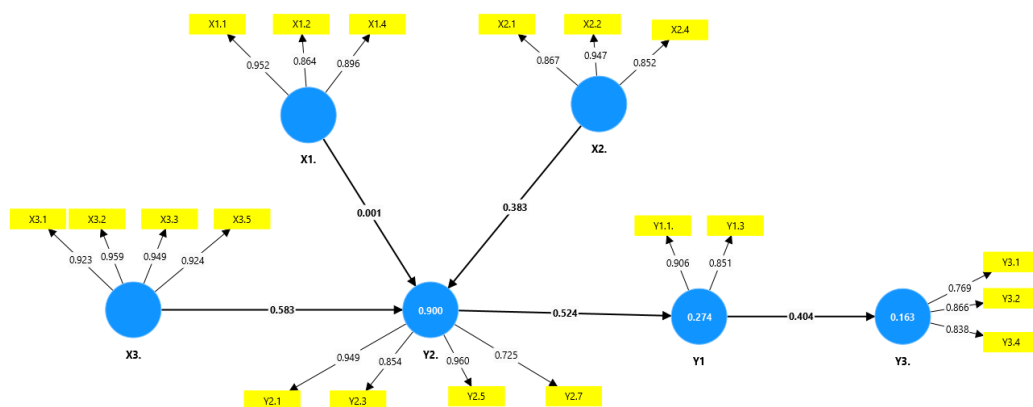
To measure the validity of convergence, it was done by looking at the Average variance extracted (AVE) value. Convergent validity is related to the principle that the indicators or manifest variables of a construct have a strong correlation. The AVE shows the proportion of variance that can be explained by these latent construct indicators, compared to the variance caused by measurement errors. If the AVE value is greater than 0.5, the items or indicators used in the SEM-PLS model meet the validity criteria or are declared valid. The following are the average variance extracted (AVE) values in the SEM-PLS model with the help of the Smart PLS 4.0 program on Table 4.

Variable	Average Variance Extracted (AVE)
X1	0.818
X2	0.792
X3	0.882
Y1	0.773
Y2	0.769
Y3	0.681

Source: Authors

Table 4: The result of Average Variance Extracted (AVE).

It can be seen that all the variables used in the SEMPLS model have an AVE value of > 0.5 so it can be concluded that the SEMPLS model



Source: Authors

Figure 2: Results of type II data analysis (after reconstruction).

built is valid. Apart from the value of loading factor and AVE to see the validity of convergence, SEM-PLS must also meet the criteria of discriminatory validity. The validity of discrimination from the outer model uses the cross loading value criterion. Indicators that have a cross loading value of > 0.7 , these indicators meet the criteria for the validity of discrimination.

R-square test

Models in the SEM-PLS can be tested for fit or fit through Goodness of fit (GoF). The value of GoF is obtained through the root of the multiplication of the R-square mean (R2) and the communality mean. The R-square value of each construct is obtained through the bootstrapping procedure while the communality value is obtained through the blindfolding procedure. The following are the average values of R2 and communality respectively presented in Table 5.

Variable	R-square	R-square adjusted
Y1	0.274	0.270
Y2	0.900	0.898
Y3	0.163	0.159

Source: Authors

Table 5: R-square result.

Hypotesis testing

Hypothesis testing is conducted to examine the relationships between latent variables or constructs in the structural model of SEM-PLS. The bootstrapping method is used for hypothesis testing in this study, as it is more efficient than the jackknifing method, which does not account for confidence intervals. The significance level applied in this analysis is 5%, and the findings are based on the results from the SmartPLS 4 program. The following are the outcomes of the analysis, providing insights into how different factors influence the model variables.

The analysis on table above shows that social factors like education and health do not significantly

influence the adoption of CSA technology, likely due to limited awareness and trust among farmers. However, economic factors such as income and financial capacity play a crucial role, as wealthier farmers can afford the costs of adopting CSA technologies. Environmental factors, particularly water availability, strongly drive the adoption of CSA, especially in areas facing water scarcity.

Moreover, increased productivity directly enhances food security, showing the importance of improving farming methods through CSA. Finally, CSA adoption boosts productivity, reinforcing the link between technology use and better food security (Wakweya, 2023). These findings highlight the need for targeted policies that address economic constraints and environmental challenges to promote CSA adoption.

SEM-PLS analysis also provides valuable insights into the indirect relationships between variables, commonly referred to as specific indirect effects (Hair, 2022). These indirect effects are essential for understanding the pathways through which one variable influence another, offering a deeper understanding of the causal relationships within the model. This information is instrumental in identifying the most relevant paths for further investigation and ensuring that the structural model is robust and accurate. The following table presents the results of the specific indirect effects analysis, conducted with the SmartPLS 4.0 program, which helps to highlight the key indirect relationships in the model and provides a clearer view of the variables' interdependencies as follows (Table 7).

The specific indirect effects analysis highlights the critical roles of environmental and economic factors in driving the adoption of Climate-Smart Agriculture (CSA) technologies, enhancing agricultural productivity, and improving food security. Environmental factors, especially related to water availability and climate resilience, are essential in encouraging CSA adoption, as these

Variable	Original sample (O)	Sample mean (M)	Standard deviation (stdev)	t-statistics (stdev)	P values
X1 -> Y2	0.001	-0.007	0.130	0.007	0.994
X2 -> Y2	0.383	0.375	0.146	2.630	0.009
X3 -> Y2	0.583	0.600	0.114	5.113	0.000
Y1 -> Y3	0.404	0.413	0.067	6.014	0.000
Y2 -> Y1	0.524	0.527	0.068	7.736	0.000

Source: Authors

Table 6: Path analysis (direct effects).

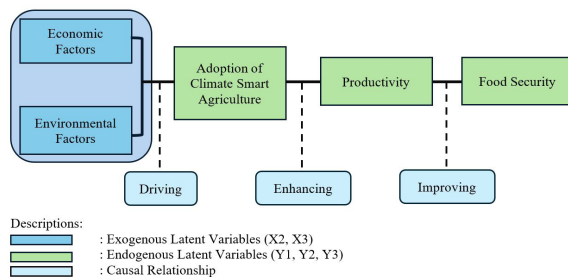
Variable	Original sample (O)	Sample mean (M)	Standard deviation (stdev)	t-statistics (stdev)	P values
X3 -> Y2 -> Y1	0.305	0.317	0.073	4.160	0.000
Y2 -> Y1 -> Y3	0.212	0.222	0.060	3.511	0.000
X2 -> Y2 -> Y1 -> Y3	0.081	0.083	0.040	2.030	0.042
X1 -> Y2 -> Y1 -> Y3	0.000	-0.002	0.030	0.007	0.995
X3 -> Y2 -> Y1 -> Y3	0.123	0.133	0.046	2.695	0.007
X1 -> Y2 -> Y1	0.001	-0.003	0.069	0.007	0.994
X2 -> Y2 -> Y1	0.201	0.198	0.081	2.476	0.013

Source: Authors

Table 7: Results of bootstrapping procedure on the SEM-PLS model (indirect effects).

technologies help mitigate the impacts of climate change. Economic factors, such as financial resources and access to markets, also play a significant role in enabling farmers to invest in CSA technologies, thereby boosting productivity and food security.

On the other hand, social factors like education and health, while important, have a less direct influence on CSA adoption. This may be due to limited access to information, low levels of trust among farmers, or the lack of social networks that support the adoption of technology (Dadzie et al., 2022). Additionally, farmers tend to prioritize economic factors, such as financial capability, and environmental challenges, such as water availability, when deciding to adopt CSA. Therefore, while social factors do play a role, their influence is limited unless supported by more fundamental economic and environmental factors. This suggests that although social capital can help raise awareness, it is not enough on its own to drive significant technological change without sufficient economic and environmental support. Therefore, a multi-dimensional approach is required: policies should integrate economic empowerment and environmental sustainability, alongside social initiatives (Falah et al., 2025), to effectively promote CSA adoption and improve food security. By addressing these key factors, CSA technologies can become more accessible and impactful for farmers, fostering long-term agricultural resilience.



Source: Authors

Figure 3: Critical roles of environmental and economic factors.

Economic variables (X2) → CSA technology adoption (Y2)

The challenges faced by farmers in tidal swamp lands, along with the Agricultural Performance Index (IP) 300, underscore the critical role of economic factors in enabling the adoption of Climate-Smart Agriculture (CSA) technologies. Economic variables such as business diversification, income, production capacity, and access to capital significantly influence farmers' ability to implement CSA practices. Diversification of livelihoods, such as engaging in horticultural activities (vegetables and fruits) before the rice planting season, helps mitigate economic risks by providing additional sources of income.

This, in turn, strengthens the financial resilience of farmers, enabling them to invest in CSA technologies, such as more efficient irrigation systems or salt-tolerant seeds. Higher income levels facilitate the purchase of essential agricultural equipment (Peng et al., 2022), such as water pumps and tractors, which are crucial for managing the environmental challenges of tidal swamp lands. Additionally, achieving higher production capacity reaching 8-9 tons per hectare per planting season allows farmers to reinvest their agricultural outputs into more efficient technologies. Finally, access to capital is vital, as it enables farmers to finance the necessary tools and machinery, ensuring their capacity to adapt to unpredictable land conditions (Tabe-Ojong et al., 2024). Therefore, strengthening these economic factors is crucial for enhancing farmers' resilience to climate change and promoting widespread adoption of CSA technologies, ensuring sustainable agricultural practices in this challenging environment.

Environmental variables (X3) → CSA technology adoption (Y2)

Sustainable agricultural practices, effective environmental management, and the use of environmentally friendly production inputs are highly relevant to SDGs Goal 13: Climate Action

(Rehman et al., 2022), which emphasizes the global need to address climate change. In the agricultural context, the adoption of CSA technologies plays a crucial role in mitigating the negative impacts of climate change, enhancing resilience to natural disasters, and reducing greenhouse gas emissions (Hussain et al., 2022). Practices such as crop rotation and the use of straw as mulch help to improve soil fertility, which is particularly significant in areas with tidal swamp lands. Additionally, the use of crop varieties that are resistant to salinity and drought is essential in such regions, where these environmental stresses are prevalent. Moreover, effective environmental management, such as the sustainable use of natural resources, can optimize the use of water and land (Li et al., 2022).

The implementation of efficient irrigation systems and prudent resource management helps farmers adapt to erratic rainfall patterns, a growing phenomenon caused by climate change. Maintaining soil quality is also critical, as it directly influences agricultural yields and ensures the sustainability of food production (Qiao et al., 2022), even in the face of climate impacts. By reducing the excessive use of chemicals and replacing them with organic inputs or environmentally friendly technologies, the agricultural sector can minimize its carbon footprint.

Overall, the adoption of CSA directly contributes to SDGs Goal 13: Climate Action by mitigating the effects of climate change, reducing carbon emissions, and improving food security through more sustainable and eco-friendly practices. The application of CSA by farmers in climate-vulnerable areas, such as tidal swamp regions, is pivotal in achieving global sustainability goals, given its contribution to building agricultural resilience against the ever-evolving challenges posed by climate change.

Adoption of CSA technology (Y2) → Productivity (Y1)

The adoption of CSA technologies plays a critical role in enhancing agricultural productivity, not only by promoting environmental sustainability but also by improving production efficiency and resilience to external challenges such as climate change. Key CSA practices, such as the use of superior seeds, integrated pest and disease management through techniques like mulch fences (Figure 4a), efficient irrigation systems for water management (Figure 4b, 4c), and the application of lime to improve soil quality (Figure 4d), are all pivotal in boosting agricultural productivity. In addition to these practices, the use of water pumps to ensure consistent water supply

during the dry season stands out as a vital aspect of CSA. By integrating such technologies, CSA not only fosters environmental sustainability but also equips farmers with the necessary tools to enhance their crop yields, even in challenging environments such as tidal swamp areas (Chiang et al., 2024).

In the research area, which is characterized by tidal swamp land, the adoption of CSA has been shown to significantly boost rice productivity, with yields reaching up to 8-9 tons per hectare per planting season. This serves as a clear example that CSA technology can help farmers overcome environmental challenges, such as soil salinity and water scarcity, while achieving higher yields compared to traditional farming methods. This success underscores the potential of CSA to improve productivity even in regions that face severe climatic and environmental pressures (Mpala and Simatele, 2024). Overall, the adoption of CSA technologies highlights that sustainable and productive agriculture is not solely reliant on economic factors but also on the implementation of technologies that integrate environmental sustainability with increased output (Abegunde and Obi, 2022).



Source: Authors

Figure 4a: Efficient irrigation systems for water management.



Source: Authors

Figure 4b: Key CSA practices through techniques like mulch fences.



Source: Authors

Figure 4c: Efficient irrigation systems for water management.



Source: Authors

Figure 4d: The application of lime to improve soil quality.

Productivity (Y1) → Food security (Y3)

Increasing agricultural productivity directly contributes to food security by enhancing the availability and stability of food stocks (Mutungi et al., 2023). As farmers achieve higher yields, they are able to allocate a portion of their harvest typically 15-25% toward ensuring food security for their households. This reserved portion serves as a safeguard against periods of food scarcity, such as during seasonal fluctuations or unexpected agricultural setbacks. In regions where rice productivity reaches 8-9 tons per hectare per planting season, reserving 15-25% of the harvest translates to an approximate 1.2 to 2.25 tons (or 1,200 to 2,250 kg) of dry rice. This surplus is essential for maintaining a reliable food supply, especially during lean months, adverse climatic events, or when market conditions cause food prices to spike (Nyathi & Mlambo, 2024). It provides farmers with the ability to feed their families even when other food sources may be limited or unaffordable.

Furthermore, this practice reinforces the resilience of rural communities by reducing their reliance

on external markets, which can be volatile and subject to disruptions (Zhou and Gu, 2025). By maintaining a strategic reserve of food, farmers are better equipped to withstand external shocks and avoid food insecurity. This approach also complements Climate-Smart Agriculture (CSA) practices, which further enhance productivity through the use of innovative technologies such as efficient irrigation systems, pest management techniques, and drought-resistant crop varieties. Ultimately, setting aside 15-25% of the harvest not only strengthens food security at the household level but also contributes to broader regional food stability (Aryal et al., 2019). This aligns with the objectives of SDGs 2: Zero Hunger, promoting food availability, reducing vulnerability to climate-related risks, and fostering self-sufficiency. By supporting farmers' ability to produce and secure food for their families, this practice plays a pivotal role in achieving sustainable and long-term food security in the face of an increasingly uncertain climate (Chao, 2024).

Conclusion

This study provides compelling evidence that the adoption of Climate-Smart Agriculture (CSA) technologies is a factor in increasing agricultural productivity and food security, particularly in ecosystems highly vulnerable to climate change, such as tidal wetlands. Respondent characteristics indicate that although most farmers have farming experience, they have limited education and land size, which prevents them from adopting new methods without external support. Structural model analysis indicates that social factors, such as education and health, do not significantly impact CSA adoption due to limited awareness and weak trust networks. Instead, economic and environmental factors emerge as the strongest drivers. Economic means—in terms of diverse income sources, higher production levels, and the availability of funds—enable farmers to invest in CSA innovations such as efficient irrigation equipment, machinery, or high-yielding seeds. Natural factors, particularly water and soil management and climate-resilient technologies, play a key role in facilitating CSA adoption because these technologies have a direct impact on pressing local issues such as salinity, drought, and irregular rainfall.

The findings also show that CSA adoption has a direct and significant impact on agricultural productivity, as rice yields with CSA can reach 8–9 tons per hectare in tidal swamps, compared to traditional farming. This increased productivity

translates into improved household and local food security, as farmers can store 15–25% of their harvest—1.2–2.25 tons of rice per growing season—as a safety buffer against market fluctuations, seasonal deficits, and climate-related risks. By extending beyond immediate food needs, this buffer boosts community resilience by reducing dependence on external food markets and creating a secure food buffer.

It is important to emphasize that, in this study, CSA adoption is not only an agro-innovation but also a strategic pathway towards achieving broader sustainability goals. By effectively utilizing resources, reducing greenhouse gas emissions,

and increasing resilience to climate shocks, CSA directly contributes to SDG 2 (Zero Hunger) and SDG 13 (Climate Action). This highlights the need for a multifaceted policy response that integrates economic empowerment, environmental sustainability, and social protection systems. Improving access to capital, enhancing knowledge diffusion, promoting farmer networks, and ensuring equitable access to CSA technology are key steps to facilitate adoption. This way, CSA can be scaled up into a viable solution for resilient agriculture, vulnerability reduction, and sustainable agricultural resilience in the most climate-vulnerable regions.

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