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Agris on-line Papers in Economics and Informatics

Volume XVIII Number 1, 2026

Domestic Production Linkages and Sectoral Shifts in Central Europe: An Input–Output Perspective

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Abstract

This paper examines changes in productive structures and domestic inter-industry linkages in five Central European countries- the V4 group and Austria- over 2000–2023. Despite previous studies, evidence remains limited on how domestic inter-industry linkages and sectoral transformations have evolved across these economies, particularly in the primary sector and agriculture. Using national input-output tables from the Asian Development Bank, demand multipliers (output, import, and value added) were calculated at the industry level and aggregated by sector and subsector to reflect sectoral trends and relationships. The analysis focuses on structural transformation, with emphasis on the primary sector and agriculture. Findings confirm a more stable sectoral structure in Austria, while structural shifts persisted in the V4 countries even after 2010. Transformation was most pronounced in the early period, with the primary sector declining in favour of secondary and tertiary sectors, dominated by manufacturing and services. Agriculture's value added remained relatively stable, despite weakening domestic linkages and rising import dependence. At the same time, integration into global value chains increased reliance on imported inputs across sectors. The results suggest that V4 countries should strengthen agricultural resilience by focusing on innovation to improve domestic value added creation and reduce vulnerability to external shocks.

Keywords

Input-output analysis, sectoral transformation, domestic inter-industry linkages, primary sector, agriculture, V4 countries, Austria.

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Introduction

The input-output tables (IOTs) are a valuable analytical tool for assessing the significance of specific sectors within the national economy. Compared to basic macroeconomic aggregates such as GDP or its main components, IOTs offer a more disaggregated view of the economy while enabling in-dept study of the productive structures, inter-industry linkages, or structural changes at the industry level.

Literature review

IOTs are commonly used to examine national economies from both the demand (consumption) and supply (production) perspectives. On the demand side, the analysis focuses on the composition of the final demand–private and government consumption, investments, and exports. The supply side represents the sectoral distribution of production and gross value added. Sectors of manufacturing and services are often disaggregated into several subsectors.

Although initially developed to study domestic industry linkages, over time, these methods have proven to be versatile and adaptable to other types of analysis. Nowadays, IO analysis is widely applied to current issues, such as environmental impacts, climate change, global value chains disruptions (Uku and Shehu, 2024; Almanáz-Gómez, et al., 2023), or the COVID-19 pandemic (Aponte, 2025). All these phenomena often trigger structural adjustments in the countries' production systems in response to economic shocks, as industries adapt to new economic conditions.

Despite the growing versatility of IO methods, they are still predominantly applied in studies focused on specific industries. Recent literature offers numerous examples: analysis of fisheries and aquaculture in Norway during the pandemic in 2019-2021 (Aponte, 2025); Chinese fisheries

or port sectors in 2002-2017 (Wang and Wang, 2019, 2021); the Australian construction industry (Zhu et al., 2021); agriculture and food industries in V4 countries during 2000-2014 (Bartóková, 2019; Ďurčová and Oravcová, 2019); Turkey's tourism in the early 2000s (Atan and Arslanturk, 2012); the ICT sector in European countries during 1995-2005 (Rohman, 2013); or the Brazilian energy sector (Brito et al., 2025).

The position of an industry within the economy can be evaluated based on IO domestic demand multipliers, or its inter-industry linkages. Demand multipliers reflect how changes in final demand affect output, imports, value added, or employment. Inter-industry linkages, assessed via demand and supply multipliers, reveal the industry's interconnectedness to other domestic industries (Miller and Blair, 2009). The comparison of the industry's linkages to the average requirements of the whole economy determines its position as the buyer/supplier of the intermediate inputs and allows for their classification as more/less connected (dependent/independent) to the rest of the economy (Timmer et al., 2015).

Empirical studies (e.g., Bon and Xu, 2006; Allison, 1994) suggest that the economy's IO structures tend to remain relatively stable over time, unless the economy is undergoing serious structural changes. The study of Aponte (2025) found minimal changes in Norway's industries classification based on normalised demand and supply linkages during the pandemic, which points to only limited structural impact of COVID-19. This suggests that strong domestic demand linkages support industry's resilience and adaptability to supply chain disruptions.

Norbu et al. (2021) examined changes in demand and supply linkages at the industry level across selected Asian countries. The findings confirm that despite certain imbalances in the overall economic development, growing sectors can (indirectly) stimulate production in connected industries. Primary sectors, like agriculture and extractive industries, rely mostly on inputs coming directly from nature and thus tend to manifest weaker demand linkage. Service sectors also show stronger supply-side linkages, while manufacturing industries–often internationally integrated–might depend on strong external stimuli.

As mentioned before, the IOTs are also useful for analysing structural transformation and its impact on domestic linkages, job creation, and value added generation. The study of structural transformation often relies on Hirshman's theory (1958), stating that development of one sector would trigger intermediate demand for inputs in others. Thus, the development policies and investments should prioritise economic activities strongly linked to others.

The processes of the structural transformation, studied mostly within the theories of economic growth, are typically manifested by a shift from primary industries toward manufacturing and, subsequently, to services. (Sen, 2019) This transition also means fundamental structural changes in employment, production, and factor use in general. (Baymul and Sen, 2019) While the traditional development usually means a gradual decline of employment in agriculture, with the simultaneous transfer of workers to industry, some low-income economies now experience more direct transfers of workers from agriculture to non-business services (Baymul and Sen, 2019).

Bilenko (2022) studied the structural transformation of agriculture and its impact on labour productivity in Central and Eastern European countries (CEE) during 1991-2020. His results suggest that even though sources of labour productivity growth were altered considerably by the global financial crisis in 2008, agriculture still recorded the highest average productivity increase (12% p.a.) during the 1990s and 2010s. As for the value added (VA), during the entire period, the dominant factor was the growth of VA in industry, followed by the services sector and agriculture.

This paper focuses on domestic demand industry linkages in the Central European region. The V4 countries, as former transition economies, have undergone a significant structural transformation since the early 1990s. Their initial transition conditions were rather unfavourable due to obsolete productive capacities, lack of modern infrastructure, and weak institutions (Solimano, 1991). EU accession required macroeconomic stabilisation, anchoring inflation, and fiscal reforms. At the same time, the ongoing convergence processes were creating new challenges (Nuti et al., 1993). During the first decade of transformation (1990s), the private sector's share on GDP grew to 60% and trade with the EU increased by nearly 70%. (Feldman and Watson, 2000) EU accession also boosted agricultural output and productivity in the region, with stronger growth in Slovakia and the Czech Republic than in Hungary and Poland (Jambor and Gorton, 2025). Similarly,

Zsarnóczai and Zéman (2019) found greater similarity of various indicators for the agricultural industry between Slovakia, the Czech Republic, and Hungary, while Poland was considered more like Balkan countries. They also confirmed above-average growth in output and VA in agriculture for EU-12 countries compared to the EU-28. However, the overall comparison to EU averages for various agricultural indicators showed that V4 countries were significantly lagging behind the EU countries in the 2010s (Szabó et al., 2018).

Due to their geographical proximity, the V4 countries and Austria are frequently compared. While macroeconomic indicators might suggest similar positions, a detailed analysis of structural factors and inter-industry linkages might point to undergoing structural changes or notable differences, particularly between Austria and V4. However, a certain kind of closeness is expected for V4 countries.

This paper aims to assess the extent to which economic structure and sectoral changes differ among these countries. The analysis focuses on three main sectors, divided into six subsectors, addressing the following questions: *Do V4 countries share similar sectoral structures throughout 2000-2023, and how do these compare with Austria? Has the transformation process in V4 countries continued in the 2010s? Did the V4 countries follow the standard path of economic transformation (i.e., from primary to secondary and tertiary sectors)? What were the impacts of structural changes on agriculture's capacity to generate domestic value added during the observed period? And how have globalisation and foreign trade impacted the domestic inter-industry linkages between 2000 and 2023?*

To address these questions, the paper assesses the evolution of domestic production linkages by quantifying output multipliers (demand linkages) but also other demand-derived multipliers, (import and VA multipliers) over the period 2000-2023. The paper is structured as follows: Introduction and Literature review, Materials and methods, Results and discussion, Conclusions.

Materials and methods

In general, national IO tables supply industry-level data, both from the point of view of producers and buyers of inputs, which enables the analysis of demand and supply inter-industry linkages and the calculation of various types of multipliers.

IO models and the study of structural changes are based on Leontief's theory (Leontief, 1953), which assumes that each national economy is composed of "*n*" interconnected industries. The structure of the production and its uses for industry "*i*" can be presented in linear form as follows (Miller, Blair, 2009):

$$x_i = Z_{i1} + Z_{i2} + ... + Z_{ij} + ... + Z_{in} + y_i \quad (1)$$

The output of each sector (x_i) can either serve as inputs for other industries (i.e., the intermediate consumption Z_{ij}) or be consumed directly by consumers, firms, government, or foreign countries (i.e., the final demand y_i) (Timmer et al., 2015). Based on this equation, we can determine the structure and volume of direct inputs (technical coefficients matrix, A) or the basic IO's analysis equation, i.e., the Leontief inverse matrix *L*:

$$L = (I - A)^{-1} \quad (2)$$

The *L* matrix enables to calculate the total direct and indirect effects of any increases in the final demand for production in each industry (simple output multipliers or demand linkages) or can be used to derive the impacts of changing demand in the domestic economy on imported inputs (import multipliers). These multipliers can be viewed as summary measures for estimating likely effects of economic changes or impacts generated by a particular industry on the national economy (Kubala et al., 2014). Using the same techniques, we can also study the industry-level impacts of changing demand on value added, employment, CO_2 emissions, or energy consumption (Lábaj, 2017).

Results and discussion

This study is based on national input-output data from the Asian Development Bank (ADB) for the period of 2000-2023, which corresponds to the available data (ADB, 2024). The IO analysis focuses on the region of Central Europe, notably the V4 countries (Slovakia–SK, Czech Republic –CZ, Hungary–HU, Poland–PL) and Austria (AT). The analysis was first performed at the individual industry level for all 35 industries in each country, with calculation of output, import, and value added multipliers. The results were then aggregated by sector and subsector to obtain average values, ensuring that the sectoral multipliers accurately reflect the sectoral shifts and inter-industry relationships. For comparability and analysis purposes, the 35 industries were grouped into three sectors as follows: the primary sector comprised agriculture, forestry, fishing,

mining, and quarrying; the secondary sector was subdivided into low-, medium-, and high-tech manufacturing; and the services sector was subdivided into business services and public and personal services. This approach follows OECD and Eurostat methodologies based on R&D intensity (Galindo-Rueda and Verger, 2016; Eurostat, 2025; United Nations Statistics Division, 2025).

Firstly, we looked closely at the composition and use of output (Figure 1). Across the selected countries, GDP composition was comparable, with 50-60% of domestic output being directed to intermediate consumption (IC; input for domestic industries) and 40-50% to final consumption – either domestic (DE; domestic expenditures, 20-30%) or foreign (EX; exports, 10-20%). The share of imports (IM) accounted for 10-20%, mirroring export levels. Over the observed period, the shares of domestic IC decreased, mainly in favour of exports. The most pronounced shifts occurred between 2000 and 2010; afterwards, the values remained relatively stable, as confirmed by the closeness of average and median values. Slovakia exhibited the most significant changes, corresponding with its considerable growth in trade openness.

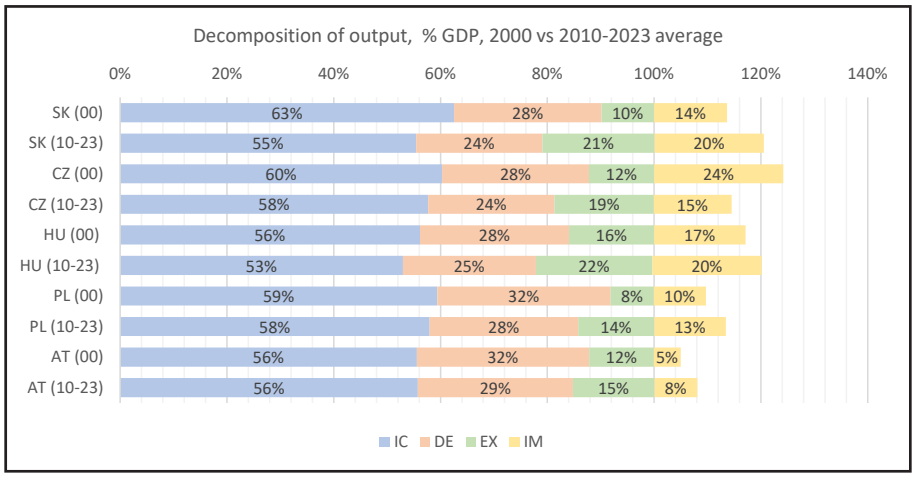
The declines in shares for domestic IC (average relative change of -5.9% for V4 and -4.7% overall) or DE (average relative change of -13.4% for V4 and -12.8% overall) were more than offset by a substantial rise in foreign demand (average relative change of +70% for the V4 and +61% for the whole sample). These findings support earlier studies indicating that structural shifts tend to occur rather at the sectoral level than within the output distribution (Olczyk and Lechman, 2011).

For the production-side analysis, intermediate consumption matrices were used to evaluate changes in the share of subsectors (Figure 2). Comparison of 2000 values with average shares from 2010-2023 confirms the similarity of production patterns in V4 countries.

Approximately one-third of output comes from business services, while manufacturing generates 40-50% of the domestic output, with high-tech industries ranging from 20% (PL or AT) to 30% (SK). The primary sector's contribution was the lowest, with further declines throughout this period, in all countries except Austria. These findings also conform with Hirshman's theory (Hirshman, 1958) or Sen (2019), who associated structural transformation processes with shifts from the primary sector toward manufacturing and, later, to the services.

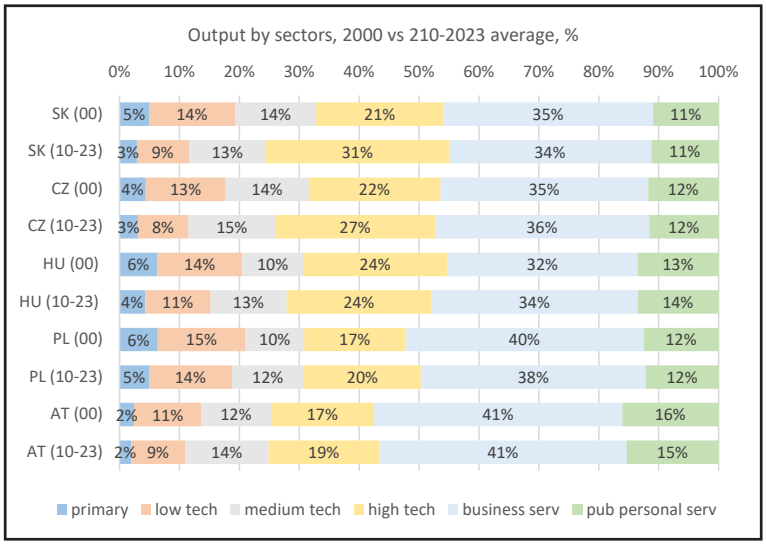
The distribution of VA by sectors (Figure 3) showed patterns similar to previous findings. Although certain minor shifts occurred between 2000 and 2010, they were mostly marginal (relative changes often below 1%). The primary sector and low-tech manufacturing experienced slight reductions in their VA shares, while medium- and high-tech manufacturing, along with public and personal services, grew only slightly (not discernible in the figure due to rounding of values). These trends for the primary sector's position and that of agriculture are consistent with Zsarnóczai and Zéman (2019).

While the VA generated by primary sectors mostly copies the sector's share on domestic output, in the case of manufacturing, the VA share consistently lags behind output across all 3 subsectors. The most prominent gap is present



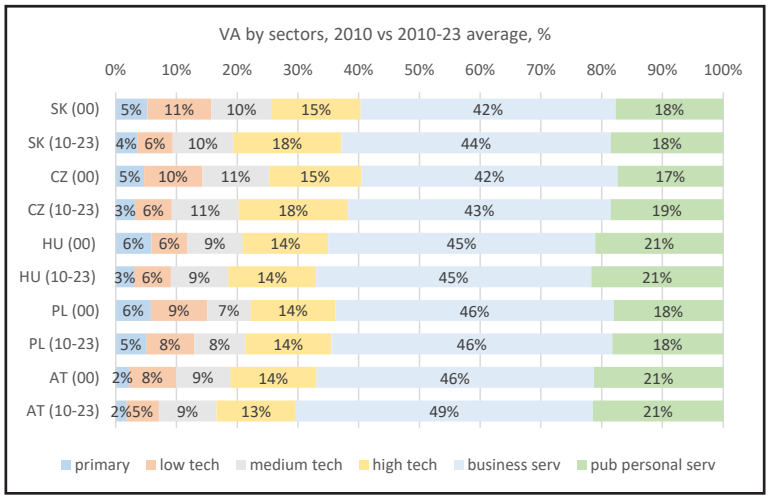
Source: Author's work

Figure 1: Decomposition of output, % GDP, 2000 vs 2010-2023 average.



Source: Author's work

Figure 2: Output by sectors, 2000 vs 2010-2023 average (%).



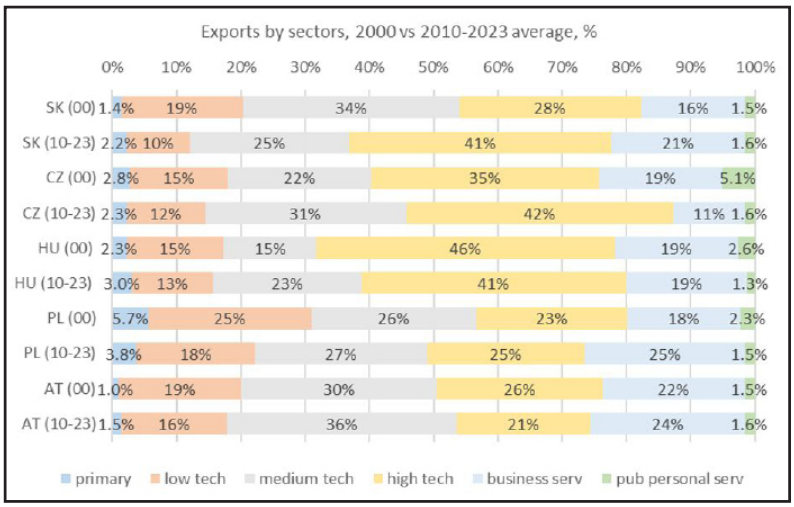
Source: Author's work

Figure 3: Value added by sectors, 2000 vs 2010-2023 average (%).

for SK high-tech manufacturing, where a 31% share of output generates only 18% of the VA. For business services, however, the relationship between production and VA is opposite, the share of VA surpasses that of production. Overall, for the sample's countries, the VA is mostly created in services (60-70%) that represent 45%-56% of production, reflecting general trends also observed by Bilenko (2022) in his study of CEE countries.

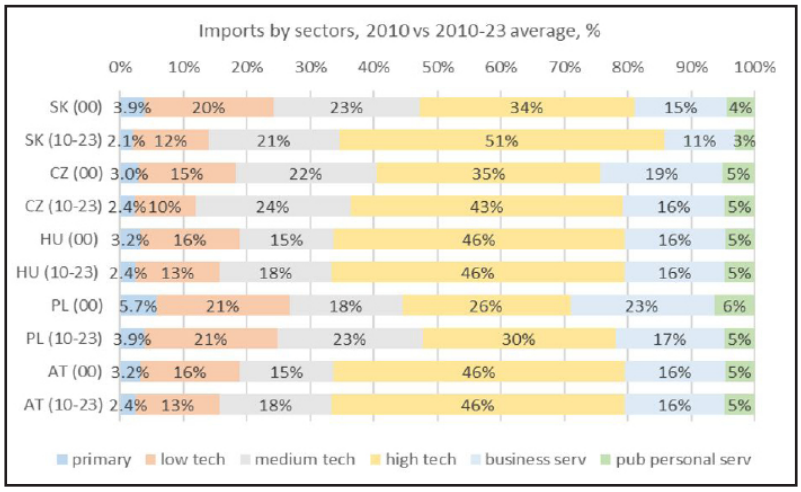
Export structures (Figure 4) confirm that all 5 countries primarily export manufactured goods (from 70% in PL to 77% in HU and SK), with the highest shares for the high-tech subsector. Exports in both services subsectors accounted for 22% of total exports on average. The import side followed a similar pattern, with manufacturing taking up 77% on average and services around 20% of total imports (Figure 5).

The low export and VA shares of the primary sector (and agriculture in particular) do not necessarily indicate an unfavourable position in international markets. As shown by Zsarnóczai and Zéman (2019) or Jambor and Gorton (2025), agriculture in EU-12 countries experienced above-average growth of output and VA compared to average results of EU-28, which was also reflected in their trade flows. However, according to Zdráhal (2024), in the 1990s only HU demonstrated a comparative advantage in agricultural production, while CZ, PL, and SK showed comparative disadvantages.



Source: Author's work

Figure 4: Exports by sectors, 2000 vs 2010-2023 average (%).

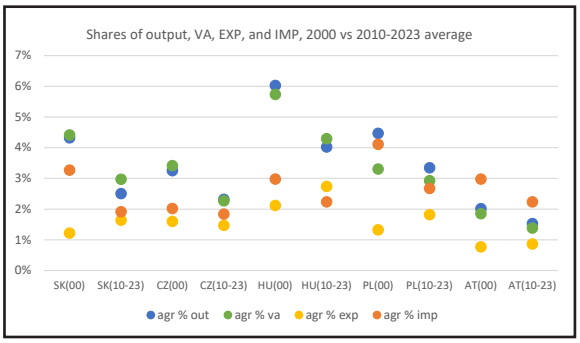


Source: Author's work

Figure 5: Imports by sectors, 2000 vs 2010-2023 average (%).

Lastly, we examined the changes in position of the agricultural sector across observed countries (Figure 6). Agriculture accounted for a major share of the primary sector, averaging 82% of output, 78% of VA, 67% of exports, and 83% of imports. Across all countries, shares of output, VA, and IMP decreased, while EXP shares grew. The highest increases were recorded for HU, PL, and SK. In AT, the share of agri-exports remained stable, while shares for other categories decreased slightly, on average by 0.5-0.7% relative to their previous values. This again could point to a more stable structure of the Austrian economy, with stronger domestic linkages resilient to external competition.

The observed decline in domestic linkages, combined with rising export shares, points to increasing integration of agriculture into global markets. This trend represents both opportunities and risks. On the one hand, higher exports can boost domestic revenues and support domestic investment.



Source: Author's work

Figure 6: Shares of agriculture on output, VA, exports, and imports, 2000 vs 2010-2023 average (%).

On the other hand, greater dependence on imported inputs and foreign demand creates vulnerability to price volatility, trade shocks, and supply chain disruptions. As such, policymakers should consider strategies to strengthen domestic supply chains and diversify export destinations. They should also encourage value added creation within the country to retain more benefits locally.

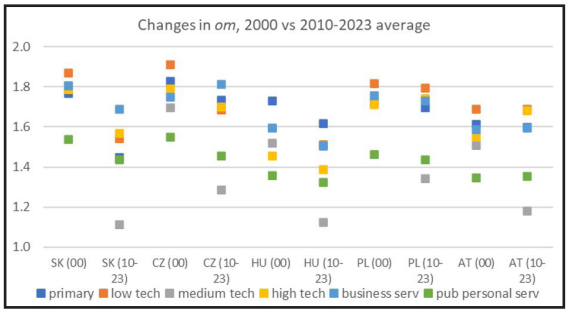
Multiplier analysis

Based on the industry-level data, the output multipliers (om) were calculated for each industry (Figure 7). Here again, the most significant changes occurred between 2000 and 2010, confirming the ongoing structural shifts associated with the transition process in V4. Post-2010 developments were more gradual, with only slight changes on subsector levels. The overall drop in om values would suggest a somewhat general trend of weakening domestic demand linkages accompanied by increasing reliance of industries on imported inputs and their deepening integration into international production chains.

In the primary sector, especially agriculture, *om* values revealed an obvious downward trend across all countries. The largest declines in multiplier values occurred for SK (-20%), and to a lesser extent, for CZ and HU (-5-6%). For AT and PL, the primary sector recorded only minor drops (around 1%). These results are consistent with those of Olczyk and Lechman (2011) or with agri-trends presented by Zsarnóczai and Zéman (2019) and Jambor and Gorton (2025).

The largest overall decreases in *om* averages were present for medium-tech manufacturing with relative declines in multiplier values of around -25%. E.g., in SK, in 2000, 1€ of domestic demand would have been able to generate up to 1.7€ of new domestic production, whereas after 2010, the total effect of the same stimuli would be lower by 0.4€. Similar reductions occurred for all SK subsectors. In the case of CZ, HU, PL, and AT, only the medium-tech experienced the drop in the *om* values exceeding 20%. For AT, the values of *om* confirm the stability of the production structures, with 4 subsectors changing by less than 1%.

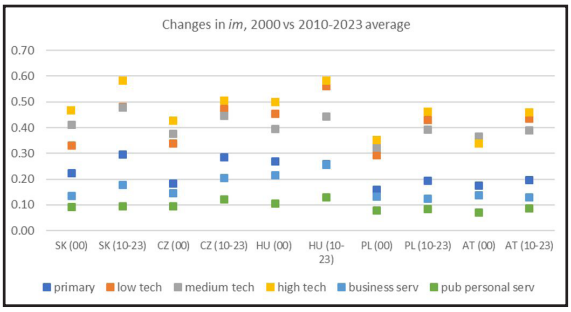
The comparison of average and median values for period 2010-2023 shows only minimal differences, revealing no discernible trends. For some subsectors, changes were as small as 0.02€, supporting the view that in the absence of deep structural shifts, economic structures tend to remain stable and resilient, as presented also by Aponte (2025), Timmer et al. (2015), or Bon and Xu (2006).



Source: Author's work

Figure 7: Changes in output multipliers, 2000 vs 2010-2023 average.

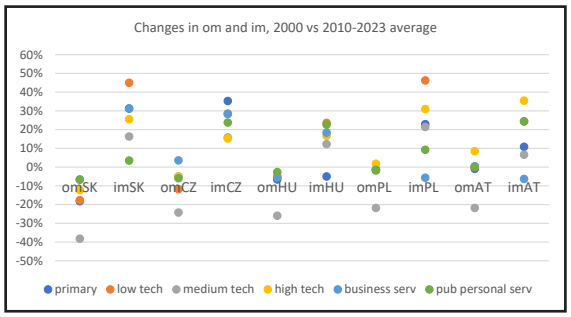
As mentioned before, domestic demand linkages are reflected in the om, while the linkages with foreign suppliers are represented by the import multipliers (*im*). The comparison of im across countries highlights the growing dependence on foreign inputs (Figure 8). As values of *om* were becoming less important, the values of *im* were growing steadily. This pattern, present for every country and every subsector, points to a shift toward international production networks.



Source: Author's work

Figure 8: Changes in import multipliers, 2000 vs 2010-2023 average.

The Figure 9 illustrates this divergence in *im* and *om* values. Over the past 20 years, deeper integration into international production chains also meant the substitution of domestic inputs by the imported ones, resulting in the decline of domestic suppliers (negative changes in *om*) and growing importance of foreign ones (positive changes in *im*) for most of the subsectors of our sample. This trend might be attributed to various cost-reduction strategies through cheaper imports or to the relocation of production processes to V4 countries while keeping the original and established foreign suppliers.

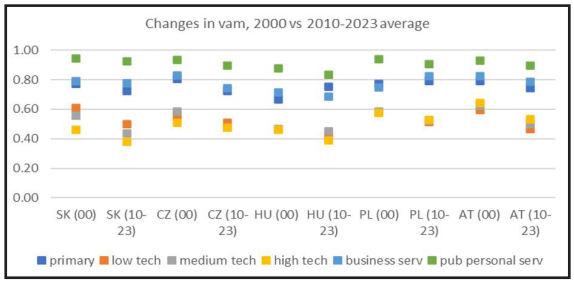


Source: Author's work

Figure 9: Changes in output and import multipliers, 2000 vs 2010-2023 average (%).

VA multipliers (*vam*) indicate that public and personal services have the highest impact on the economy, followed closely by business services (Figure 10). Although a slight decline was present after 2010, these subsectors remain the most influential. Interestingly, the lowest vam values appeared for hi-tech manufacturing. This could be explained not only by the smaller VA share of hi-tech but also by a considerable reliance on imported components.

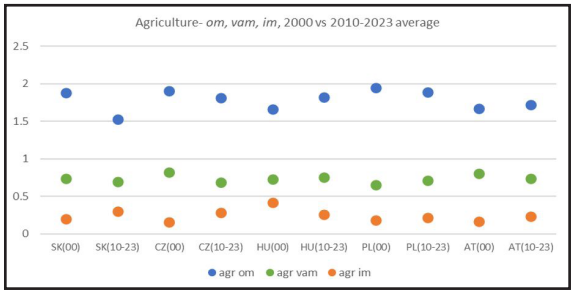
The positions of the primary sectors and agriculture remain relatively stable, with 1€ of new domestic demand generating 0.72€ (SK) to 0.79€ (PL) of new VA. These results are in slight contrast with the findings of Maró et al. (2024), who reported a relatively low agricultural productivity and efficiency in CEE countries compared to Western Europe. However, they align with Jambor and Gorton (2025), who emphasised increases in agricultural output and productivity in this region, especially for SK.



Source: Author's work

Figure 10: Changes in VA multipliers, 2000 vs 2010-2023 average (%).

The comparison of the 3 demand multipliers for agriculture (Figure 11) shows overall drops in *om* values and increases in *im* values between 2000 and 2010 for all countries (on average -0.14€ for *om* and +0.08€ for *im*), except for HU, where the trend was reversed (+0.16€ vs -0.16€). Interestingly, the highest increase in *im* values was recorded for CZ and AT, where the impacts of new demand for imported agri-inputs rose by almost 77% or 38%, respectively, compared with 2000 values. Vam values remained largely stable, with slight increases only for HU and PL. Generally, the impact of 1€ of new agriculture demand generated, on average, 0.75€ of overall new VA during the 2010s.



Source: Author's work

Figure 11: Agriculture- *om, vam, im*, 2000 vs 2010-2023 average.

This analysis focused on the structural characteristics of V4 countries and Austria. Results suggest that the transformation process can no longer be considered as the main driver of structural changes in V4 countries. Instead, the production structures are now shaped by countries' or industries' integration into global value chains. These findings also highlight a structural gap between the manufacturing sector's dominant role in production and exports and its more modest contribution to VA creation. This reflects a limited national orientation on R&D and innovation domains.

Conclusion

The main objective of the analysis was to verify to what extent the economic structure and its sectoral changes differ among selected countries. We examined production structures and their evolution across six subsectors, following the path set by research questions. The key findings directly address these questions:

Do V4 countries share similar sectoral structures throughout 2000-2023, and how do these compare with Austria? Has the transformation process in V4 countries continued in the 2010s? Did the V4 countries follow the standard path of economic transformation (i.e., from primary to secondary and tertiary sectors)?

The findings indicate that sectoral structures in Central Europe are still quite similar, particularly among the V4 countries. The transformation process continued through the early 2000s and up to 2010.

During 2010-2023, sectoral changes were not as pronounced, with only slight shifts in the positions of industries or subsectors. These followed the typical path of economic transformation, with the primary sector gradually receding in favour of manufacturing and services. The only V4 exception was Poland, with its agriculture and the whole primary sector increasing in relevance. The Austrian economy maintained a relatively stable sectoral composition throughout the observed period.

How have globalisation and foreign trade impacted the domestic inter-industry linkages between 2000 and 2023?

The analysis also showed how the gradual opening to foreign trade impacted domestic production structures – a decrease in domestic demand/supply linkages as shown in intermediate consumption shares (*om*), which was offset by the increase of imported inputs (*im*) but also by higher exports.

The analysis of VA confirmed that despite strong performance in high-tech manufacturing outputs and exports, the largest VA shares come from the two services subsectors. While the high-tech subsector accounts for 20-30% of manufactured output and 21-46% of exports, it generates only 14-18% of VA. This underscores the V4 countries' position in global value chains as assemblers of high-tech goods based on imported components rather than creators of new domestic VA. As such, V4 countries should focus more on supporting innovation and technology to stimulate more technologically driven economic progress.

What were the impacts of structural changes on agriculture's capacity to generate domestic value added during the observed period?

Additionally, the agricultural industry, as one of the key industries (Bartóková, 2019), holds a specific position in national economies. The findings show that the primary sector is impacted mostly by the developments in agriculture. Although its contribution to output and VA has declined, its share in foreign trade has been growing steadily. This creates both an opportunity and a risk. Higher foreign sales could generate more funds for domestic producers, but rising import dependence makes agri-markets more vulnerable to external shocks. That is why policymakers should put more focus on strengthening domestic agricultural resilience, e.g., through targeted subsidies and support for local cooperation. These measures could help ensure that growth in agricultural exports contributes to sustainable domestic economic development.

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References

[1] Allison, T. (1994) "The stability of input structures in a supply-driven input-output model: A regional analysis", *Environmental Assessment and Information Science Division Argonne National Laboratory*, 27 p. DOI 10.2172/10158759.

[2] Almanáz-Goméz, M. A., Llano, C., Pérez, J. and Mandras, G. (2023) "The European regions in the global value chains: New results with new data", P*apers on Regional Science*, Vol. 102, No. 6, pp. 1097-1127. ISSN 1056-8190. DOI 10.1111/pirs.12760.

[3] Aponte, F. R. (2025) "Economic interdependencies and sectoral impacts: An input-output analysis of the Norwegian fisheries and aquaculture sector amidst COVID-19", *Fisheries Research*, Vol. 281, No. 1, pp. 1-13. ISSN 1872-6763. DOI 10.1016/j.fishres.2024.107247.

[4] Asian Development Bank (2024) National input-output tables at current prices - Austria, Czech Republic, Hungary, Poland, Slovakia, years 2000–2023. [Online]. Available: https://kidb.adb.org/globalization/current [Accessed: May 16, 2025].

[5] Atan, S. and Arslanturk, Y. (2012) "Tourism and Economic Growth Nexus: An Input Output Analysis in Turkey", *Procedia - Social and Behavioral Sciences*, Vol. 62, No. 10, pp. 952-956. ISSN 1877-0428. DOI 10.1016/j.sbspro.2012.09.162.

[6] Baymul, C. and Sen, K. (2019) "Kuznets Revisited: What Do We Know About the Relationship between Structural Transformation and Inequality?", *Asian Development Review*, Vol. 36, No. 1, pp.136-167. ISSN 1996-7241. DOI 10.1162/adev_a_00126.

[7] Bartóková, Ľ. (2019) "The Position of Agriculture and Food Sector in V4 Countries", *AGRIS on-line Papers in Economics and Informatics*, Vol. 11, No. 3, pp. 13-22. ISSN 1804-1930. DOI 10.7160/aol.2019.110302.

[8] Bilenko, Y. (2022) "Labor productivity in the agriculture, structural shifts and economic growth in the Central and Eastern European countries", *Agricultural and Resource Economics*, Vol. 8, No. 4, pp. 5-32. ISSN 2414-584X. DOI 10.51599/are.2022.08.04.01.

[9] Bon, R. and Xu, B. (2006) "Comparative stability analysis of demand-side and supply-side input-output models in the UK", *Applied Economics*, Vol. 25, No. 1, pp. 75-79. ISSN 1466-4283. DOI 10.1080/00036849300000116.

[10] Brito, K. S., Borba Barroso, P. D. and Cavaliero, C. K. N. (2025) "The relevance of input-output analysis in public policies propositions for green hydrogen in Brazil", I*nternational Journal of Hydrogen Energy*, Vol. 145, No. 7, pp. 1033-1046. ISSN 1879-3487. DOI 10.1016/j.ijhydene.2025.06.057.

[11] Ďurčová, J. and Oravcová, D. (2019) "Structural changes and agricultural sector in V4 countries – Input-output analysis", *Journal of Environmental Management and Tourism*, Vol. 10, No. 7, pp. 26-35. E-ISSN 2068-7729. DOI 10.14505//jemt.v10.7(39).26.

[12] Eurostat (2005) "*High-tech industry and knowledge-intensive services (htec)*", statistical classification. [Online]. Available: https://ec.europa.eu/eurostat/cache/metadata/EN/htec_esms.htm [Accessed: Feb. 25, 2025].

[13] Feldman, R. A. and Watson, C. M. (2000) "Central Europe: From Transition to EU Membership", *Finance and development*, Vol. 37, No. 3. ISSN 0015-1947.

[14] Galindo-Rueda, F. and Verger, F. (2016) "OECD Taxonomy of Economic Activities Based on R&D Intensity ", *OECD Science, Technology and Industry Working Papers*, No. 2016/04. OECD Publishing. DOI 10.1787/5jlv73sqqp8r-en.

[15] Hirshman, A. O. (1958) "*The strategy of Economic Development*". Yale University Press. 218 p. ISBN 10 0300001177.

[16] Jambor, A. and Gorton, M. (2025) "Twenty years of EU accession: learning lessons from Central and Eastern European agriculture and rural areas", *Agricultural and Food Economics*, Vol 13, No. 1, pp. 1-17. ISSN 2193-7532. DOI 10.1186/s40100-025-00346-w.

[17] Kubala, J., Lábaj, M. and Silanič, P. (2015) "Štrukturálne väzby v slovenskej ekonomike v roku 2010: identifikácia kľúčových odvetví", *Ekonomický časopis/Journal of Economics*, Vol. 63, No. 8, pp. 795-816. ISSN 0013-3035. (In Slovak).

[18] Lábaj, M. (2017) "Štruktúrna dekompozícia globálnych hodnotových reťazcov: Slovenská ekonomika v medzinárodnom porovnaní (Structural Decomposition of Global Value Chains: Slovak Economy in an International Context)", *Politická ekonomie*, Vol. 65, No. 5, pp. 562-582. E-ISSN 2336-8225. DOI 10.18267/j.polek.1162. (In Slovak).

[19] Leontief, W. (1953) "Domestic Production and Foreign Trade; The American Capital Position Re-Examined", *Proceedings of the American Philosophical Society*, Vol. 97, No. 4, pp. 332-349. ISSN 0003-049X.

[20] Maró, Z. M., Borda, Á. J. and Balogh, J. M. (2024) "Challenges and Trends in Agricultural Employment: The Case of Hungary", *AGRIS on-line Papers in Economics and Informatics*, Vol. 16, No. 16, pp. 109-128. ISSN 1804-1930. DOI 10.7160/aol.2024.160409.

[21] Miller, R. E. and Blair, P. D. (2009) "*Input-Output analysis. Foundation and Extentions*", 2nd ed., Cambridge, New York: Cambridge University Press. ISBN 978-0-521-739-02-3. 784 p. DOI 10.1017/CBO9780511626982.

[22] Norbu, N. P., Tateno, Y. and Bolesta, A. (2021) "Structural transformation and production linkages in Asia-Pacific least developed countries: An input-output analysis", *Structural Change and Economic Dynamics*, Vol. 59, No. 12, pp. 510-524. ISSN 1873-6017. DOI 10.1016/j.strueco.2021.09.009.

[23] Nuti, D. M, Riecke, W. and Portes, R. (1993) "*Economic transformation in central Europe-A progress report*", European Commission, 316 p. ISBN 92-826-5680-2.

[24] Olczyk, M. and Lechman, E. (2011) "Structural convergence among selected European countries. Multidimensional analysis", MPRA Paper No. 33656. pp. 1-30. University Library of Munich, Germany.

[25] Rohman, I. K. (2013) "The globalization and stagnation of the ICT sectors in European countries: An input-output analysis", *Telecommunications Policy,* Vol. 37, No. 4-5, pp. 387-399. ISSN 0308-596. DOI 10.1016/j.telpol.2012.05.001.

[26] Sen, K. (2019) "Structural Transformation around the World: Patterns and Drivers", *Asian Development Review*, Vol. 36, No. 2, pp. 1-31. ISSN 1996-7241. DOI 10.1162/adev_a_00130.

[27] Solimano, A. R. (1991) "*On economic transformation in East - Central Europe: a historical and international perspective*", World Bank Group, Policy, Research, and External Affairs working papers, No. 677. 38 p. [Online]. Available: http://documents.worldbank.org/curated/en/977191468750318520 [Accessed: Feb. 25, 2025].

[28] Szabó, L., Grznár, M. and Zelina, M. (2018) "Agricultural performance in the V4 countries and its position in the European Union", *Agricultural Economics – Czech*, Vol. 64, No. 8. pp. 337-346. E-ISSN 1805-9295, ISSN 0139-570X. DOI 10.17221/397/2016-AGRICECON.

[29] Timmer, M., Dietzenbacher, E., Los, B., Stehrer, R. and de Vries, G. J. (2015) "An Illustrated User Guide to the World Input–Output Database: The Case of Global Automotive Production", *Review of International Economics*, Vol. 23, No. 3, pp. 575-605. ISSN 1467-9396. DOI 10.1111/roie.12178.

[30] Uku, S. and Shehu, E. (2024) "Theoretical Background of Input-Output Analysis and its Application in Albania", *European Scientific Journal,* Vol. 20, No. 16, pp. 161-173. ISSN 1857-7431. DOI 10.19044/esj.2024.v20n16p161.

[31] United Nations Statistics Division (2025) "*'High-technology' and 'knowledge-based services' aggregations based on ISIC Rev. 4. UNSD Classification Registry*", ID 3463. [Online]. Available: https://unstats.un.org/unsd/classifications/Econ/Registry/Detail/3463 [Accessed: May, 20, 2025].

[32] Zsarnóczai, J. S. and Zéman, Z. (2019) "Output value and productivity of agricultural industry in Central-East Europe", *Agricultural Economics*, Vol. 65, No. 4, pp. 185-193. ISSN 1805-9295. DOI 10.17221/128/2018-AGRICECON.

[33] Zdráhal, I. (2024) "The Revealed Comparative Advantage of Agri-Food Industries in Selected Countries in the Central and Eastern Europe: Gross-Versus Value-Added Trade Flows", *AGRIS on-line Papers in Economics and Informatics*, Vol. 16, No. 2, pp. 133-150. ISSN 1804-1930. DOI 10.7160/aol.2024.160210.

[34] Zhu, R., Hu, X. and Liu, C. (2020) "Structural analysis of inter-industrial linkages: an application to the Australian construction industry", *Construction Management and Economics*, Vol. 38, No. 10, pp. 934-946. ISSN 1466-433X. DOI 10.1080/01446193.2020.1785627.

[35] Wang, Y. and Wang, N. (2021) "Exploring the role of the fisheries sector in China's national economy: An input–output analysis", *Fisheries Research*, Vol. 243, No. 11, pp. 1-8. ISSN 1872-6763. DOI 10.1016/j.fishres.2021.106055.

[36] Wang, Y. and Wang, N. (2019) "The role of the marine industry in China's national economy: An input–output analysis", *Marine Policy*, Vol. 99, No. 1, pp. 42-49. ISSN 0308-597X. DOI 10.1016/j.marpol.2018.10.019.

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A Heuristic Approach to Ensemble-Based Deep Learning Models for Plant Disease Classification and Farming Decision Support

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Abstract

Leaf based plant diseases detection is one of the significant factors affecting crop yield and productivity. Most of the current techniques used for disease prediction are trained using observational records featuring numerous plant image parameters, with a higher frequency of diseased images compared to blight-free images. Hence, discriminating against the crucial insights from irrelevant and redundant images has been a crucial and challenging study. This research inspects the suitability of machine learning models in disease prediction focusing both specific and wide range of plant leaf images. Also, most classical methods are pretentious by various issues such as the format of image statistics, computation, and representation. To address this crucial setback in the present prediction methods, the proposed system develops a hybrid model utilizing stacked ensemble learning, which enhances the detection of plant disease attacks beyond what conventional learning methods. The proposed stacked ensemble-based disease prediction framework is designed to identify both misclassified and correctly classified images. This approach features a two-tier classification mechanism that involves a base learner (Level 0) and a meta learner (Level 1). It considers both image datasets and image features as inputs to facilitate the two-tier classification process. It also focuses on extracting internal features from the damaged leaves. The proposed model was trained with over 30,000 images at various levels. The experimental results revealed that the stacked ensemble learning technique outperformed with a prediction accuracy of 99.93%..

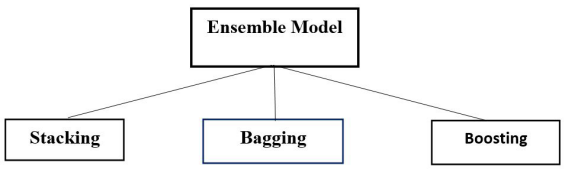
Keywords

Stacked ensemble learning, conventional learning, base learners, meta learners, inception, classification and accuracy.

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Introduction

Early detection of plant diseases focuses mainly on monitoring the well-being of the plant to prevent the spread of infections. (Li et al., 2021) outlined that the importance of diseases that appear on fruit trees have a great influence on agricultural production. In this research investigates the benefits of using ensemble-based machine learning in plant disease detection. Ensemble techniques are typically applied in three different ways, as illustrated in Figure 1. In this, bagging ensemble model is also known as the parallel ensemble and this computes the prediction result by averaging the responses of the N classifiers, where N is the total number of classifiers used in the system. A boosting model, often referred to as a sequential ensemble, achieves the desired result by adjusting the weights with each iteration. The boosting ensemble technique has potential to reduce the bias. Wherein, the stacking model trains multiple classifiers in parallel, and the result is obtained from the second-level classifier (Chen et al., 2023). Table 1 elucidates the merits and demerits of three existing ensembles techniques. Thus, after conducting a deep analysis the proposed framework is modelled using stacking ensemble approach, it is premeditated using four effective deep learning classifiers.



Source: compiled by the authors

Figure 1: Types of ensemble models.

Bagging	Boosting	Stacking
Parallel and popular ensemble method with prediction variance	Sequential ensemble with predictive data analysis	Multiple Classifiers are trained parallel
Results are obtained by averaging the responses of the N learners	On each iteration, update the model by weights until desired result is obtained	Results are obtained from the second level classifier
Reduce the variance	Reduce the bias	Increases the accuracy of classification model

Source: compiled by the authors

Table 1: Ensemble techniques.

Literature survey

In the study by Li et al. (2021), stacking ensemble learning is introduced as a method for diagnosing diseases in fruit-bearing trees. This approach combines various machine learning algorithms to improve predictive performance by leveraging multiple models. The diagnostic model was developed using a dataset comprising 10,000 pear images. To enhance performance, three types of ensemble learning classifiers and two types of deep learning classifiers were evaluated and tested. The stacking ensemble learning classifier achieved the highest accuracy, with 98.05% on the validation dataset and 97.34% on the test dataset, outperforming the other classifiers. Additionally, three lightweight Convolutional Neural Networks (CNNs) SEMobileNet, Mobile-DANet, and Mobile Net V2 were merged to create a new network named Es-MbNet for identifying types of plant diseases.

The model training incorporated transfer learning and a two-step training approach, where the first step focused on initializing the network weights. In the second step, pre-trained models utilized the weights from the initial phase to make predictions on the target dataset, effectively optimizing the model's parameters. This method, proposed by Chen et al. (2023), achieved an impressive average accuracy of 99.37% on a local dataset. To assess the model's robustness, it was also evaluated using the open-source Plant Village dataset, yielding an average accuracy of 99.61%. The objective of this study is to classify plant diseases using images captured directly in the field. To enhance predictability, ensemble learning techniques were explored to construct a robust network aimed at identifying four distinct pear leaf diseases. Various convolutional neural network architectures including EfficientNetB0, InceptionV3, MobileNetV2, and VGG19 were compared and combined. This ensemble approach enhanced predictive performance through the implementation of a bagging strategy and weighted averaging (Fenu and Malloci, 2023). Quantifiable experiments were performed to assess the model using the DiaMOS plant dataset, followed by the application of data augmentation to enhance the model's generalization capabilities. The results are evaluated with a range of metrics, including accuracy, recall, precision, and f1-score. The results showed that the proposed ensemble convolutional neural network outperformed the single convolutional neural network in classifying diseases in real-field conditions.

Typically, challenges such as variations in brightness, similarities in diseases, intricate backgrounds, and the presence of multiple leaves in images pose difficulties for machine learning and deep learning algorithms in making accurate predictions. Leaf diseases significantly impact the quality of agricultural products, making it essential for farmers to quickly halt their spread. This study introduces a stacking ensemble of a lightweight learning CNN framework aimed at improving the recognition accuracy of images depicting plant leaf diseases. (Enkvetchakul and Surinta, 2022), proposed four lightweight CNN architectures InceptionResNetV2, NASNet-Mobile, MobileNetV2, and Efficient Net B1 to develop an effective CNN model for plant leaf disease detection. The experimental findings indicated that EfficientNetB1 outperformed the other CNN models. The analysis utilized classifiers including logistic regression, support vector machine, K-nearest neighbors, random forest, and long short-term memory network. Among these, the random forest method proved to be the most suitable model. Ocular diseases tend to develop slowly, and since they can be severe and untreatable, regular check-ups are necessary to catch them early, though this can increase the workload. Consequently, an automated system powered by deep learning could facilitate early detection of these diseases.

Agarwal et al. (2022), identified healthy and unhealthy plants, using the CNN model. The study sheds light on how well deep learning methods work for automatically identifying plant diseases, which has a big influence on farming operations. In Kaur et al. (2022), deep learning

and object detection techniques are presented in this paper to detect or characterize infected areas in tomato leaf diseases. This research work determines and measures the level of infection in tomato leaves.

Gautam et al. (2024) presented a novel approach for mango leaf disease classification and detection. The novel approach, ESDNN, is an ensemble-stacked deep neural network used to increase the precision of illness detection and classification in mango leaves. It is composed of many deep neural networks. The research indicates that the ESDNN model is a useful tool for early diagnosis and management methods since it can reliably identify and classify several mango leaf diseases.

Ranjan and Kumar (2023) highlighted the fruit Fly Optimization Algorithm (FOA) and described their proposed ideas, and distinctions. Sunil et al., (2022), presented a systematic review on Fruit Fly Optimization Algorithm and Its Applications. The authors conduct a thorough literature analysis to provide an overview of the main ideas, variations, and uses of the FOA across a range of industries. The goal of the study is to shed light on the FOA's adaptability and efficacy as an optimization method. Ayan (2024) used an approach-based genetic algorithm-based hyperparameter optimization to optimize CNN hyperparameters for crop pest classification. Using evolutionary algorithms to optimize critical hyperparameters, it is reliable and classifies agricultural pests.

Tiwari et al. (2020) presented a solution for the detection of multiple ocular diseases from fundus images. Based on the combined dataset of ocular disease images, the faster ensemble model had an accuracy of 87%, while the ensemble model had an accuracy of 88%. This research work has adopted the stacked ensemble deep learning model to resolve the problem of automatic identification of mango-leaf diseases. In the proposed approach, initially, the images are segmented for the region of interest and input to a stack of various deep neural networks. The outcome of the deep neural network is aggregated with a machine learning model to identify leaf diseases.

One of the previous works by Patil et al. (2024) on ensemble of Deep Convolutional Neural Networks (DCNNs) for crop classification using aerial imagery outlined the aerial photos preprocessing method and demonstrated on raining the model with a distinct set of filter sizes and scales. The classification accuracy significantly increased by combining the outputs from these DCNNs using an ensemble technique.

Kalita et al. (2023) outlined an enhanced deep CNN approach in the identification of grape leaf diseases. Preprocessing grape leaf photos, training CNNs on a tagged image dataset, and assessing the model's accuracy in categorizing various grape leaf illnesses are probably the steps in the methodology. To support early disease detection and control in grape production, it is intended to increase the precision and dependability of grape leaf disease identification.

Liu et al. (2020) discussed in detail about decision trees, support vector machines, and neural networks are combined to predict diseases. Uddin et al. (2019) used a combination of deep learning networks and K-means segmentation approaches to predict and categorize potato leaf illnesses.

Nishad et al., 2022) described the application of Vision Transformer (ViT) for disease classification in tomato leaves. ViT is a transformer-based model well-known for its performance in image classification tasks. Pre-processed photos of tomato leaves are fed into several ViT models for training and assessment. (Saleem et al., 2020), presented a deep learning meta-architecture approach for image-based plant disease identification. Cutting-edge deep learning methods to increase plant disease identification efficiency and accuracy. Improve the identification system's performance, probably entails creating meta-architecture that integrate several deep learning models or include unique architectural components. The method consists of labelling datasets, preprocessing plant photos, training deep learning models on them, and assessing how well the algorithms identify different plant illnesses. Iniyan and Jebakumar (2022) proposed a multi-layer stacked ensemble learning technique increase the accuracy of yield predictions for soybean crops.

Kale et al. (2021) proposed deep learning models to detect the factors of mango crop production and quality. Yousuf and Khan (2021) describes an ensemble model based on Random Forest and K-Nearest Neighbor (KNN) for the detection of plant diseases from the leaves. The proposed ensemble has detected the diseases using four phases. In the first phase, the segmentation of leaf images is done by K-Means Clustering. The second phase is to feature extraction process. In this phase, the GLCM approach is adopted. The third phase consists of a feature selection approach. For that, the Random Forest method is applied, and finally the classification of plant disease by KNN and SVM. The proposed approach outperformed the SVM method. (Sutaji and Yıldız. 2022), presented a compact and effective model is

proposed to predict the illness by combining the Xception and MobileNetV2 models.

Nagaraju et al. (2022) dealt wit an image augmentation method for identifying and categorizing diseases in maize crops. The technique creates augmented photos that boost the quality and diversity of the dataset used to train machine-learning models, to increase the accuracy of disease recognition. Al-gaashani et al. (2022) used pre-trained models and feature extraction techniques to detect the diseases of tomato leaves. To improve classification accuracy, the method makes use of feature concatenation and transfer learning approaches. Through feature concatenation and information transfer from pre-trained models, the strategy enhances the robustness of disease classification in tomato leaves. Chy et al. (2023) adopted an optimized model to detect corn diseases. The corn diseases are Corn common leaf rust, Corn Common rust, Corn Northern Leaf Blight, and healthy leaves. The obtained overall accuracy is 97.6%, and each category accuracy was greater than 95%.

Most of the exiting works have utilized an independent classifier for decision-making. While, in the proposed work, two-level classification is proposed. The proposed system has implemented the classification task as two level, at level -1 base learner with InceptionV3, Xception, and Densenet201. (Hasan et al., 2022) outlined the various deep learning models. The CNN model is used for the Meta classifier generation (Mishra et al., 2020). Generally, in stacking, if the base classifiers are machine learning, the Meta classifier is also machine learning. Since the proposed method adopted three advanced deep learning models as the base learners, the Meta classifier must also be a deep learning model (Panchal et al., 2023). Thus, the proposed method uses CNN as the meta-learner.

Materials and methods

The benchmarked Kaggle dataset Village Plant is used to experiment with the proposed method. This dataset contains potato, corn, grape, and apple plants have healthy and diseased leaf images. Table 2 provides leaf disease details, and the total number of images present in the dataset.

Leaf disease description

The early blight disease of potatoes is caused by the fungus Alternaria solani. This kind of disease generally appears on the leaflet of a potato after 3 to 4 weeks of finding symptoms like brown spots, dark spots, and angular spots. Climatic conditions or soil conditions tend to stimulate diseases. Black rot diseases are causing severe losses in apple and grape plants due to the fungus causal agent. It produces dark brown discoloration and decay, mainly in the leafy part of the plant. It is a common disease caused by berry rot and leaf spot. Apple scab is caused by fungus in the apple leaves with velvety olive-green spots with unclear margins. Later, the lesions enlarge and become darker, with more distinct margins. Heavily infected leaves become dizzy and drop early in the summer season. The northern leaf blight is very easy to find along field edges, likely due to increased air movement for spore dispersal. It lacks the freckles in the lesions and bacterial streaming. Symptoms may include a detectable change in color, shape, or function of the plant as it responds to the pathogen. Leaf wilting is a typical symptom of verticillium wilt, caused by fungal plant pathogens.

S.no	Plant type	Diseases	Number of images	Sample Image
1	Potato	Early_blight	1002	
		Late_blight	1000	
		Healthy	152	

Source: compiled by the authors based on the dataset

Table 2: Disease details and the total number of images present in the dataset. (To be continued).

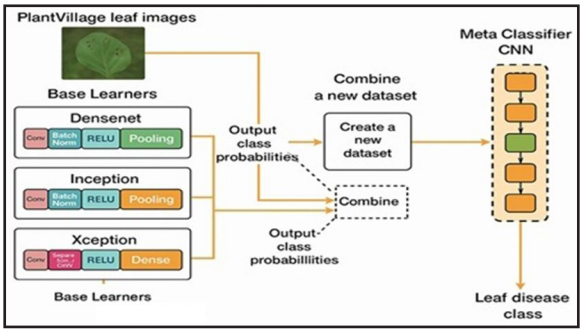
S.no	Plant type	Diseases	Number of images	Sample Image
2	Corn	Northern_Leaf_Blight	985	
		Cercospora_leaf_spot Gray_leaf_spot	513	
		Common_rust_	1192	
		Healthy	1162	
3	Grape	Black_rot	1180	
		Esca_ (Black_Measles)	1383	
		Leaf_blight_ (Isariopsis_Leaf_Spot)	1076	
		Healthy	423	
4	Apple	Apple_Apple_scab	630	
		Cedar_apple_rust	275	
		Black_rot	621	
		Healthy	1645	

Source: compiled by the authors based on the dataset

Table 2: Disease details and the total number of images present in the dataset. (Continuation).

System architecture

Figure 2 depicts the system architecture of the proposed system. The dataset contains healthy and diseased potatoes, corn, grape, and apple images. In the pre-processing step, the images are resized from 256x256x3 to 76x76x3. Image resizing is an essential part of handling the image data to make efficient use of the memory. The pre-processing steps include fixing the image resize by checking the lower values of the original image size. The proposed approach reduces the image ratio from 256, and 256, and 3 to 76, 76, and 3. This pre-processed data is then fed to the base learners twice, once with individual plants and once with combined plants, for the leaf image disease classification. In the first case, the leaf images of potatoes, corn, apples, and grapes are input individually. The execution time, accuracy, recall, and precision are calculated separately. In the second step, all the plant leaf images are combined into a single dataset and then fed as input for the model. The execution time and the performance metrics are computed for both, and the outputs are analyzed in the experimental section. The system architecture for both single plant and combined leaf image disease classification is similar, except for the input and output layers of deep learning models. Various modules are designed for single-plant and combined-plant leaf image classification using deep convolutional neural networks. The modules for pre-processing data and apply various classifiers and deep convolutional neural networks are as follows

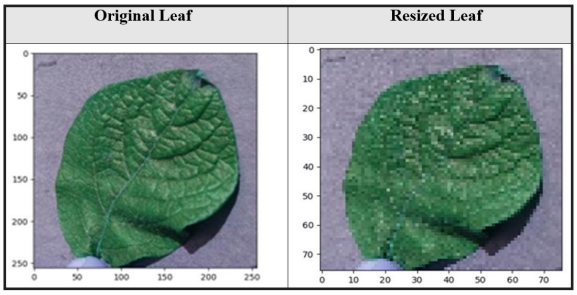


Source: compiled by the authors

Figure 2: Proposed stacked ensemble system architecture.

Resizing image

Image resizing is a process of scaling down or scaling up the dimensions of the images concerning maintaining the aspect ratio. When the image resizes is less than the aspect ratio, the image content cannot be preserved. But still, the image content is preserved without any loss (Iqbal and Talukder, 2020). The processing of original image data may consume more memory than predicting the final output. Thus, the proposed system applied various values to the height and width of the image to get the desired range. When the images were resized to 128x128x3, the system was unable to generate the array for all the images due to insufficient memory in the Kaggle as well as the local machine with the configuration of 64GB RAM. So, the proposed system resized the images gradually from 256, 128, 100, 84, and 76. Apart from 76X76X3, for the other above-mentioned resized images, the Numpy array could not be generated due to a lack of memory. This pixel reduction has two advantages. First, the training and testing time of the DL model will be reduced. If the number of pixels is high in the input image, the design complexity of the neural network model will also be increased. Figure 3 displays the original image 256, 256, and 3 and resizes that image into 76, 76, and 3.



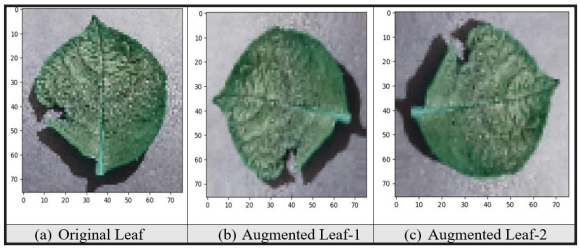
Source: compiled by the authors based on the dataset images

Figure 3: Potato plant leaf image resize.

Image data augmentation

Data augmentation generates new samples from the existing data. It is technically arranged and modified with some small changes to the dataset to assess the new training data by increasing the number of training sets. This training set ability is increased to generalize the variability and decrease the overfitting available in the data. Data augmentation improves the accuracy of the deep learning techniques and minimizes the data scarcity for the deep learning model. The techniques included in the data augmentation are flipping the image, resizing, cropping, and rotating the image. The data augmentation provides better performance by generating more samples. More samples are very useful to train the system so that the model can recognize more insights into the features of the input image. The proposed system thus

generates two more samples of every leaf image by rotating the image to 90 degrees. Figure 4 shows the sample of potato leaf image augmentation.



Source: compiled by the authors based on the dataset images

Figure 4: Potato plant leaf image data augmentation. (a) original image (b), original image is rotated into 90°, (c) rotated image is again rotated into 90°.

Base classifier (Level-0-Classifier)

The proposed stacked ensemble model adopted three deep learning models, namely Xception, Inception, and Densenet201 deep neural networks, as the base learners. The base learners create a new dataset that is inputted into the meta-classifier. The proposed model is also verified with combined-plant leaves (potato, corn, apple, and grape) and trained to recognize inter-plant leaf disease detection (Xie et al., 2020). The inter-plant leaf disease detection result analysis is explained in the experimental result section.

Meta classifier

The proposed method uses CNN as a meta-classifier. The input for the Meta classifier is a two-dimensional array, which consists of each classifier's predicted probability. The calculated probability value (0 to 1) for each disease in a leaf image. For possible 'n' diseases on a leaf, the classifier produces different predicted probability values based on the features recognized in the leaf (Vishnoi et al, 2022). If the leaf has a particular disease, then the classifier predicts. The probability value of that specific disease is higher than that of other diseases. The proposed method's performance on image classification is verified by adopting three different algorithms as metaclassifiers.

Proposed system algorithm

Step 1: Select the plant folder from plant village data source.

Step 2: Load the selected plant normal and diseases images in a directory *D*.

Step 3: Plant leaf image dataset

$D = \{D1, D2, D3, \ldots Dn\}$, where $D1, D2, D3, \ldots$ are plant image directories.

Step 4: Map the directory names as leaf disease names to generate labelled data.

Step 5: Split the selected plant images into training and testing set $DT = \{DT1, DT2, DT3, \ldots DTn\}$ *and* $DS = \{DS1, DS2, DS3, \ldots DSn\}$.

Step 6: Set rotation range = 90 of data augmentation to each $DT1, DT2, DT, \ldots$ in *DT* to double the training set.

Step 6: ***for each*** *DT*1 to *DTn*

for each image $(i1, i2, i3, \ldots, im)$, where *m* is the total number of images in the directory *DTi*

a. $ri_x \leftarrow_{\text{Resize}} image\ (i_x)$ into 76X76 pixel, where $x \rightarrow 1, 2, 3 \ldots m$

b. $ri_{x\ \text{Convert}} \rightarrow narray\ [76, 76, 3]$

c. $Nri_x \leftarrow ri_x/255[0,1]$

d. X_train$\leftarrow_{append} Nri_x$

e. Y_train $\leftarrow_{append} DTi$

end for

end for

Step 7: ***for each*** *DS*1 to *DSn*

for each image $(i1, i2, i3, \ldots, im)$, where *m* is the total number of images in the directory *DSi*

a. $ti_x \leftarrow_{\text{Resize}} image\ (i_x)$ into 76X76 pixel, where $x \rightarrow 1, 2, 3 \ldots m$

a. $ti_{x\ \text{Convert}} \rightarrow narray\ [76, 76, 3]$

b. $Nsi_x \leftarrow_{append} ti_x/255[0,1]$

c. X_test$\leftarrow_{append} Nsi_x$

d. Y_test $\leftarrow_{append} DSi$

end for

end for

Step 8: ***for each*** l in narray(range (0, len(X_train)

for each i in ***n***, where ***n*** is the total number of level-0-classifiers

for each j in disease (***d***), where ***d*** is the total number of diseases $\{(p_{i1l}, p_{i2l}, p_{i3l} \cdots, p_{ijl})\}$ predicted probabilities of ***j*** on the leaf array (***l***)

end for

end for

Generate predicted probability ***row set*** for the leaf l to generate the new input dataset (*D´*) for the Meta classifier

$\{(p_{11l}, p_{12l}, p_{13l} \cdots, p_{1jl}),$
$(p_{21l}, p_{22l}, p_{23l} \cdots, p_{2jl}), \ldots,$
$(p_{n1l}, p_{n2l}, p_{n3l} \cdots, p_{njl}), y_d\}$

end for

Step 9: ***for each*** row i_1 from the newly generated dataset (D')

Input i_1 to train the Meta Classifier ***for each*** output category $y_k \in \{y_1, y_2, y_3, \ldots y_n\}$,

Calculate probability $p\left(\frac{n}{i_1}\right) = \frac{\exp(i_1 n)}{\sum_{j=1}^{n} \exp(i_1 n)}$ is calculated for the image i_1

Classify row $i_1 \leftarrow y_k \in \{y_1, y_2, y_3, \ldots y_n\}$

Results and discussion

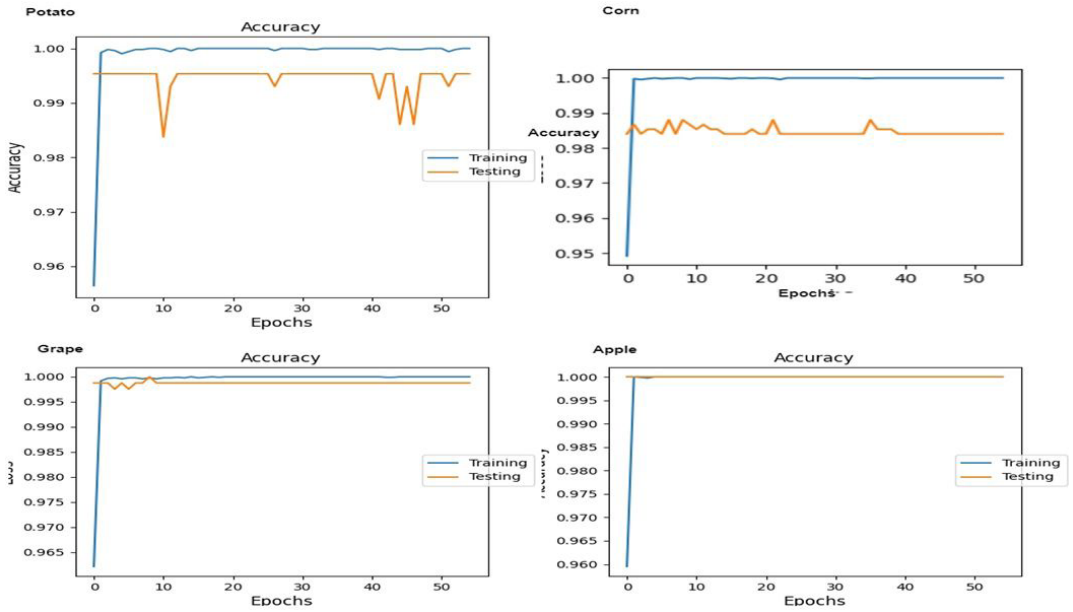
The proposed stacking ensemble system was trained and tested using the plant village dataset. The dataset covers samples of potato, corn, apple, and grape healthy and diseased leaf images. The model's performance outcomes as shown in Table 3 have reported significant improvement than the other classical approaches. The proposed model could predict diseases accurately. Model accuracy, precision, recall, and F1-score are estimates as per the equations 1, 2, 3, and 4 are applied to calculate (Wang et al., 2021). The classification accuracy lag in apple and potato leaf images was due to insufficient number of samples. Also, in sufficient datasets may report model under fitting and hence data sets play a vital role in data driven decision support systems. Also, the proposed stacking approach accuracy and loss results are shown in Figure 5 and Figure 6. In the testing phase of the proposed system, the misclassification is 0 for the apple. For the corn plants, the number of misclassifications is 12, the potato misclassification is 2 and the grape plants misclassification is 1.

The accuracy of the apple leaf images is significantly higher when compared to standalone machine learning and deep learning methods like VGG16 and random forest. The hybrid model's accuracy is lower than that of the proposed method for apple leaf images. For corn leaf images, deep learning models, including InceptionV2, ResNet50, and CNN, as well as machine learning algorithms, show lower accuracy than the proposed method. Likewise, the accuracy for grape and potato images surpasses that of the machine learning models. The proposed system was also evaluated using a unified dataset comprising all plant leaf images, referred to as combined plants. Table 4 presents the precision, recall, and F1 score results obtained for the combined plants through the proposed method. Analyzing the results for combined plants versus individual plants reveals that the performance metrics for combined potato plants are superior to those of individual potato plants. In contrast, the performance metrics for combined grape and corn plants are slightly lower (in fractional values) than those for the individual plants. However, the differences in performance results between combined and individual plants are minimal, owing to the classifiers utilized in level 0 classification.

Plant	Plant Disease / Evaluation Metrics	Precision	Recall	F1-score
Apple	Apple__Apple scab	1	1	1
	Apple___Black_rot	1	1	1
	Apple___Cedar_apple_rust	1	1	1
	Apple___healthy	1	1	1
Corn	Corn_Cercospora_leaf_spot Gray_leaf_spot	0.97	0.92	0.95
	Corn_Common_rust	1	1	1
	Corn_Northern_Leaf_Blight	0.96	0.98	0.97
	Corn_healthy	1	1	1
Grapes	Grape_Black_rot	1	1	1
	Grape_Esca_(Black_Measles)	1	1	1
	Grape_Leaf_blight	1	1	1
	Grape_healthy	1	1	1
Potato	Potato_Early_blight	1	1	1
	Potato_Late_blight	0.99	1	0.99
	Potato healthy	1	0.94	0.97

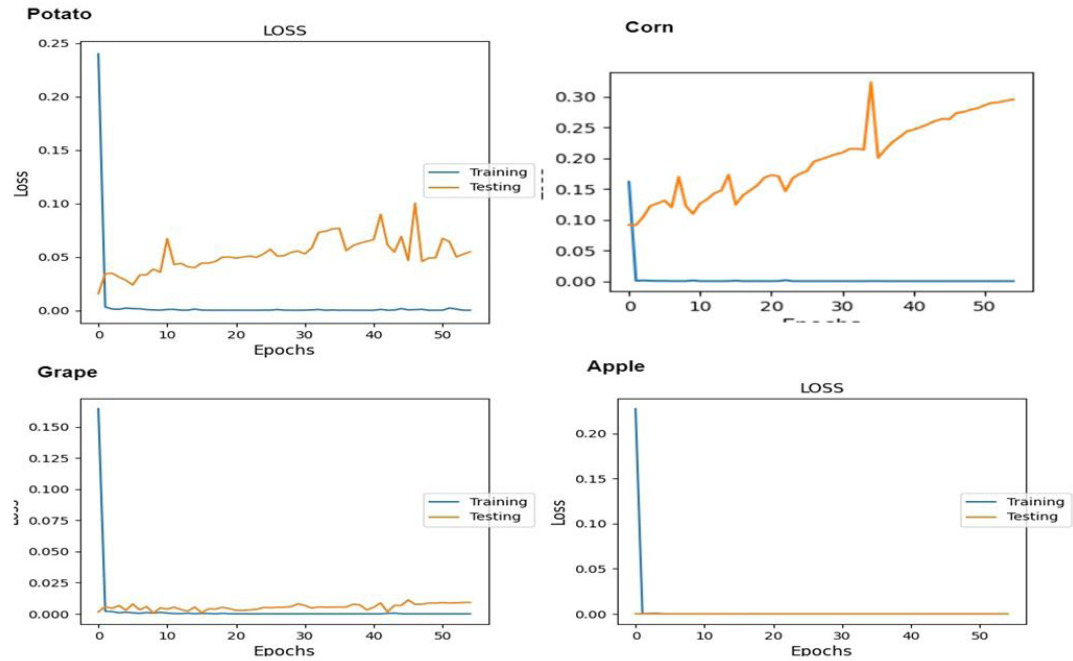
Source: compiled by the authors based on the dataset images

Table 3: Performance metrics results of individual plants.



Source: Own elaboration based on the model output

Figure 5: Accuracy results of a) potato b) corn c) grape d) apple individual plants leaves disease classification.



Source: Own elaboration based on the model output

Figure 6: Loss results of a) potato b) corn c) grape d) apple combined plants leaves disease classification.

Plant	Plant Disease / Evaluation Metrics	Precision	Recall	F1-score
Apple	Apple___Black_rot	1.00	1.00	1.00
	Apple___Cedar_apple_rust	1.00	1.00	1.00
	Apple___healthy	1.00	1.00	1.00
Corn	Corn_(maize)___Cercospora_leaf_spot Gray_leaf_spot	0.95	0.92	0.94
	Corn_(maize)___Common_rust	1.00	1.00	1.00
	Corn_(maize)___Northern_Leaf_Blight	0.96	0.96	0.96
	Corn_(maize)	0.99	1.00	0.99
Grape	Grape-Black_	1.00	1.00	1.00
	Grape___Esca_(Black_Measles	1.00	1.00	1.00
	Grape___Leaf_blight_(Isariopsis_Leaf_Spot)	1.00	1.00	1.00
	Grape___healthy	0.99	1.00	0.99
Potato	Potato___Early_	1.00	1.00	1.00
	Potato___Late_blight	1.00	1.00	1.00
	Potato___healthy	1.00	1.00	1.00

Source: compiled by the authors based on the dataset images

Table 4: Performance metrics results of disease detection in apple, corn, grape & potato.

The total number of misclassifications in the combined plant dataset is low, with just 20 leaf images misidentified by the proposed method. The suggested stacked learning approach shows improved performance even when the dataset's size is increased two or threefold compared to the individual plant datasets. Consequently, the base classifiers in this design are sufficiently robust to assist the meta-learner in making precise predictions about leaf image diseases. Regarding runtime for the initial epoch, the processing times are as follows: apple takes 3 seconds and 7 milliseconds, grape requires 4 seconds and 6 milliseconds, potato also takes 3 seconds and 7 milliseconds, and corn needs 3 seconds and 6 milliseconds. For the combined plants, the first epoch lasts 6 seconds and 5 milliseconds.

Conclusion

This research work highlights the potential of stack ensembled model as a powerful and reliable framework for plant disease detection using leaf images. By effectively integrating multiple learning models in a two-tire classification system, also it overcomes the limitation of single-model techniques. The proposed stacked ensemble model has been designed using InceptionV3, Efficient Net, and DenseNet201 as base learners and CNN as its meta-learner. The predicted probability values from the base learners are compiled into a new dataset for the meta-model to produce the final prediction. This system was tested with two sets of image inputs. The first set included images of leaves from four distinct plants: potato, corn, grape, and apple, which were processed individually to compute performance metrics. In the second scenario, all the previously stated images were combined into a single input set to evaluate performance. In both instances, the experimental results demonstrated high performance, with minimal deviation between the two cases. It is principally attributed using three cutting-edge neural architectures that yield accurate probability predictions. The experimental findings further demonstrated that the proposed system outperforms existing methods. Its ability to accurately differentiate between healthy and diseased leaves, even in complex and diverse datasets, demonstrates its robustness and adaptability. The remarkable prediction accuracy of 99.9% highlights the efficiency of this hybrid model in capturing the subtle disease pattern and reducing misclassification rate. This research not only contributes to advancing intelligent agricultural advancements but also paves way for developing advanced scalable automated plant health monitoring systems to support sustainable farming practices.

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References

[1] Agarwal, A., Sanghi, A., Agarwal, G., Arya, Y. D. S. and Agarwal, S. (2022) "Plant disease detection using deep learning and convolutionary neural network", *Mathematical Statistician and Engineering Applications*, Vol. 71, No. 4, pp. 2499-2516. ISSN 2320-222X.

[2] Al-gaashani, M. S., Shang, F., Muthanna, M. S., Khayyat, M. and Abd El-Latif, A. A. (2022) "Tomato leaf disease classification by exploiting transfer learning and feature concatenation", *IET Image Processing*, Vol. 16, No. 3, pp. 913-925. ISSN 1751-9659. DOI 10.1049/ipr2.12397.

[3] Ayan, E. (2024) "Genetic algorithm-based hyperparameter optimization for convolutional neural networks in the classification of crop pests", *Arabian Journal for Science and Engineering*, Vol. 49, No. 3, pp. 3079-3093. ISSN 2193-567X. DOI 10.1007/s13369-023-07916-4.

[4] Chen, J., Zeb, A., Nanehkaran, Y. A. and Zhang, D. (2023) "Stacking ensemble model of deep learning for plant disease recognition", *Journal of Ambient Intelligence and Humanized Computing,* Vol. 14, No. 9, pp. 12359-12372. ISSN 1868-5137. DOI 10.1007/s12652-022-04334-6.

[5] Chy, M. S. R., Mahin, M. R. H., Islam, M. F., Hossain, M. S. and Rasel, A. A. (2023) "Classifying corn leaf diseases using ensemble learning with dropout and stochastic depth based convolutional networks", *Proceedings of the 2023 8th International Conference on Machine Learning Technologies*, pp. 185-189. ISBN 978-1-4503-9999-8. DOI 10.1145/3589883.3589911.

[6] Enkvetchakul, P. and Surinta, O. (2022) "Stacking ensemble of lightweight convolutional neural networks for plant leaf disease recognition", *ICIC Express Letters,* Vol. 16, No. 5, pp. 521-528. ISSN 1881-803X. DOI 10.24507/icicel.16.05.521.

[7] Fenu, G. and Malloci, F. M. (2023) "Classification of pear leaf diseases based on ensemble convolutional neural networks", *AgriEngineering*, Vol. 5, No. 1, pp. 141-152. ISSN 2624-7402. DOI 10.3390/agriengineering5010009.

[8] Gautam, V., Ranjan, R. K., Dahiya, P. and Kumar, A. (2024) "ESDNN: A novel ensembled stack deep neural network for mango leaf disease classification and detection", *Multimedia Tools and Applications*, Vol. 83, No. 4, pp. 10989-11015. ISSN 1380-7501. DOI 10.1007/s11042-023-16012-6.

[9] Haque, M. A., Marwaha, S., Deb, C. K., Nigam, S., Arora, A., Hooda, K. S., Soujanya, P. L., Aggarwal, S. K., Lall, B., Kumar, M. and Islam, S. (2022) "Deep learning-based approach for identification of diseases of maize crop", *Scientific Reports*, Vol. 12, No. 1, p. 6334. ISSN 2045-2322. DOI 10.1038/s41598-022-10140-z.

[10] Hasan, S., Jahan, S. and Islam, M. I. (2022) "Disease detection of apple leaf with combination of color segmentation and modified DWT", *Journal of King Saud University - Computer and Information Sciences*, Vol. 34, No. 9, pp. 7212-7224. ISSN 1319-1578. DOI 10.1016/j.jksuci.2022.07.004.

[11] Iniyan, S. and Jebakumar, R. (2022) "Crop yield prediction on soybean crop applying multi-layer stacked ensemble learning technique", In: Manogaran, G., Shanthini, A., Vadivu, G. (eds) *Proceedings of International Conference on Deep Learning, Computing and Intelligence. Advances in Intelligent Systems and Computing,* Vol 1396. Springer, Singaporepp. 335-348. Springer, Singapore. ISBN 978-981-16-9914-6. DOI 10.1007/978-981-16-5652-1_29.

[12] Iqbal, M. A. and Talukder, K. H. (2020) "Detection of potato disease using image segmentation and machine learning", *2020 International Conference on Wireless Communications Signal Processing and Networking (WiSPNET)*, IEEE. pp. 43-47. ISBN 978-1-7281-4512-2. DOI 10.1109/WiSPNET48689.2020.9198563.

[13] Jaisakthi, S. M., Mirunalini, P. and Thenmozhi, D. (2019) "Grape leaf disease identification using machine learning techniques", *2019 International Conference on Computational Intelligence in Data Science (ICCIDS)*, IEEE. pp. 1-6. ISBN 978-1-5386-9439-8. DOI 10.1109/ICCIDS.2019.8862084.

[14] Jose, V. D. and Santhi, K. (2022) "Early detection and classification of apple leaf diseases by utilizing IFPA genetic algorithm with MC-SVM, SVI and deep learning methods", *Indian Journal of Science and Technology*, Vol. 15, No. 29, pp. 1440-1450. ISSN 0974-5645. DOI 10.17485/IJST/v15i29.1235.

[15] Kale, Y. V., Shetty, A. U., Patil, Y. A., Patil, R. A. and Medhane, D. V. (2021) "Object detection and face recognition using YOLO and inception model", *International Conference on Advanced Network Technologies and Intelligent Computing*, pp. 274-287. Springer, Cham. ISBN 978-3-030-93947-8.

[16] Kalita, I., Singh, G. P. and Roy, M. (2023) "Crop classification using aerial images by analyzing an ensemble of DCNNs under multi-filter & multi-scale framework", *Multimedia Tools and Applications*, Vol. 82, No. 12, pp. 18409-18433. ISSN 1380-7501. DOI 10.1007/s11042-022-13946-1.

[17] Kaur, P., Harnal, S., Tiwari, R., Upadhyay, S., Bhatia, S., Mashat, A. and Alabdali, A. M. (2022) "Recognition of leaf disease using hybrid convolutional neural network by applying feature reduction", *Sensors*, Vol. 22, No. 2, p. 575. ISSN 1424-8220. DOI 10.3390/s22020575.

[18] Li, H., Jin, Y., Zhong, J. and Zhao, R. (2021) "A fruit tree disease diagnosis model based on stacking ensemble learning", *Complexity*, Vol. 2021, p. 6868592. ISSN 1076-2787. DOI 10.1155/2021/6868592.

[19] Liu, B., Ding, Z., Tian, L., He, D., Li, S. and Wang, H. (2020) "Grape leaf disease identification using improved deep convolutional neural networks", *Frontiers in Plant Science*, Vol. 11, p. 1082. ISSN 1664-462X. DOI 10.3389/fpls.2020.01082.

[20] Mishra, S., Sachan, R. and Rajpal, D. (2020) "Deep convolutional neural network based detection system for real-time corn plant disease recognition", *Procedia Computer Science*, Vol. 167, pp. 2003-2010. ISSN 1877-0509. DOI 10.1016/j.procs.2020.03.236.

[21] Nagaraju, M., Chawla, P. and Tiwari, R. (2022) "An effective image augmentation approach for maize crop disease recognition and classification", In: Mehra, R., Meesad, P., Peddoju, S. K., Rai, D. S. (eds) *Computational Intelligence and Smart Communication. ICCISC 2022. Communications in Computer and Information Science,* Vol 1672. Springer, Cham. ISBN 978-3-031-10312-4. DOI 10.1007/978-3-031-22915-2_6.

[22] Nishad, M. A. R., Mitu, M. A. and Jahan, N. (2022) "Predicting and classifying potato leaf disease using k-means segmentation techniques and deep learning networks", P*rocedia Computer Science*, Vol. 212, pp. 220-229. ISSN 1877-0509. DOI 10.1016/j.procs.2022.11.006.

[23] Panchal, A. V., Patel, S. C., Bagyalakshmi, K., Kumar, P., Khan, I. R. and Soni, M. (2023) "Image-based plant diseases detection using deep learning", *Materials Today: Proceedings*, Vol. 80, pp. 3500-3506. ISSN 2214-7853. DOI 10.1016/j.matpr.2021.07.281.

[24] Patil, Y., Shetty, A., Kale, Y., Patil, R. and Sharma, S. (2024) "Multiple ocular disease detection using novel ensemble models", *Multimedia Tools and Applications*, Vol. 83, No. 4, pp. 11957-11975. ISSN 1380-7501.

[25] Ranjan, R. K. and Kumar, V. (2023) "A systematic review on fruit fly optimization algorithm and its applications", *Artificial Intelligence Review*, Vol. 56, No. 11, pp. 13015-13069. ISSN 0269-2821. DOI 10.1007/s10462-023-10451-1.

[26] Saleem, M. H., Khanchi, S., Potgieter, J. and Arif, K. M. (2020) "Image-based plant disease identification by deep learning meta-architectures", *Plants*, Vol. 9, No. 11, p. 1451. ISSN 2223-7747. DOI 10.3390/plants9111451.

[27] Sunil, C. K., Jaidhar, C. D. and Patil, N. (2022) "Binary class and multi-class plant disease detection using ensemble deep learning-based approach", *International Journal of Sustainable Agricultural Management and Informatics*, Vol. 8, No. 4, pp. 385-407. ISSN 2054-5816. DOI 10.1504/IJSAMI.2022.126802.

[28] Sutaji, D. and Yıldız, O. (2022) "LEMOXINET: Lite ensemble MobileNetV2 and Xception models to predict plant disease", *Ecological Informatics*, Vol. 70, p. 101698. ISSN 1574-9541. DOI 10.1016/j.ecoinf.2022.101698.

[29] Tiwari, D., Ashish, M., Gangwar, N., Sharma, A., Patel, S. and Bhardwaj, S. (2020) "Potato leaf diseases detection using deep learning", *2020 4th International Conference on Intelligent Computing and Control Systems (ICICCS)*, IEEE. pp. 461-466. ISBN 978-1-7281-5463-6. DOI 10.1109/ICICCS48265.2020.9121067.

[30] Uddin, S., Khan, A., Hossain, M.E. and Moni, M. A. (2019) "Comparing different supervised machine learning algorithms for disease prediction", *BMC Medical Informatics and Decision Making*, Vol. 19, No. 1, pp. 1-16. ISSN 1472-6947. DOI 10.1186/s12911-019-1004-8.

[31] Vishnoi, V. K., Kumar, K., Kumar, B., Mohan, S. and Khan, A. A. (2022) "Detection of apple plant diseases using leaf images through convolutional neural network", *IEEE Access*, Vol. 11, pp. 6594-6609. ISSN 2169-3536. DOI 10.1109/ACCESS.2022.3232917.

[32] Wang, P., Niu, T., Mao, Y., Zhang, Z., Liu, B. and He, D. (2021) "Identification of apple leaf diseases by improved deep convolutional neural networks with an attention mechanism", *Frontiers in Plant Science*, Vol. 12, p. 723294. ISSN 1664-462X. DOI 10.3389/fpls.2021.723294.

[33] Xie, X., Ma, Y., Liu, B., He, J., Li, S. and Wang, H. (2020) "A deep-learning-based real-time detector for grape leaf diseases using improved convolutional neural networks", *Frontiers in Plant Science*, Vol. 11, p. 751. ISSN 1664-462X. DOI 10.3389/fpls.2020.00751.

[34] Yousuf, A. and Khan, U. (2021) "Ensemble classifier for plant disease detection", *International Journal of Computer Science and Mobile Computing*, Vol. 10, No. 1, pp. 14-22. ISSN 2320-088X. DOI 10.47760/ijcsmc.2021.v10i01.003.

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Does Fermentation of Cocoa Beans Increase Farmers' Income? A Case Study Using a Nationwide Survey in Indonesia

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Abstract

This study evaluates the impact of cocoa bean fermentation on costs and revenues among cocoa farmers using Propensity Score Matching (PSM). The study used nationally-representative data of Indonesian cocoa farmers from the Indonesian Plantation Farm Household Survey 2014 comprised 23,189 farmers. The result shows that non-fermented cocoa bean farmers achieve higher production (1.04 kg/year) compared to fermented bean farmers (0.83 kg/year), a 26.27% increase. They also have higher revenue, earning $100.67 per year versus $84.42 for fermented bean farmers, a 19.25% increase. Additionally, non-fermented farmers exhibit higher farm value per hectare ($1,772.50 compared to $1,350.00). However, non-fermented farmers incur higher costs: seed costs ($7.19 vs. $5.58), labor costs ($329.05 vs. $295.25), and fertilizer costs ($39.95 vs. $36.46). Conversely, they have lower pesticide costs ($21.95 vs. $26.12). The findings indicate that while non-fermented cocoa beans result in higher production and revenue, they also come with higher input costs. Fermented cocoa farmers benefit from lower costs but achieve lower production and revenue, highlighting the trade-offs between fermentation practices and economic outcomes.

Keywords

Cocoa bean fermentation, Propensity Score Matching (PSM), non-fermented cocoa, fermented cocoa, input costs, economic outcomes.

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Introduction

The International Cocoa Organization (ICCO) ranks Indonesia among the top 10 largest cocoa-producing countries globally (ICCO, 2023). According to the Indonesian Central Statistics Agency (BPS) (2023), Indonesia produced 650,612 tons of cocoa beans in 2022, with 56.68% of this production exported to various countries such as India, the United States, Malaysia, China, and Australia. However, despite its strategic position as a producer, Indonesia has yet to be included among the top 10 largest cocoa bean-exporting countries in the world (Global Value Chains). One of the reasons for this is the low quality of cocoa beans in Indonesia, attributed to inadequate post-harvest handling, particularly in the cocoa bean fermentation process (Wijayati and Haqqi, 2022).

Cocoa bean fermentation plays a crucial technical and economic role in determining the quality of beans and facilitating the cocoa export process. Quality standards for cocoa beans in Indonesia are governed by the National Certification Body (BSN) through the Indonesian National Standard for Cocoa Beans, designated as SNI 2323:2008/ Amd1:2010. These standards cover quality compliance, classification, packaging methods, testing procedures, color, taste, and aroma of cocoa beans. Cocoa bean fermentation is an essential process to meet these standards (Malau, 2018). Fermentation enhances the quality of cocoa beans by bringing out distinctive chocolatey aroma and flavor characteristics while preventing seed germination (Figueroa-Hernández et al., 2019). The cocoa bean fermentation process involves various microorganisms such as yeast,

lactic and acetic acid bacteria, aerobic spore-forming bacteria, and filamentous fungal species (Guzmán-Alvarez and Márquez-Ramos, 2021). This process typically spans 5 to 7 days and leads to the evolution of microorganisms and enzymes that serve as precursors to cocoa aroma (Julian, 2021). According to (Morales-Rodriguez et al, 2024), fermented cocoa beans exhibit superior quality with a darker color, stronger aroma, and drier beans. Economically, cocoa bean fermentation is carried out to meet quality requirements set by the ICCO and export destination countries (Santos, 2020).

Despite the pivotal role of fermentation in determining cocoa quality, most previous studies in Indonesia have primarily examined its effects on bean quality, production, and farmers' decision-making processes rather than directly analyzing its impact on farmers' income. Research has shown that fermentation enhances cocoa bean quality and market price, influenced by factors such as farmer education, training, and production volume (Ambarawati and Esterina, 2024). However, only a few studies have quantitatively compared the income of farmers who ferment their cocoa with those who do not, demonstrating that fermentation can significantly increase income and add value to cocoa products(Intarini et al., 2020). These dynamics are further shaped by differences in farmers' preferences, knowledge, and socio-economic conditions, as highlighted in previous research by Soemarno (2015), Ahmad (2021), Hariyati et al. (2023), and Putro et al. (2023). Building on these insights, the present study distinguishes itself by employing a more comprehensive framework, incorporating a broader range of variables, a larger sample size, and diverse research locations, thereby offering a novel contribution to the understanding of how cocoa fermentation directly influences farmers' income in Indonesia.

Thus, this study aims to factors influencing farmers fermenting cocoa beans and investigate whether fermenting cocoa beans enhances farmers' income. According to the ICCO (2020), only 10% of Indonesia's total cocoa bean exports meet quality standards for taste and bean suitability. The Food and Agriculture Organization (FAO) states that the majority of Indonesian cocoa farmers sell unfermented cocoa beans (FAO, 2024). For instance, Effendy et al. (2019) observes that over 50% of cocoa farmers in Central Sulawesi do not ferment cocoa beans, citing a perceived lack of significant price difference as a primary reason. On the other hand, 99.63% of cocoa plantations in Indonesia are smallholder farms, and the majority of smallholder farmers do not understand the fermentation process (Badan Pusat Statistik, 2023).

Understanding the relationship between cocoa bean fermentation and farmers' income is crucial for improving cocoa farming practices and enhancing the livelihoods of Indonesian farmers. This study utilizes nationally representative survey data of Indonesian cocoa farmers, making its findings highly relevant for the policymaking process. By addressing the gap in research and providing valuable insights, this study aims to inform policymakers and stakeholders in the cocoa industry. By identifying barriers to fermentation adoption and evaluating its impact on farmers' income, this research contributes to the development of targeted interventions to promote sustainable cocoa farming practices in Indonesia.

Materials and methods

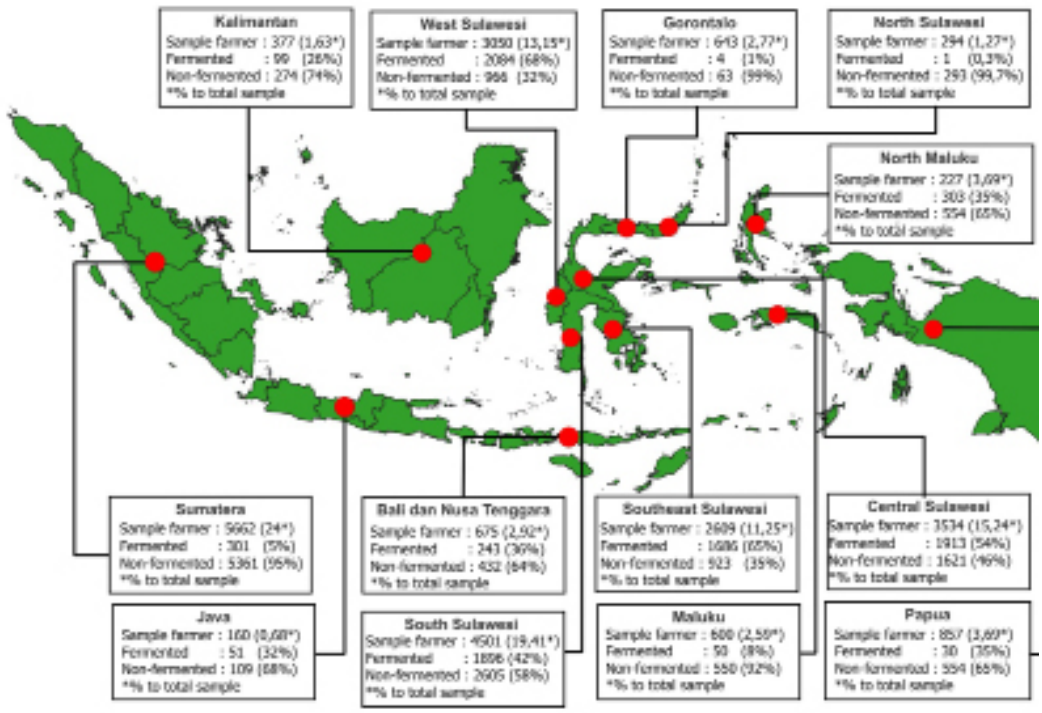
Research design

The background highlights that although cocoa bean fermentation is essential for improving quality, meeting international standards, and potentially increasing market value, most Indonesian cocoa farmers who dominate the national cocoa production still sell unfermented beans due to limited knowledge, socio-economic constraints, and perceptions of insignificant price differences. This condition has hindered Indonesia's competitiveness in the global cocoa market and contributed to low export performance. To address this gap, the present study employs a quantitative research design to systematically analyze the factors influencing farmers' decisions to ferment their cocoa and to measure the subsequent impact on income and expenses. By utilizing the nationally representative 2014 Indonesian Plantation Farm Household Survey (IPFHS), this research ensures robust and comprehensive data coverage across different regions. The quantitative approach allows comparison between farmers who ferment and those who do not, thereby directly aligning with the study's objective of assessing whether fermentation enhances farmers' income. This methodological choice not only responds to the limited prior research that directly connects fermentation with farmers' welfare but also generates evidence-based insights that can inform policymaking and targeted interventions to promote sustainable cocoa farming practices in Indonesia.

Data

This study utilizes data from the 2014 Indonesian Plantation Farm Household Survey (IPFHS), part of the Agricultural Census conducted every ten years by Indonesia's Central Statistics Agency (BPS). Although the dataset represents a cross-section from 2014, it remains the most comprehensive nationwide survey available to date. It offers a critical baseline for understanding structural issues in the Indonesian cocoa sector, specifically the low adoption of fermentation, which persist as relevant challenges in the current agricultural landscape. The dataset covers a range of plantation commodities, including coffee, cocoa, rubber, and palm oil (BPS, 2015). The rationale for using this data includes: (1) Rigorous Data Collection: The survey was conducted using stringent and standardized methods, ensuring high validity and reliability for up to ten years after publication. (2) Comprehensive Coverage: The dataset encompasses various aspects of farmers' socio-economic conditions, institutional factors, and support systems for cocoa farming in Indonesia. This breadth of information allows for a well-rounded and detailed analysis. (3) National and Regional Detail: The data provides national coverage with detailed insights into specific cocoa-producing regions in Indonesia. This extensive respondent base and geographic scope offer a comprehensive understanding of the research topic. These factors collectively ensure that the study's findings are robust and highly relevant for policy-making processes.

The research spans all cocoa-producing regions in Indonesia. Figure 1 shows the detailed distribution of these regions, starting with Sumatra Island, which includes the provinces of Aceh, North Sumatra, West Sumatra, Riau, Jambi, South Sumatra, Bengkulu, Lampung, and the Bangka Belitung Islands. Java Island comprises the provinces of West Java, Central Java, East Java, and Banten. The Bali and Nusa Tenggara regions encompass Bali, West Nusa Tenggara, and East Nusa Tenggara provinces. Kalimantan Island includes the provinces of West Kalimantan, Central Kalimantan, and East Kalimantan. Sulawesi Island covers the provinces of North Sulawesi, Central Sulawesi, South Sulawesi, Southeast Sulawesi, Gorontalo, and West Sulawesi. The Maluku Islands consist of Maluku and North Maluku provinces. Papua Island includes the provinces of West Papua and Papua. In total, the research covers 7 island groups and 29 provinces across Indonesia, representing all cocoa farmers in the country.



Source: Indonesia's Central Statistics Agency (BPS), 2014

Figure 1: Distribution of sample cocoa farmers in the study.

Analytical framework

The research employs a quantitative methodology aimed at identifying patterns and measuring specific variables through statistical and mathematical tests. The collected data are selected and classified into dependent and independent variables. The data analysis consists of Binary Logistic Regression and Propensity Score Matching. Binary Logistic Regression is used to analyze the factors influencing farmers' decisions to ferment cocoa beans. Subsequently, Propensity Score Matching will be applied to determine the differences in impact between farmers who ferment cocoa and those who do not, focusing on cost and revenue aspects. These analyses are conducted with the goal of uncovering patterns and providing a more detailed explanation of the cocoa bean fermentation issues in Indonesia.

Binary logistic regression

Logistic regression is a statistical tool used to determine whether there is a relationship between independent and dependent variables (Salam et al., 2024). The dependent variable is typically binary or qualitative dichotomous data with only two possible values, often represented as 0 and 1. In this study, the binary variable is defined as 0 for farmers who do not ferment cocoa beans and 1 for farmers who do ferment cocoa beans. The formula for binary logistic regression with two categories is as follows:

$$f(y_i) = \pi_i^{y_i}(1 - \pi_i)^{1-y_i} \quad (1)$$

where: π_i = probability of the i-th event, y_i = i-th random variable, which takes the value of 0 or 1.

The logistic regression equation with a single predictor variable is presented as follows:

$$\pi(x) = \frac{\exp(\beta_0 + \beta_1 x)}{1+\exp(\beta_0 + \beta_1 x)} \quad (2)$$

To facilitate the estimation of regression parameters, $\pi(x)$ in the previous equation is transformed to yield the logit form of logistic regression as follows:

$$g(x) = \ln\left[\frac{\pi(x)}{1-\pi(x)}\right] = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_n X_n \quad (3)$$

Estimating the impact of cocoa bean fermentation on smallholder cocoa farmers' performance

The differences in impact between farmers who ferment cocoa beans and those who do not are analyzed using Propensity Score Matching (PSM). The impact on farmers is examined in terms of costs incurred and revenues received. These aspects of costs and revenues are further detailed into indicator variables as shown in the following Table 1.

Table 1 displays the indicator variables used to assess the impact experienced by farmers who do and do not ferment cocoa beans. The treatment variable used in the Propensity Score Matching (PSM) analysis is represented by 0 and 1, where 0 denotes farmers who do not ferment cocoa beans, and 1 represents those who do. Predictor variables, which are also used in the logistic regression analysis, include those variables analyzed to determine their effect on cocoa bean fermentation. The use of the same predictor variables in both logistic regression and PSM aims to provide a more accurate estimation of treatment effects and to minimize the potential for treatment effects being influenced by selection bias (Guo et al., 2020). Additionally, employing consistent variables ensures a detailed and structured depiction of the research topic being addressed (Powell et al., 2020).

The Propensity Score Matching (PSM) analysis process consists of several stages before obtaining the final values, one of which is the Match Balance

Variable	Unit	Description
Production	kg/year	Total cocoa bean production over one year
Revenue	USD/year	Total revenue from the sale of cocoa beans over one year, excluding derivatives
Farm value per land area	USD/ha	Revenue per unit area of land used
Value per kg of production	USD/kg	Revenue per kg of cocoa bean production
Seed costs	USD/year	Costs incurred for purchasing cocoa seeds
Labor costs	USD/AWU	Costs for paying labor per Agricultural Work Unit (AWU)
Fertilizer costs	USD/year	Costs for purchasing fertilizer (solid/liquid) over one year
Pesticide costs	USD/year	Costs for purchasing pesticides (solid/liquid) over one year

Source: Authors identification, 2025

Table 1: The farm performance indicators.

stage. Match Balance is a phase where the control and treatment groups are adjusted to ensure that they have similar distributions of characteristics, making the comparison between the two groups more valid. The purpose of balancing data during the PSM analysis is to align covariate variables between the two groups, reduce selection bias and confounding, and enhance the causal validity of the research findings. In this stage, data that is evenly distributed between the two groups will be used, while data that does not meet this criterion will be excluded from the matching function. According to (Kane et al., 2020), there are three methods for achieving match balance: nearest neighbor matching, caliper matching, and kernel matching. The method employed in this study is nearest neighbor matching combined with a caliper of 0.3. This method was chosen because it is easier to implement and provides more accurate data balance with the appropriate caliper setting. Additionally, this method is more sensitive to outliers, allowing researchers to achieve balance by adjusting the caliper.

The final results of Propensity Score Matching (PSM) can be observed from the Average Treatment Effect on the Treated (ATT) values. ATT measures the effectiveness of the treatment applied to the treatment group compared to the control group. In this study, the ATT value is used to assess the effectiveness of cocoa bean fermentation among the treated group, where 0 represents farmers who did not ferment their cocoa beans, and 1 represents farmers who did. The formula for calculating ATT is given as follows:

$$ATT = E\left(Y_{1j}|D_j = 1, P(X_{1j})\right) - E\left(Y_{0j}|D_j = 0, P(X_{0j})\right) \quad (4)$$

Where *E* denotes the expected value of the outcome variable for farmers who engage in fermentation (Y_{1j}) and those who do not engage in fermentation (Y_{0j}).

Propensity Score Matching (PSM) utilizes probability values derived from propensity scores, which are obtained using either logistic regression or probit models. According to (Kane et al., 2020), these two methods are quite similar, but their use depends on the assumptions and the fit of the model to the data. This study employs a logistic regression model, where the interpretation of the regression coefficients in logistic regression refers to changes in the log-odds ratio for each one-unit change in the independent variable. The dependent variable in the model is whether farmers engage in cocoa bean fermentation, while the dependent variable consists of 10 variables used in the first research question. The formula for calculating propensity scores using the logistic regression model is as follows:

$$Y_i = \ln\left(\frac{P_i}{1-P_i}\right) = \frac{e^{\beta_0+\beta_1 X_{1i}+\cdots+\beta_k X_{ki}}}{1+e^{\beta_0+\beta_1 X_{1i}+\cdots+\beta_k X_{ki}}} \quad (5)$$

Y_i represents the decision of farmers to ferment cocoa beans or not (1 = fermentation, 0 = no fermentation), β_0 is the regression constant, β_1 are the parameters to be estimated, and X_1 are the independent variables.

Results and discussion

Socio-economic characteristics of Indonesian smallholder cocoa farmers

The socio-economic characteristics provide an overview of the conditions of cocoa farmers across Indonesia's 7 islands and 29 provinces. This overview includes various aspects such as social conditions examined through age, education level, and gender; economic aspects—assessed by land ownership and capital; and institutional aspects evaluated by farmers' participation in partnerships. Additionally, there are supplementary aspects such as the number of workers (both family and non-family), the condition of cocoa plants (productive or non-productive), and the status of seeds used (certified or uncertified). The detailed socio-economic characteristics of Indonesian cocoa farmers are summarized in the following Table 2.

Table 2 presents the details of the socio-economic characteristics of cocoa farmers, distinguishing between those who ferment their cocoa beans and those who do not. The analysis of age shows that the average age of cocoa farmers is similar between those who ferment (46 years) and those who do not (47 years). In terms of education, there is a notable difference between the two groups. Both groups have a similar percentage of farmers with no formal education (28%). However, there is a significant difference in the levels of secondary and higher education. Among farmers who practice fermentation, 32.4% have secondary or higher education, compared to 37.2% among those who do not practice fermentation. Gender distribution shows no significant difference between the two groups, with a majority of cocoa farmers in Indonesia being male (91%), and females accounting for 9%. This distribution is partly because cocoa farming is generally considered more suitable for men (Rahmaniah et al., 2022).

No	Variable	Fermented			Non-fermented		
		Mean	SD.	Freq1	Mean	SD.	Freq1
1	Age (year)	46.64	12.14		47.65	12.27	
2	Education						
	No			2,442 (28.1)			4,054 (28)
	Elementary			3,439 (39.5)			5,313 (36.7)
	Middle			1,362 (15.7)			2,408 (16.6)
	High			1,453 (16.7)			2,718 (20)
3	Gender						
	Male			7,905 (91)			13,183 (91)
	Female			791 (9)			1,310 (9)
4	UAA (m2)	495.55	622.05		641.51	1,393.38	
5	Trees						
	Yielding plants	768.80	770.72		641.81	993.97	
	Non-yielding plants	87.16	300.51		60.99	188.61	
6	Capital (IDR)	63.36	103.14		288.99	429.78	
7	Contract farming						
	Participate			2,110 (24.3)			106 (0.7)
	Non participate			6,586 (75.7)			14,387 (99.3)
8	Hired labour	0.30	1.30		0.83	1.65	
9	Family labour	2.47	2.96		2.26	0.95	
10	Seed plant						
	Certified			836 (9.6)			1,710 (11.8)
	Non-certified			7,860 (90.4)			12,783 (88.2)
	Sample size (n)			8,696			14,493

Note: The value represents the number of the farmer for each category in each group for the categorical variable
Source: Authors identification, 2025

Table 2: Socio-economic characteristics of Indonesian smallholder cacao farmer.

Farmers who do not ferment their cocoa beans have an average land size of 641.51 m², while those who practice fermentation have an average land size of 495.55 m². This indicates that non-fermenting farmers generally have 146 m² more land than fermenting farmers. Despite this, fermenting farmers tend to have a higher average number of cocoa trees compared to non-fermenting farmers. On average, fermenting farmers have 768 productive and 87 non-productive cocoa trees, while non-fermenting farmers have 641 productive and 61 non-productive trees. This is contrasted by the average capital expenditure. Non-fermenting farmers spend an average of $289, whereas fermenting farmers spend only $63.33 per observation cycle (one year). This discrepancy in capital expenditure reflects various factors, including the larger land area of non-fermenting farmers, leading to higher expenses for fertilizers, pesticides, labor costs, and other inputs.

Partnership networks are one of the ways farmers seek additional support for their agricultural activities. In terms of partnership networks, data shows that farmers who engage in cocoa bean fermentation are significantly more involved in such partnerships, with 24.3% of these farmers participating, compared to only 0.7% among those who do not practice fermentation. Farmers involved in partnerships typically receive training related to cocoa farming, especially on fermentation techniques. Additionally, most partnership agreements require farmers to sell their cocoa in fermented form. Consequently, a substantial proportion of farmers practicing fermentation are associated with these partnership networks.

The labor used in cocoa farming is divided into two categories: family labor and non-family labor. Family labor consists of relatives who often work voluntarily without payment, although they may work on a rotational basis. Non-family

labor refers to workers who are not related to the farmer and are paid according to an agreed-upon rate between the two parties. Farmers who practice fermentation tend to employ less non-family labor, with an average of 0.30 workers, compared to 0.83 for non-fermenting farmers. On the other hand, the number of family laborers employed by fermenting farmers is higher, averaging 2.47, compared to 2.27 for non-fermenting farmers. Overall, this indicates that fermenting farmers use more family labor compared to non-family labor, partly to reduce costs or capital expenditures.

The characteristics of cocoa farmers vary between those who practice fermentation and those who do not, including aspects such as the use of cocoa seedlings. Cocoa seedlings used by farmers fall into two categories: certified and non-certified. Farmers who do not engage in fermentation tend to use certified seedlings more frequently (11.8%) compared to those who practice fermentation (9.6%). These socio-economic differences influence farmers' decisions to either practice or forgo fermentation. To statistically substantiate this, the study will examine the factors influencing farmers' decisions to engage in fermentation, which will be discussed in the following sections.

Factors influencing farmers fermenting cocoa beans

The factors influencing farmers to ferment cocoa beans are detailed in Table 3. The variables age and education show significant results with β values of 0.007 and 0.56, respectively. These values indicate that each one-unit increase in age and education will increase the likelihood of farmers fermenting cocoa beans by 0.7% and 5.6%, respectively. Research conducted by (Effendy et al., 2019) and (Rifin, 2020) suggests that older farmers tend to have more complex experiences in farming, harvesting, post-harvest processing, and sales. Additionally, they have higher levels of wisdom in accepting and applying acquired technological innovations. This finding aligns with research by (Daudu et al., 2021) on the education variable. The study indicates that the higher the education level attained by farmers, the better their ability to access information, understand and apply technology, manage economic incentives, and comprehend quality standards. Collectively, these abilities encourage farmers to adopt and apply innovations in agriculture.

Variable	β	S.E.	Sig
Age	0.007	0.001	0.000
Education	0.056	0.013	0.000
Gender	-0.003	0.047	0.941
UAA	0.000	0.000	0.019
Yielding plants	0.000	0.000	0.000
Non-yielding plants	0.001	0.000	0.000
Capital	0.000	0.000	0.000
Contract farming	3.154	0.125	0.000
Hired labor	-0.011	0.012	0.373
Family labor	0.035	0.007	0.000
Seed plants	-0.229	0.045	0.000
Constant	-0.663	0.311	0.033
Number of obs	23.189		
LR chi^2	345.69		
Prob > chi^2	0.000		
Pseudo R^2	0.120		

Source: Authors computation, 2025

Table 3: Estimated factors influencing farmers fermenting cocoa beans.

Before interpreting the individual parameters, it is crucial to evaluate the overall performance of the binary logistic regression model. The likelihood ratio test yields a Chi-square value (LR chi^2) of 345.69. The magnitude of this value indicates that the estimated model is highly suitable for predicting the factors influencing cocoa fermentation adoption. With a p-value (Prob > chi^2) of 0.000, the result is statistically significant at the 1% level ($p<0.01$), confirming that the logistic regression model is valid and feasible for use. This signifies that the set of predictor variables (age, education, UAA, yielding and non-yielding plants, capital, family labor, and seed plants) significantly improves the model's fit compared to the null model (intercept only). Furthermore, the Pseudo R-squared value of 0.120 suggests that the model explains approximately 12% of the variability in the farmers' decision to ferment cocoa beans, while the remaining 88% of the variation is influenced by unobserved variables outside the model. Although this R-squared value is typical for cross-sectional studies in social sciences, the highly significant Chi-square statistic confirms that the explanatory variables collectively play a substantial role in determining fermentation adoption.

The gender variable shows insignificant results in influencing farmers to ferment cocoa beans, meaning there is no significant difference between male and female farmers in making decisions

or applying fermentation to cocoa beans. This condition arises because both male and female farmers manage cocoa beans with equal experience in farming, capital, and market access. Moreover, decisions are made collectively or based on the consensus of a group or community. Therefore, there is no tendency for one party to have more access or capability in determining various aspects, particularly in fermenting cocoa beans. This finding is consistent with the research by (Maduka et al., 2023), which states that both male and female farmers have equal access to resources, information, and training in agriculture and are equally involved in decision-making processes. According to (Bulkis et al., 2020), male and female farmers have their respective roles in cocoa farming, but harvesting, post-harvest activities, and marketing decisions are made together in a balanced manner.

Utilized Agricultural Area (UAA) and Yielding Plants both show significant results in influencing farmers to ferment cocoa beans. In general, these two variables are related in supporting farmers to ferment. The β values obtained are both 0.000, indicating that any increase in UAA and yielding plants has a negligible impact on the decision to ferment cocoa beans. This means that although significant, there is no practical impact on the farmers' decision to ferment cocoa beans. This is due to various reasons, including the possibility that fermentation activities are more influenced by other factors that play a more critical role once a certain production threshold is reached, such as age, education, capital, contract farming, family labor, and seed plants. However, despite this, research conducted by (Feyisa, 2020) and (Abebe and Bekele, 2015) shows that UAA has a significant positive value in applying the given innovations. This is because the larger the agricultural area, the more likely farmers are to utilize the entire area by planting all parts of the land with crops to increase income. Additionally, farmers with larger land areas have better capital management, so they tend to be more willing to accept and apply the given innovations to maximize income.

Non-yielding plants are cocoa trees that no longer bear fruit or have passed their productive age. These plants are usually not immediately replaced or cut down because farmers use them as temporary shade trees or for other ecological benefits without directly contributing to cocoa bean production. Therefore, they do not significantly influence farmers' decisions to ferment cocoa beans. In contrast, the variable Capital has a significant impact on the decision to ferment. A positive β value indicates that an increase in capital and contract farming by one unit increases the likelihood of farmers fermenting by 10%. Capital is a crucial aspect of sustaining cocoa farming operations. According to (Bukuru and Tabitha, 2021), capital influences farmers' responses to changes in farming conditions. Farmers with higher capital are more adaptable in accepting agricultural innovations. Additionally, (Attipoe et al., 2021) states that farmers with greater capital availability are more likely to adopt better technology and innovations because they have the necessary resources for operations and support infrastructure.

Farmers involved in contract farming are more likely to ferment their cocoa beans compared to those not involved. The analysis in this study shows a significant positive influence of contract farming on farmers' decisions to ferment. This occurs because farmers in contract farming often receive training and information dissemination, which encourages them to apply various innovative technologies, including cocoa bean fermentation (Callahan, 2019 and Kalimang`asi, N et al., 2014). Some contract farming arrangements even require their partners (farmers) to sell fermented cocoa beans, which directly encourages farmers to ferment before selling (Ngoong, J and Forgha, N, 2013). Furthermore, (Daudu et al., 2021) indicates that farmers involved in contract farming tend to ferment their beans due to price transparency between non-fermented and fermented cocoa, as well as technical support such as technical assistance and training.

The variables Hired labor and Family labor have different impacts on farmers' decisions to ferment cocoa beans. Hired labor has an insignificant effect, with a negative β value. This means that as the amount of hired labor increases, the likelihood of farmers deciding to ferment decreases. In contrast, Family labor has a positive and significant effect, with a β value of 3.5%. This indicates that family labor significantly influences the decision to ferment cocoa beans. Each unit increase in family labor results in a 3.5% increase in the likelihood of farmers deciding to ferment their cocoa beans. According to (Solarte-Guerrero et al., 2023) and (Kalimang`asi, N et al., 2014), this is due to cost considerations; as the number of family laborers increases, farmers can reallocate funds from hired labor costs to enhance production and quality by adopting innovations such as cocoa bean fermentation.

Seed plant is a nominal data variable where 0 = uncertified seeds and 1 = certified seeds.

The analysis in Table 3 shows that seed plant significantly influences farmers' decisions to ferment. However, the β value is -0.229, meaning that the decision to use certified seeds decreases the likelihood of fermentation. Conversely, farmers using uncertified seeds often have lower-quality cocoa yields compared to those using certified seeds. Therefore, farmers might ferment their cocoa beans to enhance quality and add value, as the cocoa beans from uncertified seeds tend to be of lower grade. Farmers who use certified seeds generally achieve better harvests, reducing the need for fermentation since their cocoa beans are already of high quality. Additionally, farmers using uncertified seeds may ferment their beans to improve quality and value (Gitaningtyas, 2022; and Effendy and Antara, 2015). Juanda et al. (2023) notes that farmers ferment cocoa beans to increase their value and quality, aiming to boost income.

Impact of cocoa bean fermentation on costs and revenues

The estimation of the impact differences between cocoa farmers who ferment their beans and those who do not is assessed in terms of revenue and costs using Propensity Score Matching (PSM). The analysis results are detailed in Table 4, where revenue aspects are measured using variables such as production per unit area, revenue, farm value per unit area, and production value per unit of production. Cost aspects are measured using variables such as seed costs, labor costs, fertilizer costs, and pesticide costs. The production per unit area variable represents the output obtained by farmers per unit of land area. This variable shows that the average production for non-fermented bean farmers is 1.04 kg/year, compared to 0.83 kg/year for fermented bean farmers. This indicates that non-fermented bean production per unit area is 26.27% or 0.21 kg/year higher than that of fermented bean farmers.

This trend is also observed in the variables of revenue, farm value per unit area, and production value per unit, where non-fermented bean farmers have higher values compared to fermented bean farmers. The average revenue for fermented bean farmers is only $84.42 per year, which is lower compared to $100.67 per year for non-fermented bean farmers. In terms of revenue, non-fermented bean farmers earn 19.25% more than their fermented counterparts. Research by (Sudibyo, 2017; and Awaliyah et al., 2023) indicates that farmers who do not ferment their beans have higher incomes because they can sell a greater quantity of cocoa beans compared to those who ferment their beans, due to damage during the fermentation process. In some cases, there is higher demand or better prices for non-fermented cocoa beans of certain quality. This condition drives higher income for non-fermented cocoa beans compared to fermented beans (Muñoz et al., 2020).

The agricultural value per hectare for non-fermented cocoa farmers is higher compared to fermented cocoa farmers. This value represents the income that farmers obtain per unit area of land. Non-fermented cocoa farmers have an average income of $1,772.50 per hectare per year, while fermented cocoa farmers have an average of $1,350.00 per hectare per year. The Average Treatment Effect (ATT) of 422.50 indicates that non-fermented cocoa farmers have a higher agricultural value per hectare by $422.50 per hectare per year compared to fermented farmers. A similar trend is observed in the value of production per unit, where non-fermented farmers have a higher value by 1.61% with an ATT of 0.03 compared to fermented farmers. Although this difference is

Variable	Fermented	Non-fermented	ATT	S.E.	t-stat
Production (kg/year)	0.83	1.05	0.22	1.07	20.40
Revenue (USD/year)	84.42	100.67	16.17	0.19	8.30
Farm value per land area (USD/ha)	1,350.00	1,772.50	422.50	40.00	10.37
Value per kg of production (USD/kg)	1.74	1.77	0.03	0.01	2.74
Seed costs (USD/year)	5.58	7.19	1.62	0.67	2.39
Labor costs (USD/AWU)	295.25	329.05	33.81	7.07	4.78
Fertilizer costs (USD/year)	36.46	39.95	3.48	1.40	2.48
Pesticide costs (USD/year)	26.12	21.95	-4.17	1.12	-3.74

Note: Currency conversion is based on the 2014 average exchange rate of approximately 1 USD = 12,000 IDR. Production is measured in kg/year and is not converted to currency.

Source: Authors computation, 2025

Table 4: Estimation results of propensity score matching.

not statistically significant, it suggests that each kilogram of cocoa beans sold by non-fermented farmers generates higher revenue compared to fermented farmers. This disparity is attributed to a decrease in quality due to failures or inefficiencies in the fermentation process. Consequently, the grading of cocoa beans affects pricing, where beans in certain grades can fetch higher prices even without fermentation (Forte et al., 2023). Moreover, price differences are influenced not only by quality but also by market factors, such as contextual variables that determine price management mechanisms within market dynamics and supply chains, institutional environmental strengths, production and product characteristics, and the presence of service sectors (Dixon et al., 2024).

Regarding costs, non-fermented farmers also incur higher expenses compared to fermented farmers. However, from a different perspective, Table 4 shows that fermented farmers have lower agricultural costs compared to non-fermented farmers. Fermented farmers spend an average of $5.58 per year on seeds, whereas non-fermented farmers spend $7.19 per year. Fermented farmers are often part of agricultural organizations or partnerships. In addition to receiving price stability, farmers in partnerships benefit from various aids, including seed provision. This assistance helps fermented farmers minimize their seed procurement costs (Daudu et al., 2021; Attipoe et al., 2021; and Ngoong and Forgha, 2013). The labor costs incurred by fermented cocoa farmers are 10% lower, or $33.81 less, compared to those of non-fermented cocoa farmers. Analysis from Table 3 indicates that fermented farmers rely more on family labor, leveraging a communal system that helps reduce labor costs (Oluyole et al., 2013). However, research suggests that family labor can be less effective in various tasks, leading cocoa farmers to potentially spend more on hired labor (Kissi and Herzig, 2024).

The cost of fertilizers for fermented cocoa farmers is 8.7% lower than for non-fermented farmers. The Average Treatment Effect (ATT) of 3.48 indicates that fermented farmers spend $3.48 less on fertilizers compared to non-fermented farmers. According to (Amerino et al., 2024., Owusu et al., 2022 and Anang, B, 2016), farmers who engage in fermentation have access to technology and information from various sources, enabling them to reduce fertilizer costs through methods such as using cover crops to improve soil nutrient content and moisture, maintain ecosystems, and extend the lifespan of cocoa trees. Additionally, Massresha et al. (2021), Feyisa (2020) and Djauhari et al. (2013) suggest that farmers who adopt innovations tend to have better access to information and training, allowing them to manage their farming practices more efficiently and reduce expenses. In contrast, non-fermented cocoa farmers incur lower pesticide costs compared to their fermented counterparts. Non-fermented farmers spend $21.95 per year on pesticides, while fermented farmers spend $26.12 per year. Fermented farmers thus incur 19.02% higher pesticide costs, which is attributed to the need to control pest and disease outbreaks that can damage the quality of cocoa beans.

Overall, the differences between fermented and non-fermented cocoa farmers in terms of revenue and costs indicate that non-fermented farmers have higher values for each indicator variable. According to (Ahmad et al., 2022., Purwaningsih et al., 2019 and Soemarno et al., 2015), fermented cocoa yields an added value ranging from $0.08 to $0.21 per kilogram, with a fermentation period of 6-8 days. In this study, the price per kilogram for non-fermented cocoa is $0.03 or 1.16% higher compared to fermented cocoa. Thus, the average price of non-fermented cocoa in the local market ranges from $0.08 to $0.22 per kilogram. This suggests that the local market price of cocoa does not differ significantly based on fermentation alone and is influenced by other factors such as grading, the type of cocoa cultivated, and the quality of the fermented cocoa beans. It is important to emphasize that this finding represents the national average spread across 7 islands and 29 provinces. This small price disparity might conceal significant differences at specific regional or community levels that possess shorter supply chains or specialized pricing schemes, which are not captured by the national average analysis. Meanwhile, the costs incurred by fermented farmers are generally lower for variables such as seed costs, labor costs, and fertilizer costs. In contrast, non-fermented farmers spend more to maintain the quality of their cocoa beans. This approach ensures that even though the cocoa is not fermented, its price remains comparable to that of fermented cocoa beans.

Conclusion

This study highlights the diverse socio-economic characteristics of Indonesian smallholder cocoa farmers and identifies key factors influencing their decision to ferment cocoa beans. Fermenting farmers tend to be younger, more educated, and more involved in partnerships, utilizing more family labor and incurring lower costs in seed procurement, labor, and fertilizers. However, non-fermenting farmers typically have larger land sizes, higher capital expenditure, and greater production per unit area, leading to higher overall revenue. The findings suggest that while fermentation can improve cocoa quality and value, it may not always translate to higher revenue due to increased costs and potential quality control issues during the fermentation process. Although national average data suggest that non-fermentation leads to higher revenues, the conclusion regarding the potential unprofitability of fermentation must be qualified as it is based on average values. In specific communities, or with appropriate policy interventions—especially considering that farmers in contract farming are more likely to ferment —profitability results could substantially differ. Policymakers and agricultural extension services should consider these dynamics when promoting fermentation practices, ensuring that farmers receive adequate support and training to maximize the benefits of cocoa bean fermentation.

However, this study has several limitations. First, the analysis utilized national survey data from 2014; while this serves as a robust nationwide baseline, it may not fully reflect long-term developments or recent changes in price policies, export conditions, and support systems. Second, the reliance on BPS survey data constrained the detailed analysis of key variables, such as individual farmer experience, the quality of local infrastructure, and the specific depth of technical support, thereby limiting insights into practical barriers. Finally, it is important to note that this study specifically focuses on the market environment, social structure, and policy support systems within Indonesia. Therefore, these results may not be directly transferable to other cocoa-producing countries with different institutional contexts, and the observed unprofitability of fermentation based on national averages might differ in specific communities with premium market access. Future research is therefore advised to collect in-depth primary data to investigate these specific factors and explore the long-term economic impacts of fermentation decisions.

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References

[1] Abebe, Y. and Bekele, A. (2015) "Analysis of Adoption Spell of Hybrid Maize in the Central Rift Valley, Oromyia National Regional State of Ethiopia: A Duration Model Approach", *Journal of Agricultural Economics and Development*, Vol. 4, No. 3, pp. 037-043. ISSN 2226-7522. DOI 10.4314/star.v3i4.30.

[2] Ahmad, Laba, M. S. and Asrandi (2022) "Perbandingan Pendapatan Petani terhadap Harga Kakao Fermentasi dan Non Fermentasi di Desa Batu Ampa Kecamatan Papalang Kabupaten Mamuju", *Jurnal E-Bussiness Institut Teknologi Dan Bisnis Muhammadiyah Polewali Mandar*, Vol. 1, No. 2, pp. 71-77. ISSN 2807-6354. DOI 10.59903/ebussiness.v1i2.15. (In Indonesian).

[3] Ambarawati, I. G. A. A. and Esterina, N. P. A. (2024) "Cocoa Producers' Decision on Fermenting Beans in Jembrana Regency, Bali Province, Indonesia", *Advances in Social Sciences Research Journal*, Vol. 11, No. 2, pp. 543-549. ISSN 2055-0286. DOI 10.14738/assrj.112.16560.

[4] Amerino, J., Apedo, C. K. and Anang, B. T. (2024) "Factors influencing adoption of cocoa agroforestry in Ghana: Analysis based on tree density choice", *Sustainable Environment*, Vol. 10, No. 1, p. 2296162. ISSN 2765-8511. DOI 10.1080/27658511.2023.2296162.

[5] Anang, B. (2016) "A Probit Analysis of the Determinants of Fertilizer Adoption by Cocoa Farmers in Ghana", *Asian Journal of Agricultural Extension, Economics & Sociology*, Vol. 8, No. 1, pp. 1-8. ISSN 2320-7027. DOI 10.9734/AJAEES/2016/21540.

[6] Attipoe, S. G., Cao, J., Opoku-Kwanowaa, Y. and Hene-Sefa, F. (2021) "Assessing the Impact of non-Governmental Organization's Extension Programs on Sustainable cocoa Production and Household Income in Ghana", *Journal of Integrative Agriculture*, Vol. 20, No. 10, pp. 2820-2836. ISSN 20953119. DOI 10.1016/S2095-3119(21)63607-9.

[7] Awaliyah, F., Langkong, J. and Syarifuddin, A. (2023) "An Overview: The Effect of Fermentation and Roasting Methods on Cocoa Quality", I*OP Conference Series: Earth and Environmental Science*, Vol. 1230, No. 1, p. 012160. ISSN 17551315. DOI 10.1088/1755-1315/1230/1/012160.

[8] Badan Pusat Statistik (2023) "*Analisis Komoditas Ekspor, 2018-2022, Sektor Pertanian, Kehutanan, Dan Perikanan; Industri Pengolahan; Dan Pertambangan*". Badan Pusat Statistik, Jul. 2023. [Online]. Available: https://www.bps.go.id/id/publication/2023/07/07/ec5db0292d5541f95c4b6231/analisis-komoditas-ekspor--2018-2022--sektor-pertanian--kehutanan--dan-perikanan--industri-pengolahan--dan-pertambangan-dan-lainnya.html [Accessed: Mar. 16, 2025]. (In Indonesian).

[9] Bukuru, E. and Tabitha, N. (2021) "Financial Factors Affecting Production Efficiency of Small Scale Coffee Farms in Burundi", *International Journal of Finance and Accounting*, Vol. 6, No. 2, pp. 57-70. ISSN 2518-4113. DOI 10.47604/ijfa.1424.

[10] Bulkis, S., Jamil, M. H., Lanuhu, N. and Italiani, F. (2020) "Gender Roles in Cocoa Sustainability Programs", *IOP Conference Series: Earth and Environmental Science*, Vol. 575, No. 1, p. 012086. ISSN 1755-1315. DOI 10.1088/1755-1315/575/1/012086.

[11] Callahan, L. (2019) "Contract-Farming in Cocoa Value Chains in Africa: Possibilities and Challenges", *Ethiopian Yearbook of International Law*, Vol. 2018, pp. 149-180. ISSN 2522-5294. DOI 10.1007/978-3-030-24078-3_7.

[12] Daudu, A. K., Oladipo, F. O., Balogun, K. S., Awoniyi, O. A. and Adisa, R. S. (2021) "Factors Determining Adoption of Bean Quality Improvement Practices by Cocoa Farmers in Cross River State, Nigeria", *Agricultura Tropica et Subtropica*, Vol. 54, No. 1, pp. 32-42. ISSN 1801-0571. DOI 10.2478/ats-2021-0004.

[13] Dixon, H., Kosma, T. and Petroulas, P. (2024) "Explaining the Endurance of Price Level Differences in the Euro Area", *Open Economic Review,* Vol. 36, No. 4, pp. 1047-1080. ISSN 1556-5068. DOI 10.1007/s11079-024-09794-1.

[14] E. Guzmán-Alvarez, R. and G. Márquez-Ramos, J. (2021) "Fermentation of Cocoa Beans", In Laranjo, M. (ed.) "*Fermentation - Processes, Benefits and Risks*", pp. 1-19. ISBN 978-1-83968-816-4. DOI 10.5772/intechopen.98756.

[15] Effendy, Fardhal Pratama, M., Rauf, R. A., Antara, M., Basir-Cyio, M., Mahfudz and Muhardi (2019) "Factors influencing the efficiency of cocoa farms: A study to increase income in rural Indonesia", *PLoS ONE*, Vol. 14, No. 4, pp. 1-15. ISSN 1932-6203. DOI 10.1371/journal.pone.0214569.

[16] FAO. (2024) "*Indonesia: Upgrading Bulk Cocoa into Fine Cocoa*", Food and Agriculture Organization of the United Nations, Jan. 2024. [Online]. Available: https://www.fao.org/one-country-one-priority-product/asia-pacific/good-practices/detail/indonesi-upgrading-bulk-cocoa-into-fine-cocoa/en. [Accessed: March 21, 2025].

[17] Feyisa, B. W. (2020) "Determinants of Agricultural Technology Adoption in Ethiopia: A Meta-Analysis", *Cogent Food & Agriculture*, Vol. 6, No. 1, p. 1855817. ISSN 2331-1932. DOI 10.1080/23311932.2020.1855817.

[18] Figueroa-Hernández, C., Mota-Gutierrez, J., Ferrocino, I., Hernández-Estrada, Z. J., González-Ríos, O., Cocolin, L. and Suárez-Quiroz, M. L. (2019) "The Challenges and Perspectives of the Selection of Starter Cultures for Fermented Cocoa Bean", *International Journal of Food Microbiology*, Vol. 301, pp. 41-50. ISSN 0168-1605. DOI 10.1016/j.ijfoodmicro.2019.05.002.

[19] Forte, M., Currò, S., Van de Walle, D., Dewettinck, K., Mirisola, M., Fasolato, L. and Carletti, P. (2023) "Quality Evaluation of Fair-Trade Cocoa Beans from Different Origins Using Portable Near-Infrared Spectroscopy (NIRS)", *Foods*, Vol. 12, No. 1, pp. 1-17. ISSN 23048158. DOI 10.3390/foods12010004.

[20] Gitaningtyas, O. P. (2022) "The Impact Of Certified Seeds Adoption On Cost Efficiency Of Horticultural Cultivation", *Journal of International Conference Proceedings*, Vol. 5, No. 4, pp. 30-39. ISSN 2622-0989. DOI 10.32535/jicp.v5i4.1897.

[21] Guo, S., Fraser, M. and Chen, Q. (2020) "Propensity Score Analysis: Recent Debate and Discussion", *Journal of the Society for Social Work and Research*, Vol. 11, No. 3, pp. 463-482. ISSN 1948822X. DOI 10.1086/711393.

[22] Hariyati, Y., Ibanah, I., Yunita, R., Putri Regina, D. A., Suharijadi, D., Ghufron R. M., Rahaditya Dimas, P. and Firmanto, H. (2023) "Nilai Tambah dan Keengganan Petani Melakukan Fermentasi Biji Kakao Rakyat Desa Jambewangi Kecamatan Sempu", *Jurnal Agribest*, Vol. 7, No. 1, pp. 8-20. ISSN 2615-4862. DOI 10.32528/agribest.v7i1.8742.

[23] Intarini, L. P., Budiasa, I. W. and Sudarma, I. M. (2020) "The Contribution of Fermentation Technology to the Value Added of Certification Cocoa in the Subak Abian Amerta Nadi Tuwed Village Melaya District Jembrana Regency", *Jurnal Manajemen Agribisnis (Journal of Agribusiness Management*), Vol. 8, No. 2, p. 144. E-ISSN 2684-7728. DOI 10.24843/JMA.2020.v08.i02.p04. (In Indonesian).

[24] Juanda, J., Hartuti, S. and Mujiburrahmad, M. (2023) "Penerapan Fermentasi Biji Kakao (Theobroma cacao L.) di Kabupaten Pidie Jaya, Aceh", *Jurnal Warta Pengabdian Andalas*, Vol. 30, No. 2, pp. 223-231. ISSN 2797-1600. DOI 10.25077/jwa.30.2.223-231.2023. (In Indonesian).

[25] Kalimang`asi, N. N., Kihombo, A. and Kalimang`asi, N. (2014) "Contribution of Contract Cocoa Production on Improving Livelihood of Smallholder Farmers", *International Journal of Scientific and Research Publications*, Vol. 4, No. 1, pp. 1-10. ISSN 2250-3153.

[26] Kane, L. T., Fang, T., Galetta, M. S., Goyal, D. K. C., Nicholson, K. J., Kepler, C. K., Vaccaro, A. R., and Schroeder, G. D. (2020) "Propensity Score Matching", *Clinical Spine Surgery: A Spine Publication*, Vol. 33, No. 3, pp. 120-122. ISSN 2380-0186. DOI 10.1097/BSD.0000000000000932.

[27] Kissi, E. A. and Herzig, C. (2024) "Labour Relations and Working Conditions of Workers on Smallholder Cocoa Farms in Ghana", *Agriculture and Human Values*, Vol. 41, No. 1, pp. 109-120. ISSN 1572-8366. DOI 10.1007/s10460-023-10470-2.

[28] Maduka, O. A., Obinna, L. O. and Maduka, A. G. (2023) "Assessment of Gender Roles in Cocoa Production Activities in Abia State, Nigeria", *Nigerian Agricultural Journal*, Vol. 54, No. 1, pp. 214-219. ISSN 0300-368X .

[29] Massresha, S. E., Lema, T. Z., Neway, M. M. and Degu, W. A. (2021) "Perception and determinants of agricultural technology adoption in North Shoa Zone, Amhara Regional State, Ethiopia", *Cogent Economics & Finance*, Vol. 9, No. 1, p. 1956774. ISSN 2332-2039. DOI 10.1080/23322039.2021.1956774.

[30] Morales-Rodriguez, W. J., Morante-Carriel, J., Herrera-Feijoo, R. J., Ayuso-Yuste, M. C. and Bernalte-García, M. J. (2024) "Effect of Addition of Yeasts and Enzymes During Fermentation on Physicochemical Quality of Fine Aroma Cocoa Beans", *Journal of Agriculture and Food Research*, Vol. 16, p. 101126. ISSN 2666-1543. DOI 10.1016/j.jafr.2024.101126.

[31] Muñoz, M. S., Cortina, J. R., Vaillant, A. E. and Parra, S. E. (2020) "An Overview of the Physical and Biochemical Transformation of Cocoa Seeds to Beans and to Chocolate: Flavor Formation", *Critical Reviews in Food Science and Nutrition*, Vol. 60, No. 10, pp. 1593-1613. ISSN 1549-7852. DOI 10.1080/10408398.2019.1581726.

[32] Ngoong, J. T. and Forgha, N. G. (2013) "An Analysis of the Socio-Economic Determinants of Cocoa Production in Meme Division, Cameroon", *Greener Journal of Business and Management Studies*, Vol. 3, No. 6, pp. 298-308. ISSN 22767827. DOI 10.15580/GJBMS.2013.6.072313748.

[33] Oluyole, K. A., Usman, J. M., Oni, O. A. and Oduwole, O. O. (2013) "Input Use Efficiency of Cocoa Farmers in Ondo State, Nigeria", *Journal of Finance and Economics*, Vol. 1, No. 1, pp. 8-10. ISSN 2328-7284. DOI 10.12691/jfe-1-1-2.

[34] Owusu, V., Akoto-Adjepong, V., Acheampong, E. and Barnes, V. R. (2022) "Farmer Perceptions and Economic Performance of Cocoa Agroforestry Shade Levels in Ghana", *Journal of Sustainable Forestry, Taylor & Francis*, Vol. 41, No. 10, pp. 922-940. ISSN 1540756X. DOI 10.1080/10549811.2021.1883444.

[35] Powell, M. G., Hull, D. M. and Beaujean, A. A. (2020) "Propensity Score Matching for Education Data: Worked Examples", *Journal of Experimental Education*, Vol. 88, No. 1, pp. 145-164. ISSN 1940-0683. DOI 10.1080/00220973.2018.1541850.

[36] Purwaningsih, Marwati, T. and dan Titiek Djaafar, F. (2019) "Nilai Tambah Biji Kakao Fermentasi Dengan Perlakuan Penambahan Starter Kering", *Research Fair Unisiri*, Vol. 3, No. 1, pp. 676-682. E-ISSN 2580-5819. (In Indonesian).

[37] Putro, S. A. C., Yusalina, Y. and Winandi, R. (2023) "Factors Affecting Export of Indonesian Cocoa Beans To Malaysia", *Jurnal Manajemen Dan Agribisnis*, Vol. 20, No. 1, pp. 90-101. ISSN 1693-5853. DOI 10.17358/jma.20.1.90. (In Indonesian).

[38] Rifin, A. (2020) "Which Farmers Ferment their Cocoa Beans in Indonesia?", *Journal of the International Society for Southeast Asian Agricultural Sciences*, Vol. 26, No. 1, pp. 123-131. ISSN 0859-3132.

[39] Salam, M., Rukka, R. M., Samma, M. A.-N. K., Tenriawaru, A. N., Rahmadanih, Muslim, A. I., Ali, H. N. B. and Ridwan, M. (2024) "The causal-effect model of input factor allocation on maize production: Using binary logistic regression in search for ways to be more productive", *Journal of Agriculture and Food Research*, Vol. 16, No. March, p. 101094. ISSN 2666-1543. DOI 10.1016/j.jafr.2024.101094.

[40] Soemarno, J., Hariyanti, Y., Soeparto, S. A. and Hartatri, S. D. F. (2015) "Study on Incentive Price of Fermented Cocoa to Overcome Reluctance of Farmer to Apply Fermentation: Case Study in Jembrana Regency", *Pelita Perkebunan (A Coffee and Cocoa Research Journal)*, Vol. 31, No. 2, pp. 130-141. ISSN 0215-0212. DOI 10.22302/iccri.jur.pelitaperkebunan.v31i2.66. (In Indonesian).

[41] Solarte-Guerrero, J.-G., Ballesteros-Possú, W. and Navia, J. F. (2023) "Socioeconomic Analysis of Cocoa (Theobroma cacao L) Agroforest in a Tropical Dry Forest", *Revista de Ciencias Agrícolas*, Vol. 39, No. 2, pp. 108-127. ISSN 0120-0135. DOI 10.22267/rcia.223902.186.

[42] Sudibyo, A. (2017) "Efect of Processing Tecniques on Flavour and Characteristics of Cocoa Processed ans Chocolate Products (Pengaruh Cara Pengolahan Terhadap Citarasa dan Karakteristik Produk Olahan Kakao dan Cokelat)", *Jurnal Industri Hasil Perkebunan*, Vol. 12, No. 1, p. 1. ISSN 2477-0051. DOI 10.33104/jihp.v12i1.2671. (In Indonesian).

[43] Wijayati, H. and Haqqi, H. (2022) "The Indonesian Global Cocoa Chain's Position in the Pandemic Era", I*nternational Journal on Social Science, Economics and Art*, Vol. 12, No. 1, pp. 10-21. ISSN 2776-3412. DOI 10.35335/ijosea.v12i1.75.

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Assessing the Impact of Covid-19 on Farm Profitability in Czechia and Slovakia: A Comparative Dupont Analysis Using Firm-Level Data

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Abstract

This study evaluates the impact of COVID-19 on agricultural profitability in Czechia and Slovakia, distinguishing between crop, livestock, and mixed farms. Using firm-level financial data from the Orbis database, an extended DuPont model incorporating labour efficiency is employed to compare profitability drivers pre- (2018–2019) and during (2020–2021) the pandemic. The findings reveal persistent national differences and highlight labour efficiency as a stabilising factor, underscoring agricultural resilience and the importance of structural efficiency in mitigating shocks.

Keywords

Profitability, agriculture, COVID-19, DuPont, RoE, labour productivity, financial leverage.

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Introduction

Profitability is a key indicator of economic performance in agriculture and a major concern in ongoing debates about the viability of farming in Europe. Widespread farmer protests across Europe in the years following the pandemic have drawn attention to mounting economic pressures in the sector, including stagnant incomes, rising input costs, and regulatory burdens (Finger et al., 2024; Matthews, 2024). The COVID-19 pandemic was widely perceived as an unprecedented global challenge that disrupted agricultural markets - through falling prices, supply chain interruptions, and labour shortages, particularly in sectors dependent on seasonal and migrant labour - with presumed implications for farm profitability (Bochtis et al., 2020; Phillipson et al., 2020; Štreimikienė et al., 2022). Despite growing recognition of the sector's resilience during the pandemic, little is known about how profitability developed at the farm level, particularly in the Central European context. A deeper understanding of the pandemic's impact on farm profitability and its underlying drivers can help managers and policymakers strengthen the sector's resilience to future crises.

Traditional profitability indicators, such as return on sales (RoS), return on assets (RoA), and return on equity (RoE), have long been used to evaluate agricultural performance. A large body of European empirical research has applied regression-based methods to identify statistically measurable determinants of these indicators, often using panel or cross-sectional data. In addition to other factors – such as farm size, market position, liquidity, and subsidies – these studies found that financial structure and investment in operational assets are fundamental drivers of farm profitability (Andrašić et al., 2018; Bereżnicka, 2018; Kryszak et al., 2021; Lehenchuk et al., 2023; Martinho, 2022; Mijić and Jakšić, 2017; Beyer and Hinke, 2018). Other studies have emphasised the strong influence of labour use and productivity (Golas, 2016; Józwiak et al., 2019; Kusz et al., 2022; Martín-Retortillo and Pinilla, 2015).

These findings empirically justify the choice of factors used in pyramid-based decomposition techniques, which break down a profitability ratio into its constituent drivers through formal mathematical relationships. The most common of these, the DuPont approach, has often been applied in European agriculture to trace the contribution of margins, capital utilisation, and capital structure to overall profitability – usually focusing on specific countries and farm types. Szymanska (2015) analysed the RoE of Polish pig farms and found that it

was strongly influenced by RoS. Ladvenicová et al. (2019) used a DuPont model to analyse changes in RoE across farms in the four Visegrad countries, showing that profitability was largely driven by RoA. Parzonko et al. (2023) examined RoE variation over time in dairy farms from five selected European countries, while Baležentis and Novickytė (2018) focused on Lithuanian family farms, and Očić et al. (2025) studied Croatian farms. These studies found that RoE was influenced by distinct factors depending on region and farm type. However, they relied on aggregated data sources such as the Farm Accountancy Data Network (FADN), which do not account for firm-level heterogeneity and thus limit statistical differentiation among individual farms. Only a small number of studies use firm-level data to enhance analytical precision and capture structural variation more effectively. Aulová et al. (2019) applied a DuPont model to analyse the impact of legal form and farm size on the profitability of Czech farms, using company-level data from the Amadeus database, which has since been integrated into the Orbis database used in this study. Lehenchuk et al. (2023) used firm-level Orbis data for a regression model as discussed above. All these studies retain the capital-based focus of the classic DuPont framework without integrating additional explanatory factors.

Building on previous research, this study applies an extended DuPont framework that includes labour efficiency as an additional driver of profitability. This extension is particularly relevant because labour was severely affected by public health restrictions and the reduced availability of seasonal and migrant workers during the pandemic (Bochtis et al., 2020; Neef, 2020; Nicola et al., 2020). Using harmonised firm-level data from Orbis, the study compares specialised crop, livestock, and mixed farms in Czechia and Slovakia across two sub-periods: pre-COVID (2018–2019) and during COVID (2020–2021). Two hypotheses are tested: (H1) farm-level RoE and its components were significantly altered during the pandemic; and (H2) pre-existing profitability differences between Czech and Slovak farms were reinforced rather than reduced.

While the effects of the COVID-19 pandemic on the European agricultural sector have been widely discussed in qualitative research (Barcaccia et al., 2020; Blažková et al., 2023; Meuwissen et al., 2021), quantitative evidence on its specific economic consequences remains limited (Benedek et al., 2021; Gómez-Limón et al., 2023). This study addresses this gap by offering a firm-level, decomposition-based comparative analysis of profitability dynamics during the pandemic in the agricultural sectors of Czechia and Slovakia. The findings provide policy-relevant insights into the resilience, efficiency, and structural differences of farms in these two countries.

Material and methods

The analysis uses firm-level data from the Orbis database (2024), which provides harmonised annual accounts for agricultural firms across Europe. Orbis is compiled by Bureau van Dijk (a Moody's Analytics company) and is available through institutional subscription. Its harmonised reporting standards ensure consistency and comparability across countries. The sample includes a large number of Czech and Slovak farms with comparable accounting standards, enabling cross-country comparisons and significance testing. Farms are classified according to the NACE system (Eurostat, 2008) into crop production (01.1-01.3), livestock production (01.4), and mixed farming (01.5).

The study focuses on the period 2020-2021 to isolate the effects of COVID-19 and excludes 2022 due to market disruptions following the invasion of Ukraine by Russia. The pandemic years are compared to the equally spaced pre-pandemic period (2018-2019). For these four years, the Orbis database provides complete financial data for 1,412 agricultural companies, categorised by country and farm type as shown in Table 1.

Type of farming	Czechia	Slovakia
Crop production	95	304
Livestock production	97	398
Mixed farming	290	228
Total	482	930

Source: Own processing based on Orbis (2024)

Table 1: Number of farms in the sample by country and production type.

In the typical DuPont logic, profitability measures can be decomposed into two components: an input-oriented volume or intensity dimension and an output-oriented margin or surplus dimension. This analytical principle provides the foundation for the multi-layered interpretation of firm performance applied in this study.

At the classical core of this model, return on net assets (RoNA) reflects the interaction between the intensity with which net assets are used to generate turnover (AT) and the margin achieved per unit of turnover (RoS). Net assets are defined as the sum of fixed assets and net working capital. The same decomposition principle can be extended in one direction to incorporate the financing structure. In this case, return on equity (RoE) combines the financial leverage (FL) as a capital-intensity dimension – represented by the relationship between net assets and equity – with RoNA as the margin component.

In the other direction, RoS – the margin element of RoNA – can itself be disaggregated following the same logic. Return on sales can be viewed as the product of a labour-intensity factor (LI), measured as the number of employees required per unit of turnover, and labour profitability (LP), representing profit per worker as the surplus component. This modification of the traditional model corresponds to the expected effects of the pandemic on the availability and profitability of labour.

Together, these three layers – labour, operational net assets, and the financing structure – apply a consistent DuPont rationale across distinct domains of firm performance. At each level, profitability is shaped by how intensively a given resource base is used and by the surplus generated from that use. This yields a stepwise decomposition that includes return on sales (RoS) and return on net assets (RoNA) as intermediate components, as illustrated in Equation (1).

$$RoS = \frac{Net\ income}{Turnover} = LP \times LI$$

$$RoNA = \frac{Net\ income}{Fixed\ assets + Net\ working\ capital} = RoS \times AT$$

$$RoE = \frac{Net\ income}{Equity} = RoNA \times FL = LP \times LI \times AT \times FL \quad (1)$$

where:

- *LP* Labour profitability = Net income / Employees
- *LI* Labour intensity = Employees / Turnover
- *AT* Asset turnover = Turnover / (Fixed assets + Net working capital)
- *FL* Financial leverage = (Fixed assets + Net working capital) / Equity

RoE and its components were calculated at the farm level for each country, farm type, and sub-period. The analysis compares the average values from the pandemic years (2020-2021) to those from the pre-pandemic years (2018-2019), yielding two sub-periods: COVID (cov) and pre-COVID (pre). This design allows for a two-dimensional comparison - both across countries (Czechia vs Slovakia) and over time (pre vs during COVID). Deviations in RoE (ΔRoE) are calculated by comparing a selected object (O) to a defined benchmark (B). The total deviation is then decomposed into partial effects using the drivers from Equation (1), as illustrated in Equation (2).

$$\begin{aligned}\Delta RoE_{O-B} &= RoE_O - RoE_B \\ &= \underbrace{\Delta RoE^{LP}_{O-B} + \Delta RoE^{LI}_{O-B}}_{\Delta RoE^{RoS}_{O-B}} + \Delta RoE^{AT}_{O-B} + \Delta RoE^{FL}_{O-B} \\ &= \underbrace{\Delta RoE^{RoS}_{O-B}}_{\Delta RoE^{RoNA}_{O-B}}\end{aligned} \quad (2)$$

Because the profitability model in Equation (1) is multiplicative, a logarithmic decomposition approach (Montgomery, 1937; Vartia, 1976) can be applied to attribute deviations in RoE to their underlying drivers. This method enables consistent quantification of the effects at component level, a technique that is commonly used in agricultural economics (Golas, 2016; Ladvenicová et al., 2019). Equation (3) presents the specific form used in this study.

$$\begin{aligned}\Delta RoE^{LP}_{O-B} &= (RoE_O - RoE_B) \times \log(LP_O/LP_B) / \log(RoE_O/RoE_B) \\ \Delta RoE^{LI}_{O-B} &= (RoE_O - RoE_B) \times \log(LI_O/LI_B) / \log(RoE_O/RoE_B) \\ \Delta RoE^{AT}_{O-B} &= (RoE_O - RoE_B) \times \log(AT_O/AT_B) / \log(RoE_O/RoE_B) \\ \Delta RoE^{FL}_{O-B} &= (RoE_O - RoE_B) \times \log(FL_O/FL_B) / \log(RoE_O/RoE_B)\end{aligned} \quad (3)$$

The choice of analysed objects (O) and their benchmarks (B) depends on the comparison perspective - either across countries or across time periods. The extended DuPont components are defined using financial variables from the Orbis database, as summarised in Table 2.

Indicators were calculated as weighted means to reduce the influence of small outliers, using farm-level two-sided t-tests to assess significance. Significance levels are indicated in Tables 3-5 using the following notation: † = $p < 0.1$; * = $p < 0.05$; ** = $p < 0.01$. All calculations were performed using Microsoft Excel. The empirical results are presented and discussed in the next section.

Symbol	Name and unit	Calculation based on Orbis data
LP	Labour productivity [th EUR/AWU]	Net Income / Employees
LI	Labour intensity [AWU/th EUR]	Employees / Turnover
AT	Asset Turnover [EUR/EUR]	(Non-current Assets + Stocks + Debtors + Other current assets – Creditors – Other current liabilities) / Turnover
FL	Financial leverage [EUR/EUR]	(Non-current liabilities + Loans and short-term debt) / Shareholders funds

Source: Own processing

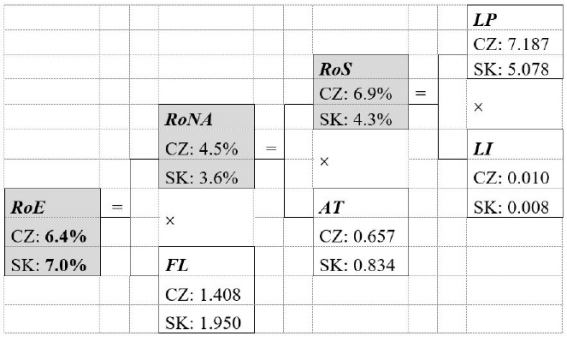
Table 2: Definitions and formulas for extended DuPont variables based on Orbis data.

Results and discussion

This section presents and interprets the empirical results of the DuPont-based decomposition of return on equity (RoE) across farm types, countries, and time periods. The analysis is structured by production specialisation - crop, livestock, and mixed farming - with each subsection comparing Czech and Slovak farms before and during the COVID-19 pandemic. Emphasis is placed on identifying the most influential drivers of differences in profitability, including labour efficiency, asset turnover, and financial leverage, and on assessing how these drivers changed during the crisis.

Crop production

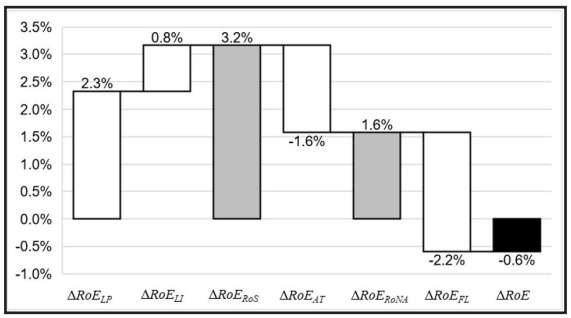
Figure 1 illustrates the DuPont decomposition of RoE for Czech and Slovak crop farms during the pandemic period (2020-2021), based on the extended model. Czech crop farms showed stronger labour profitability (*LP*) and labour intensity (*LI*), resulting in a higher RoS. In contrast, Slovak farms had higher asset turnover (*AT*) and financial leverage (*FL*), which offset weaker labour metrics and yielded a slightly higher RoE.



Source: Own processing based on Orbis (2024)

Figure 1: DuPont decomposition of return on equity (RoE) in Czech and Slovak crop farms, 2020-2021.

Figure 2 shows that Czech farms had a 3.2% RoE advantage due to their higher RoS, mainly driven by labour profitability (+2.3%). This was offset by Slovakia's higher asset utilisation (−1.6%) and greater leverage (−2.2%), resulting in a net RoE disadvantage for Czechia of −0.6%.



Source: Own processing based on Orbis (2024)

Figure 2: Components of RoE deviation between Czech and Slovak crop farms, 2020–2021.

Table 3 provides a detailed view of cross-country and temporal changes. In Czechia, the impact of the pandemic on crop production was modest: RoE rose slightly (+0.5%) due to improved labour profitability. In Slovakia, however, RoE increased more sharply (+3.0%), again driven by labour gains.

Similar patterns were observed by Očić et al. (2025), who analysed Croatian field-crop farms and reported that profitability improvements after EU accession were mainly associated with higher asset turnover, while leverage effects remained negligible. Likewise, Hyblová and Skalický (2018) found that the profitability of wheat production across EU countries depended primarily on yield and cost efficiency rather than capital structure. These parallels suggest that the profitability dynamics observed here stem largely from operational efficiency rather than financial leverage.

These results suggest that the COVID-19 pandemic did not fundamentally disrupt the profitability structure in crop farming, but rather reinforced existing patterns. Czech farms continued to benefit from labour efficiency, while Slovak ones relied more heavily on capital utilisation and financial leverage. The observed increase in labour profitability, which was statistically significant in both countries, partially supports

CZ_{cov}			$\Delta RoE_{CZ\text{-}SK\ (cov)}$			SK_{cov}		
LP	7.187		ΔRoE_{LP}	2.3%	*	*LP*	5.078	
× *LI*	0.010		+ ΔRoE_{LI}	0.8%	*	× *LI*	0.008	
= *RoS*	**6.9%**		= ΔRoE_{RoS}	3.2%	**	**= *RoS***	**4.3%**	
× *AT*	0.657		+ ΔRoE_{AT}	-1.6%	**	× *AT*	0.834	
= *RoNA*	**4.5%**		= ΔRoE_{RoNA}	1.6%		**= *RoNA***	**3.6%**	
× *FL*	1.408		+ ΔRoE_{FL}	-2.2%	**	× *FL*	1.950	
= *RoE*	**6.4%**		**= *ΔRoE***	**-0.6%**		**= *RoE***	**7.0%**	
$\Delta RoE_{cov\text{-}pre\ (CZ)}$						**$\Delta RoE_{cov\text{-}pre\ (SK)}$**		
ΔRoE_{LP}	1.2%	*				ΔRoE_{LP}	4.2%	**
+ ΔRoE_{LI}	-0.5%					+ ΔRoE_{LI}	-1.0%	†
= ΔRoE_{RoS}	0.7%		**Crop production**			= ΔRoE_{RoS}	3.3%	†
+ ΔRoE_{AT}	-0.1%					+ ΔRoE_{AT}	-0.1%	
= ΔRoE_{RoNA}	0.6%					= ΔRoE_{RoNA}	3.2%	
+ ΔRoE_{FL}	-0.1%					+ ΔRoE_{FL}	-0.2%	
= *ΔRoE*	**0.5%**					**= *ΔRoE***	**3.0%**	
CZ_{pre}			**$\Delta RoE_{CZ\text{-}SK\ (pre)}$**			**SK_{pre}**		
LP	5.908		ΔRoE_{LP}	4.6%	**	*LP*	2.310	
× *LI*	0.010		+ ΔRoE_{LI}	0.1%	**	× *LI*	0.010	
= *RoS*	**6.1%**		= ΔRoE_{RoS}	4.7%	**	**= *RoS***	**2.3%**	
× *AT*	0.667		+ ΔRoE_{AT}	-1.2%	**	× *AT*	0.844	
= *RoNA*	**4.1%**		= ΔRoE_{RoNA}	3.5%		**= *RoNA***	**2.0%**	
× *FL*	1.440		+ ΔRoE_{FL}	-1.6%	†	× *FL*	2.015	
= *RoE*	**5.9%**		**= *ΔRoE***	**1.9%**		**= *RoE***	**4.0%**	

Note: (*LP* = Labour profitability; *LI* = Labour intensity; *AT* = Asset turnover; *FL* = Financial leverage; t-test results: † = p < 0.1 * = p < 0.05; ** = p < 0.01)
Source: Own processing based on Orbis (2024)

Table 3: RoE and its components in Czech vs Slovak crop farms before and during COVID-19.

hypothesis H1, indicating that some components of RoE were affected. However, the overall stability or even improvement in RoE, particularly in Czechia, suggests that the impact of COVID-19 was more limited than expected. The persistence and partial amplification of national differences, especially in labour-related drivers, provides stronger support for hypothesis H2.

Livestock production

Table 4 shows that during the period 2020–2021, Czech livestock farms had significantly higher labour profitability (*LP*), driving a 4.7% RoE advantage from a higher RoS. Slovak farms had lower LP and weaker RoS, and although they maintained higher AT and FL, these were insufficient to close the RoE gap, which favoured Czechia by 3.7% overall.

Within-country trends show a divergent impact of COVID-19. In Czechia, RoE rose modestly (+0.9%) due to higher LP. In contrast, Slovak RoE fell significantly (−2.0%), largely due to declining LP. Although only some component shifts were statistically significant, the patterns indicate heterogeneous effects. The results for livestock farms mirror previous findings in the European context. Szymanska (2015) demonstrated that in Polish pig farms, return on sales was the main determinant of profitability, whereas financial leverage played only a minor role. Similarly, Parzonko et al. (2023) found that operational efficiency was the key source of RoE variation among European dairy farms. Overall, the results point to operational efficiency as the main source of performance divergence between Czech and Slovak animal farms, while financial leverage appears to have played only a secondary role.

The impact of the pandemic was more heterogeneous in livestock production. Czech farms experienced a modest improvement in RoE, while Slovak ones saw a significant decline, primarily due to reduced labour profitability. These findings offer only partial support for hypothesis H1: some profitability components were affected, but the magnitude of overall change remained limited in Czechia. In contrast, the growing performance gap between Czech and Slovak farms - driven by persistent or even increasing structural differences - strongly supports hypothesis H2, indicating that the pandemic reinforced rather than reduced existing disparities.

CZ_{cov}			$\Delta RoE_{CZ\text{-}SK\ (cov)}$			SK_{cov}		
LP	5.077		ΔRoE_{LP}	5.1%	*	*LP*	0.365	
× *LI*	0.009		+ ΔRoE_{LI}	-0.3%	**	× *LI*	0.011	
= *RoS*	**4.7%**		= ΔRoE_{RoS}	4.7%	**	**= *RoS***	**0.4%**	
× *AT*	0.692		+ ΔRoE_{AT}	-0.5%	**	× *AT*	0.887	
= *RoNA*	**3.3%**		= ΔRoE_{RoNA}	4.2%	**	**= *RoNA***	**0.4%**	
× *FL*	1.328		+ ΔRoE_{FL}	-0.5%	**	× *FL*	1.744	
= *RoE*	**4.4%**		**= *ΔRoE***	**3.7%**	**	**= *RoE***	**0.6%**	
$\Delta RoE_{cov\text{-}pre\ (CZ)}$						**$\Delta RoE_{cov\text{-}pre\ (SK)}$**		
ΔRoE_{LP}	1.4%					ΔRoE_{LP}	-1.9%	
+ ΔRoE_{LI}	-0.4%	*				+ ΔRoE_{LI}	-0.2%	†
= ΔRoE_{RoS}	0.9%		**Livestock production**			= ΔRoE_{RoS}	-2.1%	
+ ΔRoE_{AT}	0.1%					+ ΔRoE_{AT}	0.1%	
= ΔRoE_{RoNA}	1.0%					= ΔRoE_{RoNA}	-2.0%	*
+ ΔRoE_{FL}	-0.1%					+ ΔRoE_{FL}	0.0%	
= *ΔRoE*	**0.9%**					**= *ΔRoE***	**-2.0%**	*
CZ_{pre}			**$\Delta RoE_{CZ\text{-}SK\ (pre)}$**			**SK_{pre}**		
LP	3.582		ΔRoE_{LP}	2.7%	*	*LP*	1.439	
× *LI*	0.010		+ ΔRoE_{LI}	-0.6%	**	× *LI*	0.013	
= *RoS*	**3.7%**		= ΔRoE_{RoS}	2.2%	**	**= *RoS***	**1.8%**	
× *AT*	0.677		+ ΔRoE_{AT}	-0.7%	**	× *AT*	0.847	
= *RoNA*	**2.5%**		= ΔRoE_{RoNA}	1.5%		**= *RoNA***	**1.5%**	
× *FL*	1.367		+ ΔRoE_{FL}	-0.7%	†	× *FL*	1.714	
= *RoE*	**3.4%**		**= *ΔRoE***	**0.8%**		**= *RoE***	**2.6%**	

Note: (*LP* = Labour profitability; *LI* = Labour intensity; *AT* = Asset turnover; *FL* = Financial leverage; t-test results: † = p < 0.1 * = p < 0.05; ** = p < 0.01)
Source: Own processing based on Orbis (2024)

Table 4: Comparison of RoE drivers in Czech and Slovak livestock farms, pre- and during COVID-19.

Mixed farming

Table 5 shows that in 2020–2021, Czech mixed farms retained higher labour profitability (*LP*), contributing to a stronger impact of RoS. However, the total RoE gap narrowed, as Slovak farms benefited from higher asset turnover (*AT*) and financial leverage (*FL*), yielding only a slight Czech RoE advantage of +0.4%.

The pandemic had minimal impact on Czech mixed farms, where RoE declined slightly (−0.1%). Slovak farms, though, saw a modest increase (+2.0%), driven by improved labour profitability. However, few component shifts were statistically significant, and profitability structures remained largely stable. This stability in profitability composition is broadly consistent with earlier findings for the Central European agricultural sector. Kryszak et al. (2021) and Lehenchuk et al. (2023) showed that overall farm profitability in Poland, Slovakia and Ukraine was mainly driven by operational efficiency and liquidity rather than by leverage, with debt effects depending on the institutional environment. Similarly, Ladvenicová et al. (2019) found that RoE in the Visegrad countries was largely determined by return on assets, while financial structure factors were secondary. Aulová et al. (2019) observed a comparable pattern for Czech farms, where financial leverage had little influence on small and medium-sized enterprises but became more relevant in larger farms. Taken together, these findings suggest that the profitability patterns observed for mixed farms reflect structural and efficiency-related conditions rather than differences in financial leverage, similar to the patterns found for specialised crop and livestock farms.

The findings suggest that the effects of the pandemic on mixed farms were moderate and less polarised than in crop or livestock production. As in the other farm types, Czech farms maintained a consistent advantage in terms of labour, while Slovak ones relied more on capital-based drivers to improve RoE. The limited within-country changes in overall RoE offer only partial support for hypothesis H1, suggesting that while individual components such as labour profitability shifted, the broader profitability structure remained relatively resilient. The persistence of Czechia's advantage in labour efficiency and the stability of other structural differences provide stronger support for hypothesis H2, reinforcing the view that pre-existing disparities were maintained or modestly deepened during the crisis. The limited short-term variation further supports

CZ$_{cov}$			**$\Delta RoE_{CZ\text{-}SK\ (cov)}$**			**SK$_{cov}$**		
LP	5.161		ΔRoE_{LP}	3.4%	**	*LP*	2.308	
× *LI*	0.010		+ ΔRoE_{LI}	-0.4%	**	× *LI*	0.011	
= *RoS*	**5.1%**		= ΔRoE_{RoS}	3.0%	**	**= *RoS***	**2.5%**	
× *AT*	0.601		+ ΔRoE_{AT}	-1.9%		× *AT*	0.934	
= *RoNA*	**3.1%**		= ΔRoE_{RoNA}	1.2%		**= *RoNA***	**2.3%**	
× *FL*	1.439		+ ΔRoE_{FL}	-0.8%	†	× *FL*	1.738	
= *RoE*	**4.4%**		**= *ΔRoE***	**0.4%**		**= *RoE***	**4.0%**	
ΔRoE$_{cov\text{-}pre\ (CZ)}$						**ΔRoE$_{cov\text{-}pre\ (SK)}$**		
ΔRoE_{LP}	0.5%	*				ΔRoE_{LP}	2.4%	
+ ΔRoE_{LI}	-0.4%	*				+ ΔRoE_{LI}	-0.4%	†
= ΔRoE_{RoS}	0.1%		**Mixed farming**			= ΔRoE_{RoS}	2.0%	
+ ΔRoE_{AT}	-0.1%					+ ΔRoE_{AT}	0.1%	
= ΔRoE_{RoNA}	0.0%					= ΔRoE_{RoNA}	2.1%	
+ ΔRoE_{FL}	-0.1%					+ ΔRoE_{FL}	-0.1%	
= *ΔRoE*	**-0.1%**					**= *ΔRoE***	**2.0%**	†
CZ$_{pre}$			**ΔRoE$_{CZ\text{-}SK\ (pre)}$**			**SK$_{pre}$**		
LP	4.647		ΔRoE_{LP}	4.7%	*	*LP*	1.027	
× *LI*	0.011		+ ΔRoE_{LI}	-0.4%	**	× *LI*	0.012	
= *RoS*	**5.1%**		= ΔRoE_{RoS}	4.3%	**	**= *RoS***	**1.3%**	
× *AT*	0.614		+ ΔRoE_{AT}	-1.2%	†	× *AT*	0.912	
= *RoNA*	**3.1%**		= ΔRoE_{RoNA}	3.1%		**= *RoNA***	**1.1%**	
× *FL*	1.457		+ ΔRoE_{FL}	-0.6%	*	× *FL*	1.787	
= *RoE*	**4.5%**		**= *ΔRoE***	**2.5%**	†	**= *RoE***	**2.0%**	

Note: (*LP* = Labour profitability; *LI* = Labour intensity; *AT* = Asset turnover; *FL* = Financial leverage; t-test results: † = p < 0.1 * = p < 0.05; ** = p < 0.01)
Source: Own processing based on Orbis (2024)

Table 5: Breakdown of RoE differences in Czech and Slovak mixed farms across time periods.

the interpretation that pandemic-related effects were absorbed within existing efficiency structures rather than altering them fundamentally.

While the use of harmonised firm-level data from a common source and a consistent methodology strengthens the comparability between Czechia and Slovakia, several limitations remain. The relatively short observation window (2020–2021) may not capture delayed effects of the COVID-19 crisis. Additionally, the Orbis database likely over-represents larger, more formalised farms, potentially biasing results toward greater resilience. Finally, although the analysis reveals strong associations between profitability drivers and outcomes, it does not establish causality. These limitations should be borne in mind when interpreting the findings, even though they remain broadly consistent with the existing literature, as summarised in the following conclusion.

Conclusion

In summary, the direct impact of the COVID-19 pandemic on agricultural profitability appears to have been relatively limited. This finding holds across specialised crop, livestock, and mixed farms, though the effects were not uniform. In particular, Slovak livestock farms experienced a notable decline in profitability, while most other farm types either maintained or modestly improved their financial performance. These findings offer only partial support for hypothesis H1, indicating that while individual profitability components - especially labour-related metrics - were affected, the overall return on equity remained broadly stable. This limited impact suggests a high degree of resilience in the agricultural sector, consistent with previous findings on its countercyclical behaviour (Barcaccia et al., 2020; Meuwissen et al., 2021).

At the same time, the evidence provides stronger support for hypothesis H2, confirming that crises such as COVID-19 tend to reinforce rather than reduce existing structural differences. Pre-pandemic profitability disparities between Czech and Slovak farms - particularly those linked to labour efficiency and financial leverage - either persisted or widened during the pandemic. This aligns with broader evidence from firm-level research in other sectors showing that economic shocks tend to entrench pre-existing performance advantages (Alcalde-Fradejas and Ramírez-Alesón,

2015). Similar patterns are observed in agriculture, where persistent profitability differences have been documented among Visegrad farms, largely explained by variations in asset returns rather than capital structure (Ladvenicová et al., 2019), and where cross-country heterogeneity in farm performance remains substantial despite common policy frameworks (Kryszak and Herzfeld, 2021).

The general finding that RoE in DuPont decompositions is driven primarily by the margin term (RoS), rather than by volume- or intensity-related factors such as asset turnover or financial leverage, is fully consistent with earlier studies, as discussed above. This supports the further disaggregation of RoS into labour intensity and labour profitability, as applied in this study. The renewed low impact of labour intensity on RoE contradicts expectations based on widespread reports of labour shortages during the pandemic (Bochtis et al., 2020). Instead, it underscores the importance of labour profitability and its determinants, as analysed by Golas (2016) and Kusz et al. (2022). Incorporating these determinants into future extensions of the DuPont framework would help to address current limitations.

These findings may also help to contextualise the farmer protests that emerged in the immediate aftermath of the pandemic. Despite reports of economic pressure, the results of this study suggest that short-term profitability was not the main driver; instead, structural burdens such as regulatory complexity and long-term competitiveness issues likely played a greater role. Further research is needed to assess the motivations for protest directly.

Future studies should examine these structural challenges more closely and assess how policy can support both the resilience and sustainability of European agriculture. Differentiating between temporary shocks like COVID-19 and longer-term stressors will be essential for designing targeted and effective policy responses.

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References

[1] Alcalde-Fradejas, N. and Ramírez-Alesón, M. (2015) "Long-run profits in times of crisis: A comparison between European SMEs and large companies", *Estudios de Economia*, Vol. 42, No. 1, pp. 79-97. ISSN 0304-2758. DOI 10.2139/ssrn.2618319.

[2] Andrašić, J., Mijić, K., Mirović, V. and Kalaš, B. (2018) "The modelling factors of agricultural companies' performances", *Custos e @gronegocio Line*, Vol. 14, No. 4, pp. 223-240. ISSN 1808-2882.

[3] Aulová, R., Pánková, L. and Rumánková, L. (2019) "Analysis of Selected Profitability Ratios in the Agricultural Sector", *AGRIS on-line Papers in Economics and Informatics*, Vol. 11, No. 3, pp. 3-12. ISSN 1804-1930. DOI 10.7160/aol.2019.110301.

[4] Baležentis, T. and Novickytė, L. (2018) "Are Lithuanian Family Farms Profitable and Financially Sustainable? Evidence Using DuPont Model, Sustainable Growth Paradigm and Index Decomposition Analysis", *Transformations in Business & Economics*, Vol. 17, No. 1, pp. 237-254. ISSN 1648-4460.

[5] Barcaccia, G., D'Agostino, V., Zotti, A. and Cozzi, B. (2020) "Impact of the SARS-CoV-2 on the Italian agri-food sector: An analysis of the quarter of pandemic lockdown and clues for a socio-economic and territorial restart", *Sustainability*, Vol. 12, No. 14, p. 5651. ISSN 2071-1050. DOI 10.3390/su12145651.

[6] Benedek, Z., Fertő, I., Galamba Marreiros, C., Mossmann de Aguiar, P., Pocol, C. B., Čechura, L., Pöder, A., Pääso, P. and Bakucs, Z. (2021) "Farm diversification as a potential success factor for small-scale farmers constrained by COVID-19-related lockdown. Contributions from a survey conducted in four European countries during the first wave of COVID-19", *PloS One*, Vol. 16, No. 5, p. e0251715. ISSN 1932-6203. DOI 10.1371/journal.pone.0251715.

[7] Bereżnicka, J. (2018) "Sources of return on equity in economically diversified agriculture of the European Union countries", *Problems of Agricultural Economics*, Vol. 3, No. 356, pp. 76-93. ISSN 0044-1600. DOI 10.30858/zer/94477.

[8] Beyer, D. and Hinke, J. (2018) "Sectoral Analysis of the Differences in Profitability of Czech and German Business Ventures – an Empirical Benchmark Study", *E & M Ekonomie A Management*, Vol. 21, No. 1, pp. 127-143. ISSN 1212-3609. DOI 10.15240/tul/001/2018-1-009.

[9] Blažková, I., Svatošová, V., Chmelíková, G., Tamáš, V., Svobodová, E., Grega, L., Miškolci, S., Piecuch, D., Ujj, A., Hupková, D., Puchata, J., Bazsik, I., Jancsovszka, P., Nagyné Pércsi, K. and Dobošová, Ľ. (2023) "The effects of COVID-19 crisis on small family farms: Empirical evidence from Visegrad countries", *Agricultural Economics*, Vol. 69, No. 9, pp. 366-374. ISSN 1805-9295. DOI 10.17221/217/2023-AGRICECON.

[10] Bochtis, D., Benos, L., Lampridi, M., Marinoudi, V., Pearson, S. and Sørensen, C. G. (2020) "Agricultural workforce crisis in light of the COVID-19 pandemic", *Sustainability*, Vol. 12, No. 19, p. 8212. ISSN 2071-1050. DOI 10.3390/su12198212.

[11] Eurostat (2008) "*NACE Rev. 2-Statistical Classification of Economic Activities in the European Community*". [Online]. Available: https://ec.europa.eu/eurostat/documents/3859598/5902521/KS-RA-07-015-EN.PDF.pdf/dd5443f5-b886-40e4-920d-9df03590ff91?t=1414781457000 [Accessed: Feb. 12, 2025].

[12] Finger, R., Fabry, A., Kammer, M., Candel, J., Dalhaus, T. and Meemken, E.M. (2024) "Farmer protests in Europe 2023–2024", *EuroChoices*, Vol. 23, No. 3, pp. 59-63. ISSN1746-692X. DOI 10.1111/1746-692X.12452.

[13] Golas, Z. (2016) "The level and determinants of work profitability changes in the Czech and Polish agricultural sector in the years 2004-2014", *Agricultural Economics*, Vol. 62, No. 7, pp. 334-344. ISSN 1805-9295. DOI 10.17221/159/2015-AGRICECON.

[14] Gómez-Limón, J. A., Sánchez-Cañizares, S., Hidalgo-Fernández, A. and Castillo-Canalejo, A. M. (2023) "Profit and viability persistence: Evidence from the Spanish agricultural sector", *Agribusiness*, Vol. 39, No. 4, pp. 1300-1332. ISSN 1520-6297. DOI 10.1002/agr.21822.

[15] Józwiak, W., Sobierajewska, J., Zieliński, M., and Ziętara, W. (2019) "The level of labour profitability and development opportunities of farms in Poland", *Problems of Agricultural Economics*, Vol. 2, No. 359, pp. 28-42. ISSN 2392-3458. DOI 10.30858/zer/109927.

[16] Kryszak, Ł., Guth, M. and Czyżewski, B. (2021) "Determinants of farm profitability in the EU regions. Does farm size matter?", *Agricultural Economics*, Vol. 67, No. 3, pp. 90-100. ISSN 0139-570X. DOI 10.17221/415/2020-AGRICECON.

[17] Kryszak, Ł. and Herzfeld, T. (2021) "One or many European models of agriculture? How heterogeneity influences income creation among farms in the European Union", *Agricultural Economics*, Vol. 67, No. 11, pp. 445-456. ISSN 0139-570X. DOI 10.17221/154/2021-AGRICECON.

[18] Kusz, B., Kusz, D., Bąk, I., Oesterreich, M., Wicki, L. and Zimon, G. (2022) "Selected economic determinants of labor profitability in family farms in Poland in relation to economic size", *Sustainability*, Vol. 14, No. 21, p. 13819. ISSN 2071-1050. DOI 10.3390/su142113819.

[19] Ladvenicová, J., Bajusová, Z., Gurčík, Ľ. and Červený, D. (2019) "Dupont analysis of farms in V4 countries", *Visegrad Journal on Bioeconomy and Sustainable Development*, Vol. 8, No. 2, pp. 82-86. ISSN 1339-3367. DOI 10.2478/vjbsd-2019-0016.

[20] Lehenchuk, S., Chyzhevska, L., Meluchová, J., Zdyrko, N. and Voskalo, V. (2023) "Determinants of agricultural companies' financial performance: The experience of Poland, Slovakia and Ukraine", *Investment Management and Financial Innovations*, Vol. 20, No. 1, pp. 99-111. ISSN 1812-9358. DOI 10.21511/imfi.20(1).2023.10.

[21] Martinho, V. J. P. D. (2022) "Profitability and financial performance of European Union farms: An analysis at both regional and national levels", *Open Agriculture*, Vol. 7, No. 1, pp. 529-540. ISSN 2391-9531. DOI 10.1515/opag-2022-0108.

[22] Martín-Retortillo, M. and Pinilla, V. (2015) "On the causes of economic growth in Europe: why did agricultural labour productivity not converge between 1950 and 2005?", *Cliometrica*, Vol. 9, No. 3, pp. 359-396. ISSN 1863-2505. DOI 10.1007/s11698-014-0119-5.

[23] Matthews, A. (2024) "Farmer protests and income developments in the EU", *The Political Quarterly*, Vol. 95, No. 2, pp. 344-349. ISSN1467-923X. DOI 10.1111/1467-923X.13396.

[24] Meuwissen, M. P., Feindt, P. H., Slijper, T., Spiegel, A., Finger, R., De Mey, Y. ... and Reidsma, P. (2021) "Impact of COVID-19 on farming systems in Europe through the lens of resilience thinking", *Agricultural Systems*, Vol. 191, p. 103152. ISSN 0308-521X. DOI 10.1016/j.agsy.2021.103152.

[25] Mijić, K. and Jakšić, D. (2017) "The determinants of agricultural industry profitability: Evidence from southeast Europe", *Custos e Agronegocio*, Vol. 13, No. 1, pp. 154-173. ISSN 1808-2882.

[26] Montgomery, J. K. (1937) "*The Mathematical Problem of the Price Index*", Orchard House, Westminster: King & Son.

[27] Neef, A. (2020) "Legal and Social Protection for Migrant Farm Workers: Lessons from COVID-19", *Agriculture and Human Values*, Vol. 37, No. 3, pp. 641-642. ISSN 1572-8366. DOI 10.1007/s10460-020-10086-w.

[28] Nicola, M., Alsafi, Z., Sohrabi, C., Kerwan, A., Al-Jabir, A., Iosifidis, C., Agha, M., and Agha, R. (2020) "The Socio-economic Implications of the Coronavirus Pandemic (COVID-19): A Review", *International Journal of Surgery*, Vol. 78, No. 6, pp. 185-193. ISSN 1743-9159. DOI 10.1016/j.ijsu.2020.04.018.

[29] Očić, V., Grgić, Z., Šakič Bobić, B. and Batelda Lodeta, K. and Kovačićek, T. (2025) "DuPont profitability analysis of different types of agricultural farms in Croatia", *Journal of Central European Agriculture*, Vol. 26, No. 2, pp. 555-563. ISSN 1332-9049. DOI 10.5513/JCEA01/26.2.4686.

[30] Orbis (2024) "*Financial data of Czech and Slovak agricultural companies 2018 – 2021*" [Online]. Available: https://orbis-r1.bvdinfo.com/version-20241204-6-0/Orbis/1/Companies/Search [Accessed: Oct. 12, 2024].

[31] Parzonko, A., Parzonko, A. J., Bórawski, P. and Wicki, L. (2023) "Return on equity in dairy farms from selected EU countries: Assessment based on the DuPont Model in years 2004-2020", *Agriculture*, Vol. 13, No. 7, p. 1403. ISSN 2077-0472. DOI 10.3390/agriculture13071403.

[32] Phillipson, J., Gorton, M., Turner, R., Shucksmith, M., Aitken-McDermott, K., Areal, F., Paul Cowie, P., Hubbard, C., Maioli, S., McAreavey, R., Souza-Monteiro, D., Newbery, R., Panzone, L, Rowe, F. and Shortall, S. (2020) "The COVID-19 pandemic and its implications for rural economies", *Sustainability*, Vol. 12, No. 10, p. 3973. ISSN 2071-1050. DOI 10.3390/su12103973.

[33] Štreimikienė, D., Baležentis, T., Volkov, A., Ribašauskienė, E., Morkūnas, M. and Žičkienė, A. (2022) "Negative effects of covid-19 pandemic on agriculture: systematic literature review in the frameworks of vulnerability, resilience and risks involved", *Economic Research*, Vol. 35, No. 1, pp. 529-545. ISSN 1848-9664. DOI 10.1080/1331677X.2021.1919542.

[34] Szymanska, E. (2015) "Profitability of pig farms in Poland after integration to the EU", *Economic Science for Rural Development Conference Proceedings*, No. 39, pp. 97-107. ISBN 978-9984-48-182-1.

[35] Vartia, Y. O. (1976) "Ideal log-change index numbers", *Scandinavian Journal of Statistics*, Vol. 3, No. 3, pp. 121-126. ISSN 1467-9469.

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Food Price Inflation, GNPIP Policy, and Economics Growth in Indonesia

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Abstract

This study examines the impact of food inflation and the role of the National Food Inflation Control Movement (GNPIP) on regional economic growth measured through Gross Domestic Product (GDP) per capita, using the 2018–2023–time panel data with cross-section of 34 provinces in Indonesia. Using cross-regional panel data analysis, the results show that food inflation in general has a significant negative impact on GRDP per capita, with a delay in one period, especially through a decrease in household purchasing power, especially in low -income groups. Conversely, rice inflation shows a significant and delayed positive effect on economic growth, driven by revenue redistribution to rural producers and multiplier effects in the agricultural economy. However, corn and soybean inflation does not show a significant impact, which is caused by the limited role of these commodities in direct consumption, weak economic linkages, import dependence, and low supply elasticity. The GNPIP policy has proven to have a positive and significant influence on GRDP per capita, confirms its multiple roles in maintaining price stability while encouraging regional economic growth through increasing consumption and investment activities. Nevertheless, GNPIP is unable to moderate the relationship between rice inflation and economic growth, indicating its limited capacity in reducing the shocks of certain commodity prices. One of the important mechanisms of GNPIP is announcement effect, which helps prevent panic buying by giving positive signals to the public about food availability and price stability. This study confirms that GNPIP has a strategic role in maintaining economic stability by averting panic buying and bolstering the advancement of the domestic economy.

Keywords

GNPIP, GDP per capita, food inflation, announcement effect.

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Introduction

Indonesia as an agrarian country with a population of more than 280 million people, has a significant dependency on the agricultural sector to meet the food needs of its people (Afriyanti et al., 2023). Staple food ingredients such as rice, corn, and soybeans are strategic commodities that are not only a major source of consumption but also affect national economic stability (Mamat and Husen, 2021). These three commodities have an important role in sustaining food security and contributing directly to domestic inflation. Fluctuations in the price of food commodities are often one of the main factors that affect the level of inflation in Indonesia, which in turn can have an impact on the income of the community and overall economic growth.

One important indicator for measuring the economics growth of a country or a region is GDP per capita, which reflects the average income per individual in a country or a region. GDP per capita not only reflects the level of economic productivity but also the quality of life of the community. Per capita income (GDP per capita) is a very important indicator to measure the progress of development and economic potential of a region. This reflects people's purchasing power and shows how much the market is in an area. Regions with high GDP per capita usually have a large market, higher economic growth potential,

and a larger scale of production. Therefore, GDP per capita is often used as a proxy to measure economic growth and community welfare (Tatiana et al., 2015).

Food inflation is one of the macroeconomic indicators that is very important because it reflects changes in the price of goods and services in a country. High and unstable food inflation can reduce people's purchasing power, increase economic uncertainty, and hamper economic growth (Negi, 2022). In Indonesia, food inflation is often the main contributor to general inflation (headline inflation), mainly because of the dominance of commodities such as rice, corn, and soybeans in the pattern of public consumption. Inflation control is needed because inflation in the Indonesian economy can affect economic growth (Nuryati et al., 2006; Siregar & Ward, 2001). Therefore, food inflation controls economic stability and improves the welfare of the community.

Macroeconomic stabilization including food inflation can be done by implementing the supply side policies such as improving agricultural technology. (Siregar and Ward, 2002). As part of a strategic effort to overcome the challenges of food inflation, the Indonesian government launched the National Food Inflation Control Movement (GNPIP). This program aims to stabilize food prices through various policies, such as increasing local food production, optimizing distribution, and market interventions through cheap market operations. GNPIP is expected to reduce food price volatility, so that inflation can be controlled and its negative impacts on the economy can be minimized. The GNPIP program is implemented by the Bank Indonesia KPwDN (Domestic Representative Office) in 46 working areas of the domestic representative office of central bank during July to December 2022.

GNPIP program is an effort to control food inflation in terms of demand and supply so that it can support the purchasing power of the community and accelerate the recovery of the national economy. This effort is part of the TPIP/TPID program which is also an Extra Effort of Food Inflation Control as a follow-up to the directions of the President of the Republic of Indonesia at the National Coordination Meeting (Rakornas) Inflation Control 2022. The superior program implemented by the KPwDN (Domestic Representative Office) of Bank Indonesia. The seven excellent programs or strategies are: (i) Optimization of the K/L Budget (ministries/ institutions) and local governments for market operations (OP), cheap markets, availability of supply and price stabilization (KPSH) and maintaining people's purchasing power; (ii) Expansion of cooperation between regions (KAD) such as strengthening the role of regional - owned enterprises (BUMD) related to food; (iii) Optimization of the facilitation of strategic food distribution through the encouragement of subsidies for transportation costs; (iv) Strengthening the resilience of tubers and vegetables and other strategic food supplies by conducting a joint planting movement and replication of the best business models from upstream to downstream; (v) Increasing the use of agricultural machinery (Alsintan) and agricultural production facilities (saprotan) to encourage end-to-end food cluster increase and development; (vi) Strengthening Information and Communication Technology Infrastructure (ICT) such as EWS (Early Warning System) Regional Food Prices; and (VII) Strengthening coordination to control inflation expectations such as strengthening capacity building, socialization, and strengthening coordination and communication between related institutions. These superior programs are prepared by prioritizing structural price stability efforts, forward-booking, and digital-based to support the acceleration of the recovery of the national economy. Coordination with Bank Indonesia within the framework of the GNPIP program includes rice commodities as the main commodity, while other strategic commodities include cooking oil, sugar, broiler eggs, meat, fish, and other commodities that will be adjusted to the risk of inflation and characteristics of each region (Puspitasari et al., 2022).

Food inflation is the main component in general inflation, especially in developing countries where people have a significant proportion of expenses for food consumption. When food prices increase, people's purchasing power decreases, which can hamper household consumption and household income. This has the potential to slow down overall economic growth, reflected in the decline in GDP per capita. Food inflation has a negative influence on GDP per capita because the increase in food prices increases the burden of living costs, and reduces people's purchasing power (Bogmans et al., 2024). In Indonesia, high food inflation can hamper an increase in GDP per capita due to increased living costs and weakening purchasing power. Therefore, understanding the relationship between rice inflation, corn inflation, soybean inflation, and the effectiveness of GNPIP of GDP per capita becomes very relevant to formulate better economic policies.

When food prices increase, producers and food exporters get higher income because they sell their products at more expensive prices (Bredenkamp and Bersch, 2012; Sen et al., 2024). Prabheesh and Laila (2020) found that the increase in the price of palm oil and cooking oil had a positive impact on GDP. Study by Headey (2018) that uses a simulation model to test the relationship between real food price increases and changes in poverty, concludes the relationship between food price increases and poverty reduction. One reason is that agricultural production tends to increase in response to the increase in food prices, which can increase farmers' income. In line with the results of these studies, the research by Headey and Hirvonen (2023) states that an increase in real food prices can reduce the number of poor people. However, this effect is less significant or not even in countries with large urban populations or with a high proportion of non-agricultural population, because this group is less directly involved in food production.

Research conducted by Ivanic et al. (2012) shows that the increase in principal food prices (such as seeds) can increase real income for food producers in poor countries. However, for consumers clean food (for example, families who buy more food than they produce), the impact is actually detrimental. The effect of poverty reduction due to increase in food prices tends to be less frequent and smaller than the effect of increasing poverty. Other studies even state that higher food prices generally increase poverty levels in sub-Sahara Africa, especially for community groups who depend on food purchases (Wodon and Zaman, 2010). Negi (2022) also found that households as consumers esxperienced a total decrease in staple consumption per capita, due to price increases, because household income was reduced even though they replaced purchases from the market with their own agricultural products or subsidized foodstuffs. Other studies have shown that the increase in main food prices significantly increases poverty because of decreased net income, especially in rural areas, because the impact of price increases there is greater than in urban areas (Faharuddin et al., 2023). Thus, we hypothesize that:

H1a: Food inflation has a significant effect on GDP per capita.

H1b: Rice price change (rice inflation) has significant effect on GDP per capita.

H1c: Corn price change (corn inflation) has a significant effect on GDP per capita.

H1d: Soybean price change (soybean inflation) has a significant effect on GDP per capita.

Previous research has provided statistical evidence that in all countries, strong government policy support has an impact on increasing per capita income and faster growth (Indrajaya and Iskamto, 2023; Li and Maskin, 2021). Research conducted by (Ismail and Houssein, 2020; Solihin et al., 2021) also concluded that fiscal policy has a short causal effect on per capita income. Fiscal policies in certain fields are very important and must continue to provide more opportunities for the people to develop better and as a result, get better jobs and improve living standards. According to (Yogi et al., 2025), the development of the agro industry, integrating added value products, and empowering women and youth in agriculture is all important approaches for economic growth. George (2020) states that the growth of strong GDP per capita and GDP occurs in efficient technological conditions, improving skills, and efficient markets. In line with George's results, research conducted by Grabowski and Self (2023) found that agricultural productivity is an important determinant of the extent of economic development. The results of research by Markus and Dietrich (2018) also concluded that there was a significant effect of improving agricultural technology on economic development.

The research by Eberhardt and Vollrath (2016) found that the elasticity of agricultural output (how responsive agricultural production to changes in GDP per capita) varies depending on the type of climate of a region. In countries with moderate or cold climate, this elasticity is lower, meaning that agricultural production is less responsive to increasing GDP per capita. Conversely, in countries with tropical climates or high mountainous areas, this elasticity is higher, meaning that agricultural production is more responsive to increasing GDP per capita. Based on explanation of previous research results, we hypothesize that:

H2: GNPIP policy has a significant effect on GDP per capita.

Research conducted by Tan et al. (2024) concluded that in ensuring food production stability and market price stability, and to ensure that the intervention policy does not distort the food market, the minimum purchase price policy of food and market regulations must be adjusted to be transferred to the income support policy. Other research using the household welfare model shows that government policies on prices

produce progressive welfare impacts and that anti-exploitation steps are successful in reducing the impact of regressive welfare from asymmetrical pass-through (Benzarti et al., 2024). Thus, we hypothesize that:

H3: GNPIP policy moderates the relationship between rice price changes and GDP per capita.

Materials and methods

This research applies to a deductive approach, which involves the formulation and testing of hypotheses. In this context, we use the Dataset Time Series Cross-Sectional (TS-CS) which includes periods from 2018 to 2023. This dataset allows us to analyze historical data to explore the impact of food inflation, public policy, and regional economic conditions on GDP per capita in various provinces in Indonesia. In addition, this study uses descriptive correlational design, which allows us to formulate hypotheses and estimate the relationship between variables such as food inflation, policies, and economic conditions that are modified, with GDP per capita. Descriptive correlational design can be used to develop theory, identify weaknesses in current practice, support existing practices, make evaluations, or study actions taken in similar situations (Bala et al., 2024). This design is very suitable for testing the relationship between two or more variables, as is the focus of this research.

This research is a study with a quantitative approach using secondary data. Secondary data in the form of GDP data per capita, rice prices, corn prices, soybean prices, food inflation, and regional GDP or Gross Regional Domestic Product obtained from the Central Statistics Agency. To test our hypotheses, we employed panel data from 34 provinces within the years, 2018 to 2023 consisting of 204 province-year observations.

The control variables in this study are Gross Regional Domestic Product (GRDP), realization of foreign investment (FDI), unemployment (UNEMP), and education (EDU) to achieve more accurate and reliable estimates of the relationship between GNPIP implementation and GDP per capita. Regional GDP or Gross Regional Domestic Product serves as a key factor to account for variations in economic performance across different regions in Indonesia. By including regional GDP as a control variable, the study aims to isolate the specific impact of the GNPIP program on GDP per capita, independent of the inherent economic disparities between regions. This ensures that the analysis reflects the true effect of GNPIP, rather than being confounded by differences in regional economic output. The inclusion of regional GDP as a control variable is particularly important given the cross-sectional nature of the data, which encompasses 34 provinces in Indonesia, each with varying levels of economic development and productivity.

To test the hypothesis submitted previously empirically and handle challenges related to the Dataset Time Series Cross-sectional (TS-CS) (Beck, 2001). This study uses panel data regression to analyze the relationship between independent and dependent variables by utilizing cross-individual observations (entities) and time. The panel data regression model approaches are applied: Common Effect model (CE), Fixed Effect model (FE), and Random Effect model (RE). The Fixed Effect model (FE) is used to control the heterogeneity of individuals who are not observed but fixed by entering the variable dummy for each entity. Meanwhile, the Random Effect model (RE) assumes that the individual effect is random and does not correlate with the explanatory variable, so it is more statistically efficient if this assumption is met. The selection between FEM and brakes is carried out through the Hausman test. The Common Effect model (Pooled OLS) assumes the absence of cross-individual heterogeneity. Before the main analysis, the classic assumption test includes multicollinearity, heteroskedasticity, and autocorrelation tests. Model validity is selected based on the results of the Multiplier Lagrange test (to compare CE vs. RE) and thirst test (to select between FE vs. RE). The best model is chosen based on the consistency of estimation and parameter efficiency. The equation of values-relevance is modeled as follows:

Baseline model:

$$\begin{aligned} GDPC_{i,t} = {} & \alpha_0 + \alpha_1 FINF_{i,t} + \alpha_2 FINF_{i,t\text{-}1} + \alpha_3 FINF_{i,t\text{-}2} + \\ & + \alpha_4 GDPR_{i,t} + \alpha_5 RINF_{i,t} + \alpha_6 RINF_{i,t\text{-}1} + \\ & + \alpha_7 RINF_{i,t\text{-}2} + \alpha_8 CINF_{i,t} + \alpha_9 \text{CINF}_{i,t\text{-}1} + \\ & + \alpha_{10} CINF_{i,t\text{-}2} + \alpha_{11} SINF_{i,t} + \alpha_{12} SINF_{i,t\text{-}1} + \\ & + \alpha_{13} SINF_{i,t\text{-}2} + \alpha_{14} GNPIP_{i,t} + \alpha_{15} FDI_{i,t} + \\ & + \alpha_{16} UNEMP_{i,t} + \alpha_{17} EDU_{i,t} + \varepsilon_{it} \end{aligned}$$

Interaction model:

$$GDPC_{i,t} = \alpha_0 + \alpha_1 FINF_{i,t} + \alpha_2 FINF_{i,t-1} + \alpha_3 FINF_{i,t-2} + \alpha_4 GDPR_{i,t} + \alpha_5 RINF_{i,t} + \alpha_6 RINF_{i,t-1} + \alpha_7 RINF_{i,t-2} + \alpha_8 CINF_{i,t} + \alpha_9 CINF_{i,t-1} + \alpha_{10} CINF_{i,t-2} + \alpha_{11} SINF_{i,t} + \alpha_{12} SINF_{i,t-1} + \alpha_{13} SINF_{i,t-2} + \alpha_{14} GNPIP_{i,t} + \alpha_{15} FDI_{i,t} + \alpha_{16} UNEMP_{i,t} + \alpha_{17} EDU_{i,t} + \alpha_{18} FINF_{i,t} * GNPIP_{i,t} + \varepsilon_{it}$$

where $GDPC_{i,t}$ = Gross Domestic Product per capita of a province i at time year t, $FINF_{i,t}$ = Food inflation of a province i at time year t, $GRDP_{i,t}$ = Gross regional domestic product of a province i at time year t, $RINF_{i,t}$ = Rice inflation (Rice's change of price) of a province i at time year t, $CINF_{i,t}$ = Corn inflation (Corn's change of price) of a province i at time year t, $SINF_{i,t}$ = Soybeans inflation (Soybeans' change of price) of a province i at time year t, $GNPIP_{i,t}$ = Dummy of GNPIP policy of a province i at time year t, $FDI_{i,t}$ = Realization of foreign investment of a province i at time year t, $UNEMP_{i,t}$ = Unemployment number of a province i at time year t, $EDU_{i,t}$ = The level of education completion according to high school level of a province i at time year t , and ε_{it} = stochastic error term.

Results and discussion

The first step in data analysis to understand the main characteristics of the dataset before conducting further analysis is to analyze descriptive statistics. Descriptive statistics help describe the basic patterns in data, such as the average value (mean), middle value (median), the value most often arises (mode), as well as the dissemination of data (variance and standard deviation). This provides insight into data distribution (Table 1).

Variable	Mean	Std.dev	Min	Max
GDPC	68538.78	53377	18417.5	322615
FINF	3.973228	1.688706	-0.041182	8.603353
RINF	2.992786	521.028	-8.968773	2.174061
CINF	3.406696	8.498263	-4.483734	6.159879
SINF	4.322454	9.357972	-2.051082	3.815894
GRDP	506929	717899.9	36468.8	3443026
FDI	1039.222	1539.752	5.9212	8283.746
UNEMP	241.1729	419.138	15.38	2533.076
EDU	63.47554	10.98419	27.44	90.12

Note: GDPC Per Capita Gross Domestic Product, FINF Food Inflation, GRDP Regional Gross Domestic Product, RINF Rice Inflation, CINF Maize Inflation, SINF Soybeans Inflation, GNPIP Dummy of GNPIP Policy (0 = Period before applying policy, 1 = Period of policy application)
Source: Stata 17.0 Output

Table 1: Descriptive statistics.

High deviation standards in several variables such as GDPC and GRDP indicate a significant variation between provinces in terms of regional domestic products and GDP per capita. With significant variation, further analysis such as regression can provide deeper insights into the factors that affect GDP per capita and other variables. In general, the average GDP per capita and regional domestic product are quite high, but with significant variations. Food inflation, rice, corn, and soybeans also tend to be stable but with significant variations between provinces (Table 2).

Based on the correlation table presented, the correlation between GNPIP (Dummy of GNPIP Policy) and GDP per capita (GDPC) is 0.1440 with a significance level of 0.1. That is, there is a significant positive relationship between the GNPIP and GDP per capita policy. In other words, the period of implementing GNPIP policy tends to have a higher GDP per capita compared

	GDPC	FINF	GRDP	RINF	CINF	SINF	GNPIP	FDI	UNEMP	EDU	VIF
GDPC	1.0000										
FINF	0.0831	1.0000									1.60
GRDP	0.4722*	0.0988	1.0000								4.73
RINF	-0.1027	0.1929*	-0.0080	1.0000							2.42
CINF	-0.0019	0.0520	0.0718	-0.1598*	1.0000						1.33
SINF	-0.0191	0.0206	0.0752	0.0458	0.0172	1.0000					1.24
GNPIP	0.1440*	0.4869*	0.0756	0.4426*	0.0156	0.0768	1.000				2.38
FDI	0.3509*	0.1022	0.5922*	0.0133	0.0311	0.0540	0.0967	1.000			2.16
UNEMP	0.0320	0.0835	0.6683*	0.0303	0.0628	0.1367	-0.0073	0.3934*	1.000		3.38
EDU	0.3887*	0.1782*	0.2773*	0.0494	-0.0691	0.1360	0.1144	0.1381*	0.3608*	1.000	1.32

Source: Stata 17.0 Output
Note: GDPC Gross Domestic Product Per Capita, FINF Food Inflation, GRDP Gross Regional Domestic Product, RINF Rice Inflation, CINF Maize Inflation, SINF Soybeans Inflation, GNPIP Dummy of GNPIP Policy (0 = Period before applying policy, 1 = Period of policy application); Prov-year obs. = 204, ****p < 0.01, **p < 0.05 and *p < 0.1

Table 2: Pairwise correlation matrix and VIF among all the variables.

to the period before the implementation of the policy. However, to show a statistical relationship and the causal relationship between the two variables, as well as to find out whether the GNPIP policy really affects the GDP per capita or not, further regression analysis is needed as done in this study.

The table also shows a significant positive correlation between GDPs per capita and regional domestic product with a correlation coefficient of 0.4722. This shows that provinces with higher GDP per capita tend to have a larger regional domestic product. A significant negative correlation is found between rice, corn, and soybean inflation with GDP per capita. This shows that when food prices generally rise, GDP per capita tends to go down.

The VIF test results show that all variables in this study are within acceptable thresholds. This shows that there is no significant multicollinearity problem in the regression model used. Thus, the estimated results of regression parameters can be relied upon.

The data used in this study are panel data (combined time-series and cross-sectional data), so that there are possibilities of some statistical problems that must be considered so that the estimation results are not biased or wrong. Therefore, first diagnostic tests are carried out to identify these problems. The diagnostic test results aim to support the validity of the selected method so that the research conclusions can be relied upon.

Based on Table 3, the results indicate no evidence of heteroskedasticity or autocorrelation, satisfying key assumptions of the regression model. The error variant is constant in each group of individuals or time, and there is no inter-sector correlation in a cross-sectional unit over time. Residual distribution has no extreme skewness or kurtosis, which shows that the residual may approach the normal distribution.

Based on the results of the systematic model selection test, the Fixed Effect model (FE) was chosen as the most appropriate specifications for data panel analysis in this study. This decision is supported by the results of the Hausman test, which shows statistically ($p<0.05$), indicating that the individual effect is correlated with the explanatory variable in the model. Thus, the assumption of independence between random effects and regressors, which underlies the Random Effect model (RE) is not fulfilled, thus making FE a more consistent and unbiased approach. In addition, the multiplier Lagrange test (Breusch-Pagan) also confirms that the Pooled OLS (CE) specifications are inadequate, because there are significant variations between individuals that need to be controlled. By utilizing the transformation of within, FE effectively isolates variations in time for each entity, so that it can control unobserved heterogeneity that is constant with time-such as institutional or structural characteristics that are unique for each observation unit. The selection of FE is not only supported by statistical considerations, but also substantive relevance in the context of research, where differences in cross-entity (34 provinces) are expected to affect results systematically. Therefore, this model provides a more reliable estimation and a stronger interpretation of the causal relationship between the variables in the setting of the panel data used.

In addition, to test the resistance of research results, Generalized Least Squares (FGLS) is used as an alternative method. The FGLS method considers the more complex covarian structure, so that it can provide more robust results to violations of classic assumptions in linear regression (Bala et al., 2024).

Table 4 shows the results of the panel data regression analysis on GDP per capita (GDPC) using two models: Baseline Model and Interaction Model. This analysis was carried out with two standard error estimation methods, namely Fixed Effect Model and Feasible Generalized Least Squares (FGLS) for robustness test.

Diagnostics test	Statistics	p-value	Remark
Time (years) fixed effect	1.59	0.2105	Absent
Provinces (units) fixed effect	644.38	0.0000	Present
Group-wise Heteroskedasticity	3.48	0.0621	Absent
Contemporaneous correlation	1736.97	0.0000	Present
Panel serial correlation	2.138	0.1531	Absent
Normality Test Skewness/ Kurtosis			No Skewness and No Kurtosis
Shapiro–Wilk			Normally distributed
Shapiro-Francia			Normally distributed

Source: Author's Compilation, 2025

Table 3: Summary of diagnostic test.

Variables	FE		FGLS for Robustness Test	
	Baseline Model	Interaction Model	Baseline Model	Interaction Model
Constant	-0.8836504*	-1.006984*	3.601475***	3.51056***
	(0.5350122)	(0.5470057)	(0.0027016)	(0.5470057)
$FINF_{i,t}$	-0.0004898	-0.000881	0.0017175	0.0015633
	(0.0016729)	(0.0017115)	(0.0025958)	(0.0027484)
$FINF_{i,t-1}$	-0.0037535**	-0.0040182**	-0.0054589**	-0.0055257**
	(0.0015998)	(0.0016178)	(0.003696)	(0.0026192)
$FINF_{i,t-2}$	-0.0014247	-0.0017931	-0.0019726	-0.002094
	(0.0022729)	(0.0022973)	(0.0495453)	(0.0037262)
$GRDP_{i,t}$	0.9432101***	0.9553757***	0.646036***	0.6531412***
	(0.0407487)	(0.0422904)	(0.0010332)	(0.0513631)
$RINF_{i,t}$	-0.0004255	0.0015907	0.0001741	0.0008598
	(0.0006374)	(0.0019983)	(0.0017766)	(0.0032229)
RINFi,t-1	0.0044087***	0.0047751***	0.0063346***	0.0064487***
	(0.0011115)	(0.0011627)	(0.0012786)	(0.0018677)
$RINF_{i,t-2}$	0.001383	0.0012058	0.0014821	0.0014181
	(0.0007858)	(0.0008026)	(0.0008661)	(0.0013024)
$CINF_{i,t}$	-0.0005807	-0.0005581	-0.0003372	-0.0003276
	(0.0005342)	(0.0005342)	(0.0005917)	(0.000864)
$CINF_{i,t-1}$	0.0000286	-0.0000588	0.0002027	0.0001684
	(0.0003638)	(0.0003727)	(0.000488)	(0.0006042)
$CINF_{i,t-2}$	-0.0004327	-0.0003217	-0.0001659	-0.0001313
	(0.0003004)	(0.0003178)	(0.0004484)	(0.0005153)
$SINF_{i,t}$	0.0004605	0.0004101	0.0009614	0.0009402
	(0.0002799)	(0.0002836)	(0.000399)	(0.0004516)
$SINF_{i,t-1}$	0.000031	0.0000172	-0.0000667	-0.0000705
	(0.0002453)	(0.0002454)	(0.0004177)	(0.0003981)
$SINF_{i,t-2}$	0.0000973	0.0001251	0.00018	0.0001894
	(0.0002567)	(0.0002578)	(0.0152805)	(0.0004184)
$GNPIP_{i,t}$	0.0201898*	0.0198701*	0.0577151***	0.0573513***
	(0.0102651)	(0.0102615)	(0.0060892)	(0.0152551)
$FDI_{i,t}$	-0.01669***	-0.0168923***	-0.019897***	-0.01993***
	(0.0037627)	(0.0037647)	(0.0371774)	(0.0060764)
$UNEMP_{i,t}$	0.0367937	0.0319347	-0.130756***	-0.12962***
	(0.0265357)	(0.026905)	(0.0015375)	(0.038007)
$EDU_{i,t}$	0.0003544	0.0003761	0.0006034	0.0005893
	(0.0009615)	(0.0009609)	(0.6029539)	(0.0015325)
$RINF_{i,t} * GNPIP_{i,t}$		-0.0024016		-0.000822
		(0.0022561)		(0.0036233)
R^2	0.9741	0.9745		
F-value/Wald Chi^2	188.26	178.15	1172.78	1182.14
F-sign/Prob Chi^2	0.0000	0.0000	0.0000	0.0000

Source: Stata 17.0 Output

Note: GDPC Gross Domestic Product Per Capita, FINF Food Inflation, GRDP Gross Regional Domestic Product, RINF Rice Inflation, CINF Maize Inflation, SINF Soybeans Inflation, GNPIP Dummy of GNPIP Policy (0 = Period before applying policy, 1 = Period of policy application); Prov-year obs. = 204, ****p < 0.01, **p < 0.05 and *p < 0.1

Table 4: Panel Data Regression Results on GDP per capita (GDPC).

The effect of food inflation on GDP per capita

Hypothesis 1a (H1a) is that food inflation has a significant effect on GDP per capita. Based on table 4, it can be concluded that in the baseline model and the interaction model, food inflation in the previous 1 period shows a significant negative effect, indicating that the impact of food inflation appears delayed.

People and economic actors may not directly adjust their consumption or investment when food prices rise in a certain period. However, after one period (for example one year), the increase in food prices began to erode the purchasing power of the household, especially low-income groups that allocated most of the expenses for food. The decline in purchasing power then reduces aggregate demand, decreases production, and eventually inhibits regional economic growth (GDP per capita).

These results are in accordance with the theory of Phillips curves and short-term trade-off vs. long-term. In the short term, inflation may not immediately reduce output (because of "money illusion"). But in the medium term, the community adjusts expectations, and inflation begins to interfere with the allocation of resources, causing a decrease in productivity and growth. These results are also in line with the results of research by (Headey, 2018; Heady and Hirvonen, 2023; Prabheesh and Laila, 2020; Sen et al., 2024) which states that food inflation has a significant effect on the GDP per capita.

The effect of rice inflation on GDP per capita

Hypothesis 1b (H1b) is that rice inflation has a significant effect on GDP per capita. Based on the Table 4, it can be concluded that in the baseline model and the interaction model, rice inflation in the previous 1 period shows a significant positif effect, indicating that the impact of food inflation appears delayed.

Rice price increases can increase the income of rice farmers and agricultural businesses (grinding, distributors). This higher income is spent back in rural areas (multiplier effects), encouraging local consumption and micro economic activity. However, this effect takes time to spread throughout the economic chain, so the impact is only seen in the next period. In areas with a strong agricultural base, the increase in rice prices diverts income from urban consumers to rural producers. If farmers have a tendency to consume high marginal, then their income increases quickly circulating in the local economy, encouraging growth. However, this positive effect is limited and contextual, meaning that it only occurs if the increase in rice prices is not too high or does not trigger broad inflation, and if the market remains controlled (not speculative). These results are in line with the results of research by (Headey, 2018; Heady and Hirvonen, 2023; Prabheesh and Laila, 2020; Sen et al., 2024) which states that food inflation has a significant effect on the GDP per capita.

The effect of corn inflation on GDP per capita

Hypothesis 1c (H1c) is that corn inflation has a significant effect on GDP per capita. Based on the table above (output stata), it can be concluded that in the baseline model and the interaction model, corn inflation (CINF) in the current period (t), one year earlier (t-1), and two years earlier (t-2) did not have a significant effect on GDP per capita.

There is no statistical evidence that corn inflation (both at this time and delayed) can affect regional economic growth. Corn is not a major consumption commodity, widely used as input, and the sector has not been integrated, so the price fluctuations do not create a strong multiplier effect. These results are consistent with the theory of consumption structure and income elasticity (Engel's Law) which states that non staple food commodities have low-income elasticity. Changes in the price of corn do not significantly change the pattern of consumption or savings, so it does not trigger economic growth.

The effect of soybean inflation on GDP per capita

Hypothesis 1d (H1d) is that soybean inflation has a significant effect on GDP per capita. Based on the Table 4, it can be concluded that in the baseline model and the interaction model, there is no significant relationship between soybean inflation (currently or delayed) with regional economic growth. This is due to import dependence, small production scale, and limited economic linkage, so that the fluctuations in soybean prices do not create measurable multiplier effects.

These results are consistent with the market theory of import commodities. Soybean inflation in Indonesia is mostly influenced by external factors, namely global prices, exchange rates, and logistics costs. In this theory, price increases do not create domestic added value. In addition, based on the theory of market structure and supply elasticity, soybean farmers include smallholder farmers with low supply elasticity. That is, they do not quickly respond to price increases by increasing production, so there is no growth effect from the supply side side.

The effect of GNPIP policy on GDP per capita

Hypothesis 2 (H2) is that GNPIP policy has a significant effect on GDP per capita. Based on the Table 4, it can be concluded that in the baseline model and the interaction model, the results were received both for FE and FGLS

for Robustness Test. This shows that GNPIP has a direct influence on GDP per capita.

The results show that the GNPIP policy has a positive and significant effect on GRDP per capita indicates that the government's efforts in controlling food inflation do not only have an impact on price stability, but also make a significant contribution to regional economic growth. The GNPIP program can help maintain community purchasing power, especially in low-income groups, most of whose expenses are allocated for food needs. Increasing aggregate purchasing power has the potential to encourage household consumption, which is the main component of the Gross Regional Domestic Product (GRDP). Furthermore, food price stability creates a more conducive business climate, thus encouraging investment and production activities in the agricultural and food sector. This contributes to increasing productivity and regional economic growth. In addition, the GNPIP policy that is collaborative between the central and regional governments, as well as involving various stakeholders such as Bulog, Bank Indonesia, and other institutions, strengthens coordination in inflation control. Efficiency and effectiveness in implementing the policy also supports the achievement of significant results on GRDP per capita. The results of this study are in line with studies conducted by Eberhardt and Vollrath (2016) which states that food price stabilization policies can increase economic growth through increasing domestic consumption. In addition, these results also support the research of George (2020) and Grabowski and Self (2023) who found that coordinated food policy interventions have a positive impact on regional economic performance. Furthermore, research by Li and Maskin (2021) and Markus and Dietrich (2018) also emphasized the importance of cross-sectoral and integrated policies in creating a sustainable macroeconomic impact. This shows that GNPIP, as a policy that integrates various aspects of inflation control and local economic development, has the potential to become an important instrument in regional economic development.

The role of GNPIP policy in moderating the effect of rice inflation on GDP per capita

Hypothesis 3 (H3) is that GNPIP policy moderates the relationship between rice price changes and GDP per capita. Based on the Table 4, it can be concluded that in the baseline model and the interaction model, GNPIP is unable to moderate the effect of rice inflation on GDP per capita. These results are contrary to the results of research by (Benzarti et al., 2024; Tan et al., 2024). Although GNPIP does not affect directly through moderation with rice inflation, there are other mechanisms that explain how GNPIP can increase GDP per capita.

Although GNPIP does not have significant indirect effects through moderation with rice inflation, this program can still increase GDP per capita through other mechanisms such as controlling general inflation, increased production efficiency and food distribution, other supporting policies, and "Announcement Effect". Announcements about the implementation of GNPIP can increase market and public confidence in food price stability. Higher confidence can encourage investment and consumption, which in turn can increase GDP per capita. The announcement of GNPIP policy that guarantees food availability continuously can provide positive signals to market participants that they do not need to worry about supply lack.

For example, if the government announces that national rice stocks are sufficient to meet the needs for the next few months, people tend not to do "panic buying". Thus, the announcement helps maintain price stability because excessive demand (due to panic buying) can be avoided. This price stability then has a positive impact on people's purchasing power and household consumption, which in turn increases GDP per capita. The cheap market movement initiated by GNPIP also has a strong announcement effect. If the government announces that there will be cheap market operations in various regions, people will feel calmer because they know that they can still get important commodities at affordable prices. This announcement can prevent price speculation and panic buying, because people believe that prices will remain stable or even down in the short term. This helps keep general inflation under control and increases people's purchasing power. In addition, the announcement of this program can also encourage coordination between related parties in managing food inflation, to produce a broader and more sustainable impact. Therefore, GNPIP still has an important role in increasing GDP per capita even though it does not go through the path tested in this model.

The "announcement effect" of the GNPIP program can increase GDP per capita through several major mechanisms: (1) Increasing public confidence and stability of inflation expectations, (2) encouraging investment and economic activity, (3) increasing people's purchasing power, (4) strengthening food security and local

production, (5) increasing market efficiency through digitalization, and (6) encouraging coordination between institutions. All these factors are interrelated and contribute to increasing economic stability, productivity, and community income, which in turn increases GDP per capita significantly. Announcement of GNPIP gives a strong signal to the public and economic actors that the government and Bank Indonesia are committed to maintaining food price stability. When inflation expectations are stable, consumers and producers tend not to react excessively to changes in short -term prices. For example, people will not rush to hoard food or reduce consumption for fear of rising prices. The stability of inflation expectations helps to maintain public purchasing power (purchasing power), so that household consumption remains stable or even increased. Stable consumption or increased contributions directly to economic growth, which in turn can increase GDP per capita. Announcement of the GNPIP program which includes concrete steps such as optimizing food distribution, subsidies for transportation costs, and increasing agricultural production gives positive signals to domestic and foreign investors about macroeconomic stability in Indonesia.

ICT infrastructure (information and communication technology) can encourage the adoption of digital technology, which increases market efficiency (Indrajaya et al., 2023). Investors tend to be more confident to invest in sectors related to food production and distribution, such as agriculture, logistics, and information technology, for example the development of the EWS (Early Warning System) to monitor food prices in real-time. Distributors can further respond to supply and demand imbalances, while consumers can buy products at more competitive prices. Increasing market efficiency contributes to reducing transaction costs and increasing productivity, which in turn can increase overall economic output.

One of the main objectives of GNPIP is to maintain the affordability of food prices, which is a priority in the 4K strategic framework (price affordability, availability of supply, smooth distribution, effective communication). When the price of food is stable or down due to the announcement of the GNPIP program, people's purchasing power increases. This allows households to allocate their income to other goods and services, such as education, health, or recreation. The overall increase in household consumption will encourage local and national economic growth, which in turn increases GDP per capita. Announcement of GNPIP which includes programs such as joint planting movements, optimization of agricultural machine tools (Alsintan), and replication of the best business models provide encouragement to farmers and micro, small and medium businesses (MSMEs) to increase production. When local production increases, dependence on food imports can be reduced, which in turn can save the country's foreign exchange. These foreign exchange savings can be diverted to support domestic economic development. In addition, an increase in local production also creates a longer economic value chain, ranging from upstream (production) to downstream (distribution and sales). Policy synergy between Bank Indonesia as cenral bank and the Indonesia government's fiscal policy has the potential to increase people's income along the value chain (Wardani, 2022).

The GNPIP announcement shows that the government and Bank Indonesia work together in an integrated manner to overcome the problem of food inflation. This synergy gives a positive signal to the public and economic actors that the policies taken are comprehensive and sustainable. Good coordination between institutions can accelerate the implementation of inflation control programs, so that the positive impact can be felt faster by the community. This contributes to the acceleration of the national economy recovery, which in turn increases GDP per capita. Thus, GNPIP does not only function as a means of controlling inflation, but also as a catalyst to support sustainable national economic growth.

Conclusion

Conclusion

Based on the results of the discussion and analysis of the effect of food inflation and GNPIP policy on GRDP per capita, it can be concluded as follows. Food inflation has a significant negative impact on GRDP per capita, but the effect is only seen in a delayed manner (one period). The increase in food prices erodes people's purchasing power, especially low-income groups that allocate most of their expenses for food needs. This decrease in purchasing power reduces aggregate demand, decreases production, and ultimately inhibits regional economic growth.

Rice inflation is different from food inflation in general, rice inflation shows a significant

positive effect on GRDP per capita, although it is also delayed for a period. This is caused by multiplier effects in the agricultural and rural sectors, where the increase in rice prices increases the income of farmers and agricultural businesses, which then encourages consumption and local economic activities. However, this positive effect is contextual and only occurs if the price increase is not too high and does not trigger broad inflation or market speculation.

Corn and soybean inflation does not have a significant effect on GRDP per capita, both in the current period and the previous period. This is caused by the limited role of the commodity as the main consumption material, import dependence (especially soybeans), and weak economic linkages and low supply elasticity. Thus, the price fluctuations in the two commodities do not create a broad impact on regional economic growth.

GNPIP Program has proven to have a positive and significant influence on GRDP per capita. This policy not only plays a role in maintaining food price stability, but also encourages economic growth through the maintenance of people's purchasing power, increasing household consumption, and a conducive business climate creation in the agricultural and food sector. The effectiveness of GNPIP is also strengthened by collaboration between the central government, regions, and various institutions such as Bulog and Bank Indonesia.

Although GNPIP does not have significant indirect effects through moderation with rice inflation, this program can still increase GDP per capita through other mechanisms such as controlling general inflation, increased production efficiency and food distribution, other supporting policies, and "Announcement Effect". It can provide positive signals to market participants that they do not need to worry about supply lack.

Recommendations

The government needs to continue to strengthen the policy of food price stabilization, especially for strategic commodities such as rice and other staple foods. The GNPIP program must be maintained and expanded in scope, with a focus on distribution efficiency, speculation control, and timely price intervention.

Considering that food inflation greatly affects the purchasing power of low-income people, social assistance programs such as food assistance or subsidies must be increased, especially when there is a significant increase in food prices.

In order to strengthen the positive effects of rising rice prices, the government needs to encourage the development of the local commodity-based agricultural sector through increased productivity, access to credit, and strengthening the supply chain. Thus, price increases can be truly utilized to encourage rural economic growth.

Commodity such as soybeans is very dependent on imports, so there needs to be a strategic effort to increase domestic production or find local alternatives (substitution). In addition, food diversification campaigns can reduce pressure on certain commodities and increase national food security.

GNPIP has not been able to moderate the impact of rice inflation on economic growth, so it is necessary to conduct an in-depth evaluation of the policy implementation mechanism. The government can consider a more proactive incentive scheme or market intervention so that the increase in rice prices does not have a negative impact on consumer groups, as well as still benefit producers.

The success of GNPIP shows the importance of coordination between institutions. For the future, collaboration between the central government, regional governments, BI, Bulog, and business actors must be strengthened through an integrated and responsive monitoring and evaluation system of market dynamics.

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References

[1] Afriyanti, G., Mariya, A., Natalia, C., Nispuana, S., Wijaya, M. and Phalepi, M. (2023) "The role of the agricultural sector on economic growth in Indonesia", *Indonesian Journal of Multidisciplinary Sciences (IJoMS)*, Vol. 2, No. 1, pp. 167-179. E-ISSN 2808-6724, ISSN 2808-5957.

[2] Bala, A., Hassan, A. and Muhammad, M. (2024) "Do board characteristics matter in the relationship between intellectual capital efficiency and firm value? Evidence from the Nigerian oil and gas downstream sector", *Future Business Journal*, Vol. 10, No. 1, pp. 74. E-ISSN 2314-7210. DOI 10.1186/s43093-024-00351-3.

[3] Beck, N. (2001) "Time-series-cross-section data: What have we learned in the last few years?", *Annual Review of Political Science*, Vol. 4, pp. 271-293. ISSN 1094-2939. DOI 10.1146/annurev.polisci.4.1.271.

[4] Benzarti, Y., Garriga, S. and Tortarolo, D. (2024) "Can VAT cuts and anti-profiteering measures dampen the effects of food price inflation?", *National Bureau of Economic Research*, NBER Working Paper. No. w32241, 60 p. ISSN 0077-3611. DOI 10.2139/ssrn.4762948.

[5] Bogmans, C., Pescatori, A. and Prifti, E. (2024) "How do economic growth and food inflation affect food insecurity?", *IMF Working Papers*, No. 2024/188, 57 p. ISSN 1018-5941. ISBN 9798400287336, DOI 10.5089/9798400287336.001.

[6] Bredenkamp, H. and Bersch, J. (2012) "Chapter 4 Commodity price volatility: Impact and policy challenges for low-income countries", International Monetary Fund, pp. 55-67. ISBN 9781616353797. DOI 10.5089/9781616353797.071.ch004.

[7] Eberhardt, M. and Vollrath, D. (2018) "The Effect of Agricultural Technology on the Speed of Development", *World Development*, Vol. 109, pp. 483-496. ISSN 0305750X. DOI 10.1016/j.worlddev.2016.03.017.

[8] Faharuddin, F., Yamin, M., Mulyana, A. and Yunita, Y. (2023) "Impact of food price increases on poverty in Indonesia: Empirical evidence from cross-sectional data", *Journal of Asian Business and Economic Studies*, Vol. 30, No. 2, pp. 126-142. ISSN 2515-964X. DOI 10.1108/JABES-06-2021-0066.

[9] George, T. (2020) "A new look at agricultural development and the non-agriculture economy in low-income countries", *Global Food Security*, Vol. 26, p. 100449. ISSN 2211-9124. DOI 10.1016/j.gfs.2020.100449.

[10] Grabowski, R. and Self, S. (2023) "Agricultural productivity growth and the development of manufacturing in developing Asia", *Economic Systems*, Vol. 47, No. 2. ISSN 0939-3625. DOI 10.1016/j.ecosys.2023.101075.

[11] Headey, D. (2018) "Food Prices and Poverty", *The World Bank Economic Review*, Vol. 32, No. 3, pp. 676-691. ISSN 1564-698X. DOI 10.1093/wber/lhw064.

[12] Headey, D. and Hirvonen, K. (2023) "Higher food prices can reduce poverty and stimulate growth in food production", *Nature Food*, Vol. 4, No. 8, pp. 699-706. E-ISSN 2662-1355. DOI 10.1038/s43016-023-00816-8.

[13] Indrajaya, D. and Iskamto, D. (2023) "Do fund's village, economic growth, inequal income distribution, unemployment rate, and human development index affect poverty in Indonesia?", *Proceedings of the International Conference on Sustainable Collaboration in Business, Technology, Information, and Innovation (SCBTII 2023),* Atlantis Press. ISSN 2352-5428. DOI 10.2991/978-94-6463-292-7_15.

[14] Indrajaya, D., Wardoyo, D. U., Santoso, T. I. and Iskamto, D. (2023) "Do Foreign Direct Investment and Innovation Influence ICT Goods Imports in ASEAN 6?", *2023 International Conference on Digital Business and Technology Management (ICONDBTM)*, pp. 1-6. E-ISBN 979-8-3503-2802-8. DOI 10.1109/ICONDBTM59210.2023.10327231.

[15] Ismail, N. and Houssein, A. (2020) "The impact of fiscal policy on GDP per capita: Evidence from Malaysia", *International Journal of Politics, Publics Policy and Social Works (IJPPSW)*, Vol. 2, No. 5, pp. 14-25. E-ISSN 2637-0980. DOI 10.35631/IJPPSW.25002.

[16] Ivanic, M., Martin, W. and Zaman, H. (2012) "Estimating the short-run poverty impacts of the 2010-11 surge in food price", *World Development*, Vol. 40, No. 11, pp. 2302-2317. ISSN ISSN 0305-750X. DOI 10.1016/j.worlddev.2012.03.024.

[17] Li, D. and Maskin, E. (2021) "Government and economics: An emerging field of study", *Journal of Government and Economics*, Vol. 1, p. 100005. ISSN 2667-3193. DOI 10.1016/j.jge.2021.100005.

[18] Mamat, H. and Husen, E. (2021) "Socio-economic aspect and carrying capacity of agricultural land resources to support the development of strategic agricultural commodities", *IOP Conference Series: Earth and Environmental Science*.,Vol. 648, p. 012019. ISSN 1755-1315. DOI 10.1088/1755-1315/648/1/012019.

[19] Negi, D. (2022) "Global food price surge, in-kind transfers and household welfare: Evidence from India", *World Development*, Vol. 158, p. 106009. ISSN 0305-750X. DOI 10.1016/j.worlddev.2022.106009.

[20] Nuryati, Y., Siregar, H. and Ratnawati, A. (2006) "Dampak kebijakan inflation targeting terhadap beberapa variabel makroekonomi di Indonesia", *Bulletin of Monetary Economics and Banking*, Vol. 9, No. 1, pp. 113-134. E-ISSN 2460-9196. DOI 10.21098/bemp.v9i1.153. (In Indonesian).

[21] Prabheesh, K. and Laila, N. (2020) "Asymmetric effect of crude oil and palm oil prices on economic growth: Evidence from Indonesia", *Bulletin of Monetary Economics and Banking*, Vol. 23, No. 2. E-ISSN 2460-9196. DOI 10.21098/bemp.v23i1.1304.

[22] Sen, A., Akpolat, A. and Balkan, I. (2024) "Commodity prices and economic growth: Empirical evidence from countries with different income groups", *Heliyon*, Vol. 10. ISSN 2405-8440. DOI 10.1016/j.heliyon.2024.e34038.

[23] Siregar, H. and Ward, B. D. (2001) "Sources of fluctuations in the Indonesian macroeconomy: An application of a simple structural VAR model", *Singapore Economic Review*, Vol 45, No. 1, pp. 73-98. ISSN 02175908.

[24] Siregar, H. and Ward, B. D. (2002) "Were aggregate demand shocks important in explaining Indonesian macroeconomic fluctuations?", *Journal of the Asia Pacific Economy*, Vol. 7, No. 1, pp. 35-60. ISSN 13547860. DOI 10.1080/13547860120110461.

[25] Solihin, A., Wardana, W., Fiddin, E. and Sukartini, N. (2021) "Do government policies drive economic growth convergence? Evidence from East Java, Indonesia", Cogent Economics & Finance, Vol. 9, No. 1. E-ISSN 2332-2039. DOI 10.1080/23322039.2021.1992875.

[26] Tan, Y., Yue, R., Chen, L., Li, C. and Chen, K. Z. (2024) "Grain price support policy and the distortion of market price", *China Agricultural Economic Review*, Vol. 16, No. 3, pp. 507-526. ISSN 1756-137X. DOI 10.1108/CAER-06-2023-0159.

[27] Tatiana, Y., Firdaus, M., Siregar, H. and Hariyoga, H. (2015) "Determinant factors of agricultural industry investment in province Bengkulu, Indonesia", *International Journal of Sciences: Basic and Applied Research (IJSBAR)*, Vol. 23, No. 2, pp. 312-323. ISSN 2307-4531.

[28] Wardani, V. (2022) "The role of Bank Indonesia in stabilizing Indonesia's economy through inflation control", *International Journal of Economics, Business and Innovation Research (IJEBIR)*, Vol. 1, No. 1. ISSN 2964-0865.

[29] Wodon, Q. and Zaman, H. (2010) "Higher food prices in sub-saharan Africa: Poverty impact and policy responses", *The World Bank Research Observer*, Vol. 25, No. 1, pp. 157-176. ISSN 1564-6971. DOI 10.1093/wbro/lkp018.

[30] Yogi, L., Tara, T. and Sarada, B. (2025) "The role of agriculture in Nepal's economic development: Challenges, opportunities, and pathways for modernization", *Heliyon*, Vol. 11, No. 2. ISSN 2405-8440. DOI 10.1016/j.heliyon.2025.e41860.

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Enhancing Innovative Potential in Ukraine's Agro-Industrial Complex: Leveraging Information Technologies for Sustainable Growth and Efficiency

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Abstract

The article analyzes key trends in enhancing the innovation potential of enterprises in Ukraine's agro-industrial complex and proposes strategies for their improvement. A model has been developed for the effective use of innovative capabilities of the regional agro-industrial pool, which adapts to various conditions. The research emphasizes significant progress in innovative processes that optimize resource management and increase productivity. It includes calculations and presents the obtained results. The study also examines the practical application of these achievements, focusing on agro-industrial companies that have successfully implemented information technologies to enhance operational efficiency, reduce costs, and promote sustainable agricultural practices. To facilitate growth and efficiency in Ukraine's agro-industrial sector, the research emphasizes the need to create a robust innovation ecosystem that combines theoretical concepts with real-world applications. Additionally, it proposes using the MS Excel FORECAST tool for analyzing future economic dynamics models. The implementation of a structured approach to strengthening innovation potential at all levels of the agro-industrial complex is expected to lead to increased investment, competitive advantages, and overall economic effectiveness for enterprises.

Keywords

Innovative potential, agro-industrial complex, information technologies, resource management, sustainable agriculture, economic efficiency.

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Introduction

The agricultural sector has traditionally been a cornerstone of Ukraine's economy, holding leading positions in global exports (State Statistics Service of Ukraine, n.d.). However, the development of the agro-industrial complex is constrained by internal management challenges, outdated technologies, and, critically, the destruction of infrastructure due to the ongoing war. Despite these threats, the sector's recovery relies on enhancing the innovation potential of enterprises. The objective of this research is to analyze key trends in the agro-industrial complex and identify strategies for strengthening its innovation potential to ensure competitiveness and economic resilience.

The concept of innovation potential is widely explored through resource theory (Lavrenenko et al., 2021; Stræte et al., 2022) and various assessment methodologies (Savytskyi, 2019; Hryhoruk et al., 2020; Piletska and Tkachenko, 2020; Saunila, 2020; Shvets and Dubei, 2021). The integration of innovations is recognized as a crucial factor for competitiveness in both

classical and contemporary literature (Schumpeter, 1912; Thompson, 1965; Ansoff et al., 2019; Harkema, 2003; Heiets, 2009; Ferreira et al., 2020; Puzyrova, 2020; Akhtar, 2023), as well as for profit growth (Faivishenko et al., 2020; Cherep et al., 2021; Hlubish, 2021).

In the Ukrainian context, scholars have analyzed the economic development of agricultural enterprises (Andriichuk, 2013; Balanovska et al., 2021; Sabluk, 2008; Skotsyk, 2017; Smulka, 2020; Ragaza et al., 2022), regional economic security (Trusova et al., 2020), and strategic resource management (Ulyanchenko et al., 2021). Particular attention is paid to managerial aspects of innovation (Blikhar et al., 2022; Kychko et al., 2021) and the formation of cluster structures (Lis et al., 2021; Hrosul et al., 2021; Kovalial et al., 2022).

Innovations in agriculture encompass the systematic implementation of new technologies (Karnaushenko et al., 2023). "Innovation potential" is interpreted as untapped resource opportunities (Shulhina et al., 2011), readiness for innovation (Mykytiuk, 2015), or a dynamic system of transforming ideas into products (Harbar, 2021; Goodman and Wilkinson, 2023). However, current political and economic conditions—including funding deficits, logistics disruptions, and war damage (Ministry of Agrarian Policy and Food of Ukraine, 2022b)—significantly hinder this development. Therefore, further research is required to develop new forms of organizational interaction and digital models to optimize the use of limited resources (Kyrylov et al., 2024).

Materials and methods

Research objectives. The main objective of this research is to analyze the innovation potential of production enterprises in Ukraine's agro-industrial complex, focusing on agricultural machinery, processing, and agricultural enterprises. The purpose of the study is to identify the current state of innovation activities, assess enterprise development dynamics, and propose a comprehensive mechanism for activating innovation potential.

Research design. This study employs a mixed-methods approach that combines quantitative and qualitative methods of data collection and analysis to ensure a comprehensive understanding of the innovation landscape in Ukraine's agro-industrial complex.

Data collection. Quantitative data:

- Data on the number of enterprises in the agro-industrial complex from 2017 to 2023 were collected from the State Statistics Service of Ukraine. These data include the number of production enterprises (agricultural, machinery manufacturing, and processing) and their respective shares in the overall industry.
- A structured questionnaire was developed and distributed among agricultural enterprises in Kirovohrad, Ternopil, and Cherkasy regions. The survey aimed to collect data on enterprise size, types of machinery used, and the scale of innovation activities. A representative sample of 7% of agricultural enterprises from these regions was targeted.

Qualitative data:

- In-depth interviews were conducted with key stakeholders, including managers and decision-makers from selected agricultural enterprises. The interviews aimed to explore challenges and opportunities related to innovation, investment, and machinery utilization.
- Specific cases of enterprises that exemplify successful or unsuccessful innovation practices were analyzed to provide contextual understanding of agro-industrial complex dynamics.

Data Analysis. The collected quantitative data were analyzed using descriptive statistics to summarize the characteristics of the studied enterprises, including their size distribution and machinery usage. The dynamics of enterprise numbers and their innovation activities over the specified period (2016-2024) were analyzed to identify trends and fluctuations.

Qualitative data from interviews and case studies were analyzed using thematic analysis to identify common themes and patterns related to innovation potential, challenges, and improvement strategies. A comparative analysis of Kirovohrad, Ternopil, and Cherkasy regions was conducted to identify regional differences in innovation activities and enterprise operations.

Model development. A model for utilizing the innovation potential of the agro-industrial

regional enterprise pool was developed. This model includes:

- Synergistic effect: Potential benefits from enterprise integration to enhance innovation potential and reduce costs.
- Innovation cycles: A framework for creating innovation cycles that promote continuous improvement and adaptation to market requirements.

Validation of findings. Data from various sources (surveys, interviews, and statistical data) were triangulated to confirm findings and enhance credibility. Preliminary results and proposed models were presented to stakeholders in the agro-industrial complex for feedback and validation, ensuring that the research addresses real challenges and opportunities.

Limitations. The research focuses on three regions, which may limit the generalizability of findings to other regions of Ukraine. Reliance on data obtained through surveys and interviews may introduce bias, as respondents may have incentives to present their enterprises in a more favorable light.

Results and discussion

Ukraine's agro-industrial complex encompasses diverse business entities, including agricultural machinery manufacturing enterprises (Am), agricultural enterprises (Ae), processing enterprises (e.g., in the food industry (Fd)), intermediary enterprises (traders), and others. This study focuses on production enterprises, particularly in agriculture, machinery manufacturing, and processing, as their innovation potential is crucial for the country's strategic development.

Table 1 presents an analysis of changes in the number of production enterprises within Ukraine's agro-industrial complex from 2017 to 2023.

From 2017 to 2023, the share of agricultural machinery manufacturing enterprises (M) in the industry and agro-industrial complex experienced moderate growth, averaging 3.67% and fluctuating from (-97) to 38 units. The dynamics of processing enterprises (F) and agricultural enterprises (A): F fluctuated between (-1%) and (+4.7%), while A ranged from (-24.7%) to (+2.7%). This information is vital for understanding the evolution of Ukraine's agro-industrial complex.

During the analyzed period, notable regional and national fluctuations in the number of agro-industrial enterprises were observed. Overall, in Ukraine, agricultural machinery enterprises increased by (+16.45%), and processing enterprises by (+6.22%), while agricultural enterprises experienced a decline of (-5.29%). This uneven dynamics among agricultural enterprises is a common trend for many regions of Ukraine, reflecting the complexity and diversity of the situation. Before the war, from 2017 to 2021, only four out of 25 regions of Ukraine reported growth in the total number of agro-industrial enterprises: Poltava (+4.3%), Sumy (+3.7%), Khmelnytskyi (+62.8%), and Chernihiv (+1.8%). In contrast, two regions - Volyn (-20.1%)

Enterprises \ Year		2017	2018	2019	2020	2021	2022	2023
Industry, including (M, F)		123,876	125,859	130,324	126,337	126,386	102,500	114,155
The agro-industrial complex	M	545	561	591	616	626	529	567
	F	15,119	15,544	16,275	16,222	16,206	13,937	16,406
	Share (M, F) in the industry / Share (M, F) in the agro-industr. complex, %	12.6/17.1	12.8/17.5	12.9/18.4	13.3/19.4	13.3/19.2	14.11/21.4	14.87/21.2
	A	75,992	75,730	74,858	70,059	70,803	53,281	62,960
	Total the agro-industrial complex (manufact. sector)	91,656	91,835	91,724	86,897	87,635	67,747	79,933
Manufact. enterprises of the total		199,868	201,589	222,048	196,396	197,189	155,781	177,115
The share of A (%)		38	37.6	33.7	35.7	35.9	34.2	35.55

Note: The presented statistics do not include activities of budgetary institutions or regions temporarily occupied by the Russian Federation, offering a thorough overview of Ukraine's agro-industrial complex.

Source: Prepared by authors using statistical data from the State Statistics Service of Ukraine (n.d.), (Petrova et al., 2024).

Table 1: Study of enterprise number trends within Ukraine's agro-industrial complex from 2017 to 2023.

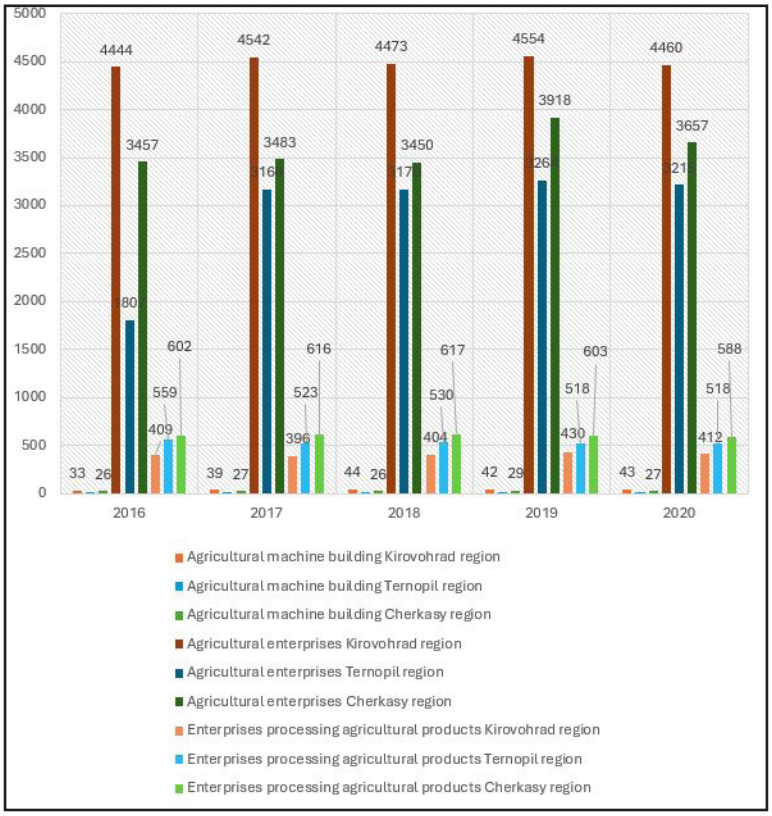
and Chernivtsi (-18.3%) - experienced decline. In most regions (19), the dynamics of agro-industrial enterprise activities differed significantly by type. This variability was particularly evident in Kirovohrad, Ternopil, and Cherkasy regions, which were selected for more detailed analysis. It can be concluded that the trends observed in these regions are representative of broader patterns throughout Ukraine.

In Kirovohrad region during the analyzed period, the number of agricultural machinery manufacturing enterprises increased by 30.30%, processing enterprises by 0.73%, while agricultural enterprises experienced a decline of 0.58%. In Ternopil region, the number of agricultural machinery manufacturing enterprises doubled (100% growth), but food industry enterprises decreased by 7.32%, and agricultural enterprises fell by 10.50%. In Cherkasy region, the number of agricultural machinery manufacturing enterprises increased by 3.85%, processing enterprises by 2.33%, and agricultural enterprises by 1.61%. Overall, the period from 2017 to 2021 was characterized by unstable dynamics in the development of agro-industrial enterprises.

In 2019, driven by expectations of positive changes after elections, there was a surge in the creation of new agricultural enterprises, with their number in Cherkasy region increasing by 78. However, this growth was short-lived, as a decline of 123 units was observed in 2020 (State Statistics Service of Ukraine, n.d.).

Figure 1 illustrates the disproportionate structure of the agro-industrial complex in almost all regions of Ukraine. Moreover, the number of agricultural machinery manufacturing enterprises, which are crucial for innovation implementation, remains low, accounting for only 0.18% to 0.87% of the total number of agro-industrial enterprises in the studied regions.

The Kirovohrad, Ternopil, and Cherkasy regions as of 2020 together account for 13.7% of Ukraine's total area allocated to grain and legume crops (with a production share of 15.4% of the total harvest in Ukraine). According to data on gross agricultural production for 2020, the combined share of Kirovohrad, Ternopil, and Cherkasy regions was



Source: Prepared by authors using statistical data from the State Statistics Service of Ukraine (n.d.)

Figure 1: Trends in the number of active enterprises within the agro-industrial complex in the Kirovohrad, Ternopil, and Cherkasy regions from 2016 to 2020.

approximately 15.1% of the country's total volume (State Statistics Service of Ukraine). These regions primarily focus on crop production, particularly the cultivation of grain and technical crops. However, quantitative analysis of agro-industrial enterprises must also include a comprehensive assessment of their innovation potential. Qualitative indicators related to the development of these enterprises are closely linked to their innovation activities. Currently, the average innovation activity of agricultural machinery manufacturing enterprises in Ukraine is 15.7%, which is lower than the approximately 20% observed in the industrial sector (State Statistics Service of Ukraine). Therefore, these enterprises are unable to adequately meet the demand for innovative products from agricultural producers.

In the agro-industrial complex processing sector, sunflower oil production is developing most rapidly, supported by state protection of sunflower seed exports. Sunflower oil exports are highly profitable for Ukraine, generating revenue of $6.4 billion in 2021 (Agronews, 2021), and constitute a significant portion of the country's processed product exports. In 2019, the implementation of new technological processes at processing enterprises was 6.8%, and the level of innovation activity among agricultural processing enterprises was 14.7% (State Statistics Service of Ukraine, n.d.). Overall, from 2016 to 2019, research and development expenditures in Ukraine demonstrated positive growth (2016 – 11,530.7 million UAH, 2017 – 13,379.3 million UAH, 2018 – 16,773.7 million UAH, 2019 – 17,254.6 million UAH), but a decline was observed in 2020 (2020 – 17,022.4 million UAH) (Tomashuk, 2023).

The authors' analysis of the innovation potential of agro-industrial enterprises revealed a number of development problems:

- Many machinery manufacturing and processing enterprises of Ukraine's agro-industrial complex do not meet the current level of innovation development and are balancing on the edge of bankruptcy.
- Equipment for soil cultivation, sowing, and fertilizers largely attempts to compete with products from developed countries, with production having decreased almost 30-50 times since Ukraine's independence (Ministry of Agrarian Policy and Food of Ukraine, 2022a).
- Most manufactured agricultural machinery belongs to the 1st or 2nd generation, characterized by low technological efficiency and single-operation capabilities (Ministry of Agrarian Policy and Food of Ukraine, 2022a).
- Some enterprises have been completely liquidated (for example, JSC "Ternopil Combine Plant," which manufactured sugar beet harvesters, went bankrupt), while others have been dismantled for scrap metal (for example, sugar processing plants, canning facilities, etc.).
- Ukrainian enterprises predominantly produce goods in single batches or small batches. For example, JSC "Elvorti" in Kropyvnytskyi (Kirovohrad region) produces seeders, cultivators, and disc harrows in limited quantities.

Thus, in the pre-war period, both agricultural machinery and processing enterprises experienced decline due to the erosion of their production capabilities. The ongoing hostilities exacerbate the situation in the agro-industrial complex. Positive transformations in the agricultural sector are possible through strengthening production and innovation potential, which is extremely necessary for producing high-quality modern products, including agricultural machinery. This necessitates a radical renewal of the sector. A crucial factor in stimulating innovation in the agro-industrial complex is the readiness of agricultural producers to implement new technologies.

During the period from 2019 to 2023, the authors conducted interviews with agricultural enterprises in Kirovohrad, Ternopil, and Cherkasy regions, using a representative sample of 7%. Respondents possessed characteristics reflecting broader population segments. The survey included agricultural enterprises of various sizes (see Table 2).

Regions	Size		
	Large	Medium	Small
Kirovohrad	0.96	0.87	1.23
Ternopil	6.41	4.35	5.35
Cherkasy	92.72	94.78	93.42

Source: Prepared by the authors using data from the interviews.

Table 2: Percentage distribution of agricultural enterprises in Kirovohrad, Ternopil, and Cherkasy regions by size.

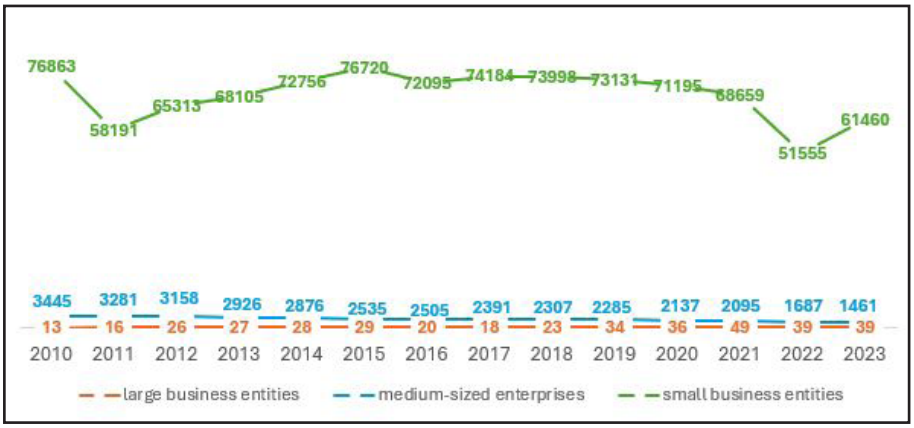
The study indicates that small agricultural enterprises predominate in Kirovohrad, Ternopil, and Cherkasy regions, which corresponds to the nationwide distribution shown in Figure 2.

Over the past thirteen years, small agricultural enterprises have comprised the "lion's share" of Ukraine's agricultural enterprises (more than 96% from 2010-2023). During the study, we developed a questionnaire and conducted interviews, the results of which are summarized and presented in Table 3.

The research results showed that during the period from 2019 to 2023, agricultural producers demonstrated a specific set of characteristics (Table 3).

The process of machinery modernization is influenced by enterprise size. Agricultural holdings are in the most advantageous position, as they replace at least 50% of their machinery and equipment and possess 75% to 100% modern foreign agricultural machinery. In contrast, small and medium agricultural enterprises are in a worse position.

The study showed that Kirovohrad region faces the lowest rates of agricultural machinery fleet renewal. Thus, 55.5% of the fleet either updates very slowly or does not update at all. The main factor affecting this problem, as noted in interview responses, is the financial constraints faced by respondents, which significantly limit their purchasing capabilities.



Source: Compiled by the authors based on statistical data (State Statistics Service of Ukraine, n.d.)

Figure 2: Dynamics of the number of active subjects of small and micro enterprises of agriculture, forestry and fisheries in 2010-2023.

Equipment Load Indicators	Cherkasy	Ternopil	Kirovohrad
Agricultural machinery fleet	Updated in the range of 10-30%, mainly through imported used agricultural machinery	Relatively updated for large and most medium agricultural enterprises, and can practically be considered updated for small ones, but in this case it is conditioned by imported used agricultural machinery	Not updated at significant rates (mainly 5-10%), and there are enterprises where no updates have occurred at all in recent years (Figure 4)
New generations of agricultural machinery	Used by 80% of respondents. At the same time, if small agricultural enterprises cannot afford to buy certain agricultural machinery, they cooperate	Used by 95% of respondents	Used by 50% of respondents
Agricultural machinery in farms	Imports predominate in percentage terms	All farms use imported multi-profile machinery, as production diversification strategies are being implemented in the region	The percentage of domestic products is higher

Source: Grouped based on questionnaire data, Petrova et al., 2024

Table 3: Comparative analysis of machinery use in the studied regions.

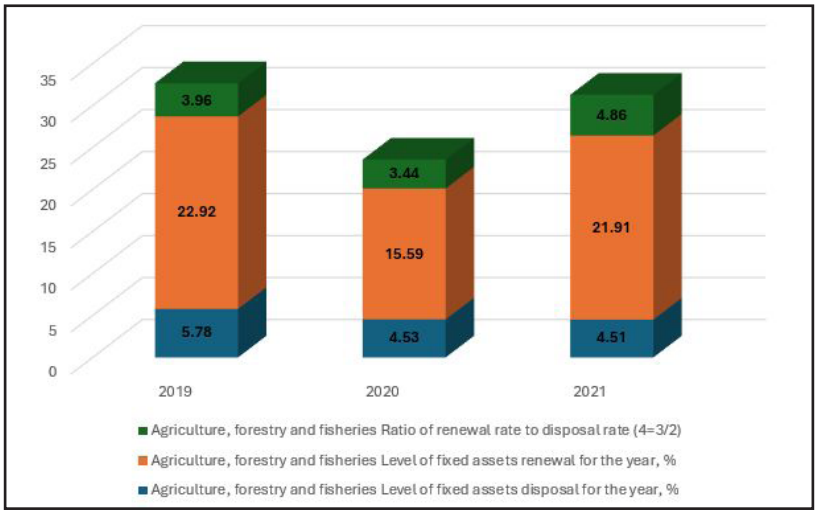
The survey results lead to the following conclusions:

- The complexity and diversity of agricultural machinery on farms is increasing, as reported by 80% of respondents. However, financial constraints prevent them from updating equipment.
- High costs hinder the transition to growing "clean" agricultural products that contain minimal amounts of health-harmful chemical compounds and are GMO-free.
- Enterprises predominantly rely on traditional technologies, and only some use no-till methods, agricultural drones, or tractors with autopilot.
- Almost all enterprises have their own, albeit outdated, machinery and do not engage in agricultural machinery leasing.

The cost of updating fixed assets in Ukraine's agriculture, especially in the studied regions, is increasing due to high prices associated with purchasing agricultural machinery (Figure 3).

During the period from 2019 to 2021, fixed asset disposal rates varied from 4.5% to 5.8%, while renewal rates fluctuated from 15.6% to 22.9%. Notably, renewal rates exceeded disposal levels by an average of 3.95 times, indicating the sector's commitment to modernization and growth. However, in 2022, combine harvester purchases fell by 2.4 times compared to the previous year, and tractor purchases were halved (Agravery, 2022, 2023).

This decline occurs during a period when Ukraine, including its agro-industrial complex, is experiencing significant losses due to military conflicts. Specifically, 84.2 thousand units of machinery and equipment have been destroyed or damaged (11% of the total available as of February 24, 2022) (Ministry of Agrarian Policy and Food of Ukraine, 2022b). The study also examined additional factors affecting the attraction of investment and labor resources to enhance the potential of agricultural enterprises (Table 4).



Source: Prepared by the authors using statistical data (State Statistics Service of Ukraine, n.d.). (the last update of this indicator on the Ukrstat website was in 2021)

Figure 3: Trends in fixed assets development of agricultural enterprises in Ukraine from 2019 to 2021.

Indicators	2017	2018	2019	2020	2021	2022	2023
Capital investments in agriculture, hunting and related services, million UAH	64084.08	66576.32	59910.06	50634.30	69966.30	51355.69	65150.63
Including machinery and equipment, million UAH (%)	48934.47 (76.36)	45460.35 (68.28)	37835.06 (63.15)	32941.86 (65.06)	47802.59 (68.32)	34446.34 (67.07)	42093.23 (64,61)
Labor costs at agricultural enterprises, million UAH	36028.21	45243.12	51830.75	53765.67	64335.68	61201.39	66012.30
Volume of agricultural, forestry and fishery products sold, million UAH	454380.10	525096.89	556325.87	605483.12	918661.15	680489.94	780089.52

Source: Prepared by authors using statistical data (State Statistics Service of Ukraine, n.d.).

Table 4: Trends in investment attraction, labor costs, and sales volumes of agricultural enterprises in Ukraine from 2017 to 2023.

Various factors influence the volume of products sold. Analysis of Table 4 shows how investment growth and labor costs affect final results. In 2023 compared to 2017, capital investments increased by only 1.66%, but were characterized by unstable dynamics during the analyzed period. During this period, labor costs increased by 83.22% (primarily due to minimum wage increases), leading to a 71.68% increase in product sales volume.

To attract investment, it is important to understand the dynamics of future behavior of economic entities, characterized by growth rates and trends during the specified period. Next, we examine the dynamics of economic entities' activities using the example of three typical small agricultural enterprises A, B, C (Table 5).

Table 6 presents forecast indicators for small agricultural enterprises (A, B, C) for 2025–2027, based on 2016–2024 data, calculated using the FORECAST function in Microsoft Excel.

While small enterprises benefit from operational flexibility and local knowledge, they face critical economic limitations when scaling. Under resource

Indicators	2016	2017	2018	2019	2020	2021	2022	2023	2024
Agricultural Enterprise A									
Enterprise capital	4930.8	5454.9	6276.5	6751.9	7616.7	9736	15129.1	13549.8	15328
Labor costs	429.42	691.5	917.67	908.43	930.2	1090.12	1020.1	1140.3	1223.6
Net revenue from product sales	2688.2	3111.5	4428.5	4166.3	4621.6	7532.7	8968	6861.4	9177.34
Innovation development costs	-	90	130	100	200	290	310	390	430
Agricultural Enterprise B									
Enterprise capital	-	-	-	40207	46293	81360	104027	121432	147981
Labor costs	-	-	-	2288	1726	1878	2194	4580	6023
Net revenue from product sales	-	-	-	55466	41893	56820	49609	44238	99058
Innovation development costs	-	-	-	470	500	680	420	630	780
Agricultural Enterprise C									
Enterprise capital	-	-	-	-	8947	8069	7802	19346	62010
Labor costs	-	-	-	-	5212	8086	9714	11087	10498
Net revenue from product sales	-	-	-	-	43281	65740	66645	96132	84069
Innovation development costs	-	-	-	-	150	190	180	510	540

Source: prepared by authors using data from enterprises A, B, C

Table 5: Performance indicators of small agricultural enterprises in 2016-2024, thousand UAH.

Indicators	MS Excel FORECAST			Function
	2025	2026	2027	
Agricultural Enterprise A				
Enterprise capital	16806.5	18244.9	19683.3	y = 1442.7x + 2205.7
Labor costs	1305.2	1387.2	1469.2	y = 0.5179x - 1043.9
Net revenue from product sales	10119.2	10944.3	11769.5	y = 827.53x + 1590.8
Innovation development costs	480.0	531.7	583.4	y = 0.5179x + 0.0857
Agricultural Enterprise B				
Enterprise capital	172222.0	195343.8	218465.5	y = 22484x + 11521
Labor costs	6863.9	7772.4	8681.0	y = 787.23x + 359.53
Net revenue from product sales	87443.1	95022.7	102602.3	y = 6222.4x + 36069
Innovation development costs	764.0	813.0	862.0	y = 0.48x + 4.12
Agricultural Enterprise C				
Enterprise capital	62700.1	75517.1	88334.2	y = 11740x - 13986
Labor costs	12566.7	13856.8	15147.0	y = 1357.3x + 4847.5
Net revenue from product sales	117571.0	116448.4	142378.3	y = 11197x + 37583
Innovation development costs	725.3	816.7	989.6	y = 1.1x - 0.16

Source: prepared by authors using data from enterprises A, B, C

Table 6: Forecast performance indicators of small agricultural enterprises A, B, C for 2025-2027, thousand UAH.

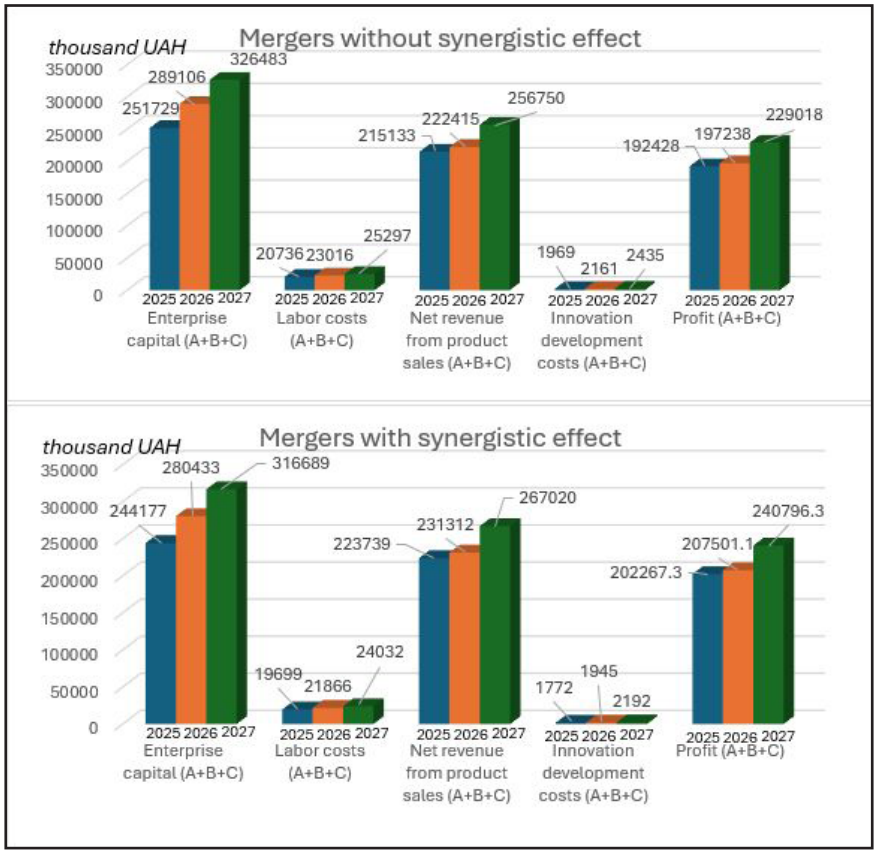
constraints, cooperation becomes the primary pathway to competitiveness. This study examines synergistic effects in two key areas: resource optimization and revenue growth, applying conservative estimates of savings and additional revenue at the level of 3–10%.

The most significant impact is observed in **capital resource savings** (estimated at ~11–13%), which enables the shared use of high-cost machinery. For instance, a modern grain harvester ($300–400 thousand) is economically unfeasible for a single 200-hectare farm due to low utilization (<10% of time). However, a cooperative of three farms (600–900 ha) can effectively utilize one unit, generating absolute savings of up to $800 thousand. This principle extends to infrastructure projects, such as grain elevators, where a joint investment of $2–3 million becomes viable. Simultaneously, **labor cost optimization** (~5%) arises from eliminating role duplication; instead of separate administrative staffs, a cooperative can employ fewer, higher-qualified specialists and optimize seasonal labor redistribution. Regarding **innovation implementation** (~10%), cooperation makes advanced technologies like precision farming ($50–100 thousand) financially accessible, reducing the investment burden from 10–20% of a single farm's revenue to a manageable 3–7% for the group. Finally, the synergistic effect contributes to a projected ~4% increase in **marketing and sales** revenue by enabling direct negotiations with exporters and optimizing logistics.

A comparative analysis of the enterprises (A+B+C) with and without cooperation effects was modeled using custom software. The calculations reveal that in 2025 alone, synergistic processes generate an additional profit of approximately **9.8 million UAH ($240 thousand)**. Figure 4 illustrates the stable growth of this indicator to 11.7 million UAH by 2027.

However, it is crucial to note that successful consolidation requires careful management, as ignoring compatibility factors can lead to "negative synergy" and integration failure.

To build a mathematical model of innovation potential for individual and consolidated



Source: Predicted and prepared by the authors using data from enterprises A, B, and C.

Figure 4: Impact of synergistic effect on cooperation between agricultural enterprises A, B, and C.

enterprises depending on investment volume, we define limitations and assumptions.

Mathematical limitations:

1. Function monotonicity – the model does not account for possible inflection points in real economic processes;
2. Exponential character – may lead to unrealistically large values during extrapolation;
3. Determinism – does not account for stochastic factors of the real economy.

Economic assumptions:

1. Stability of external conditions – the model assumes unchanged market environment;
2. Absence of competition – competitive reactions are not considered;
3. Cost linearity – proportionality between investments and potential results is assumed.

The model is based on a linear function of investment scaling:

$$Investment\ Size = Maximum\ Investment \times (i/100)$$

where i – variable from 0 to 100 with step 10, i.e., i takes values (0, 10, 20, 30, 40, 50, 60, 70, 80, 90, 100).

This relationship creates uniform distribution of analysis points from 0% to 100% of maximum investment. The linearity of this function ensures objective comparison of efficiency at different capital investment levels, which is critically important for correct economic analysis.

Mathematical model for individual enterprises. This formula reflects the law of diminishing marginal efficiency, a fundamental principle of economic theory. Mathematically, this is expressed through an exponential function with base less than one (0.98<1). The efficiency function for individual enterprises is described by the following exponential relationship:

$$Efficiency\ for\ individual\ enterprise = E_{base} \times 0.98^{(i/10)}$$

where:

E_{base} – initial efficiency reflecting the basic level of innovative productivity of a small enterprise. Accepted as 0.12 (12%);

0.98 – efficiency reduction coefficient, meaning 2% efficiency loss at each scaling stage;

(i/10) – exponent ensuring gradual efficiency reduction.

The physical meaning of this relationship is that small enterprises face resource limitations and inability to effectively utilize large investment volumes.

Mathematical model for consolidated enterprises. This formula demonstrates the economy of scale effect through an exponential function with base greater than one (1.02>1). The efficiency function for consolidated enterprises has the opposite trend:

$$Efficiency\ for\ cooperation = E_{base} \times 1.02^{(i/10)}$$

where:

E_{base} – initial efficiency reflecting the basic level of innovative productivity of a small enterprise. Accepted as 0.15 (15%);

1.02 – efficiency growth coefficient, meaning 2% efficiency increase at each scaling stage;

(i/10) – exponent ensuring progressive efficiency growth.

Innovation potential calculations. Innovation potential for individual enterprises is determined by:

$$Innovation\ Potential = Investment\ Size \times Efficiency\ for\ individual\ enterprise$$

Innovation potential for consolidated enterprises is determined by:

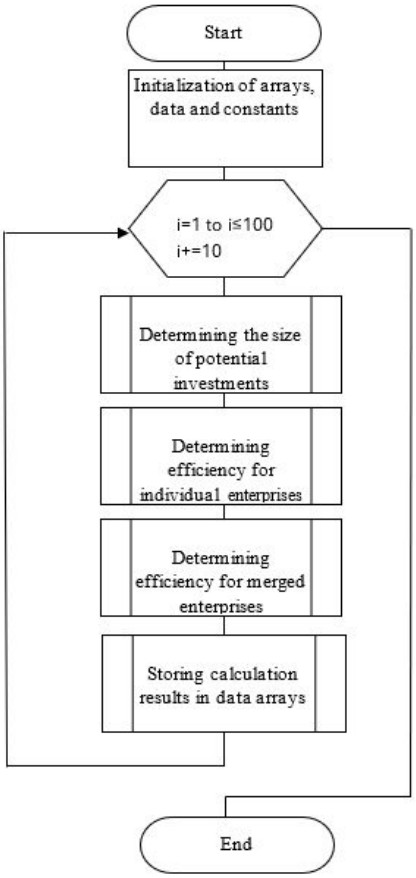
$$Innovation\ Potential = Investment\ Size \times Efficiency\ for\ cooperation$$

The algorithm flowchart for calculating innovation potential is shown in Figure 5.

An innovative approach to modeling synergistic effects through the use of exponential functions with opposite trends has been developed. This allowed quantitative description of qualitative differences in behavior of different organizational structures and ensured mathematical rigor of analysis.

The key value of the developed model is its ability to determine critical points for making strategic decisions about enterprise consolidation. The model combines mathematical objectivity with economic justification, guaranteeing practical applicability of results in real conditions.

Further model development may include



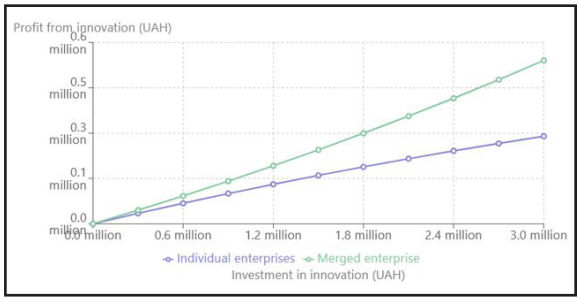
Algorithm start
Initialization – creating an empty array and calculating maximum investments
Loop cycle from 0 to 100. Result: variable i will take values (0, 10, 20, 30, 40, 50, 60, 70, 80, 90, 100)
Function calculation const investment = maxInvestment * (i / 100)
Function calculation const individualEfficiency = 0.12 * Math.pow(0.98, i/10)
Function calculation const mergedEfficiency = 0.15 * Math.pow(1.02, i/10)
Storage: adding calculation results to arrays innovationScaleData.push({ investment, individual: investment * individualEfficiency, merged: investment * mergedEfficiency })
End of algorithm

Source: Constructed by authors.

Figure 5: Algorithm flowchart for calculating innovation potential.

consideration of stochastic factors to improve forecasting accuracy, nonlinear effects, and dynamic market environment changes, making it even more realistic and useful for practical application in innovation process management.

The calculation results are presented as a graph in Figure 6, and the complete simulation was performed in Visual Studio Code environment – the result of which is shown in Analysis of the effectiveness.



Source: Constructed by authors.

Figure 6: Innovation efficiency depending on scale.

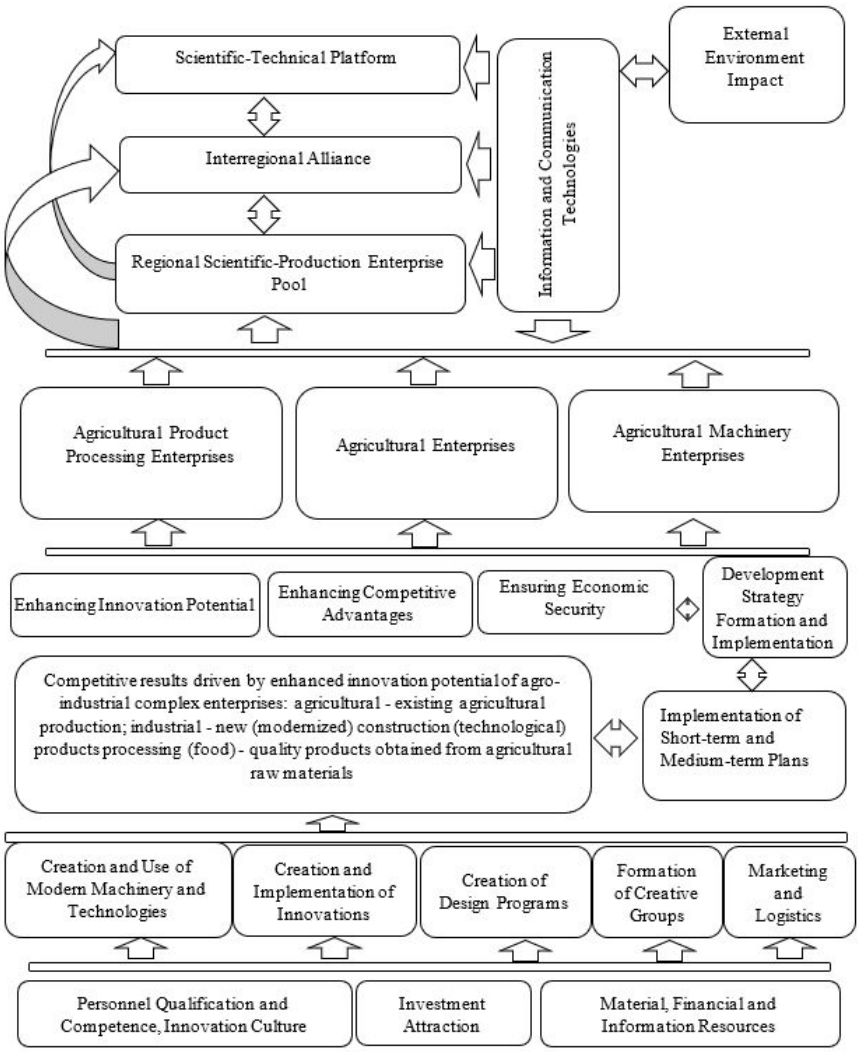
Figure 6 indicates that while large and medium agricultural enterprises possess significant development opportunities, small enterprises have yet to utilize their hidden innovation potential. Our surveys in Kirovohrad, Cherkasy, and Ternopil regions revealed that unlocking this potential requires investment, management optimization, and, crucially, the development of cooperative relationships. To address these challenges, we propose a multi-level modernization strategy.

At the state level, the role should shift from direct subsidies to creating institutional conditions for small producers. A promising direction is establishing public-private partnerships that leverage the trend toward decentralization. Partnerships between local communities and businesses can strengthen local governance capabilities, where the state acts as a partner ensuring coordinated actions and priority setting. Furthermore, we propose the creation of interregional alliances, which are temporary scientific-technical associations uniting several regions. For example, an alliance between Kirovohrad, Ternopil, and Cherkasy regions is

viable due to their complementary characteristics, such as the presence of agricultural universities, similar soil quality, and high grain yields. Such alliances would facilitate investment attraction, scientific exchange, and logistics optimization.

At the regional level, given the unstable economic situation and lack of trust, a direct transition to full-scale cooperation is difficult. Therefore, we recommend a phased approach starting with "pool"-type associations. These temporary associations allow enterprises to solve specific tasks, such as joint procurement, sales coordination, or innovation sharing, without a full legal merger. Even at this initial stage, pools generate significant synergistic effects, including reduced unit costs, shared access to new technologies, and stronger negotiating positions. In this structure, profits can be contributed to common funds and distributed proportionally, integrating local community structures with universities and production units.

Finally, a state-level scientific-technical platform should be created to integrate management bodies with business and science, promoting the self-synchronization of agricultural enterprises. A successful example of such cooperation is the testing of experimental seeders by JSC "Elvorty" in partnership with scientific institutes. The innovative potential of such an enterprise pool functions as a probabilistic dynamic system, where effective management relies on the optimal combination of informational, intellectual, financial, and technological resources. The system must be open and dynamic to respond to external changes, aligning with the law of requisite variety. Based on this analysis, we have structured the components of a comprehensive mechanism for activating innovation potential (see Figure 7).



Source: Constructed by authors.

Figure 7: Mechanism for activating innovative potential of key agricultural enterprises.

Effective development requires a market-oriented strategy focused on high-quality innovative products. To minimize risks and optimize resources, the management structure must shift from rigid hierarchy to **project teams** and creative groups led by process owners (Petrova et al., 2010). This approach stimulates "idea generators" and enhances flexibility.

Given that innovation in agricultural machinery is capital-intensive, the priority should be attracting investments to modernize existing equipment, followed by modeling the optimal level of innovative expenditures.

Forming regional associations generates "**second-level synergistic effects.**" While scaling may increase coordination costs, it significantly strengthens innovative potential. Furthermore, integrating these associations into state-supported platforms facilitates access to grants, promotes **circular economy** principles, and delivers socio-economic benefits such as job creation and environmental protection.

Conclusion

The post-war recovery of Ukraine's agro-industrial complex requires a fundamental shift toward innovative technologies. The analysis of agricultural enterprises revealed a low level of readiness for innovation due to a lack of investment and effective management. To address this, the study proposes a flexible model for forming regional agro-industrial associations (covering 3–5 regions) that integrate territorial communities, universities, and industry.

A key finding is the mathematical demonstration of the synergistic effect: while individual enterprises face diminishing returns on investment due to resource limitations, integrated structures show growing efficiency through economies of scale. Therefore, the priority for further research is the development of specialized information systems and software. These IT solutions will allow agricultural producers to transition from empirical estimates to scientifically grounded calculations, modeling investment scenarios and justifying the economic feasibility of cooperation.

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References

[1] Adamchuk, V. V., Kvasha, Y. L., Savchenko, I. F., Borys, A. M., Rykhlivskyi, P. A., Lysaniuk, V. H. and Shynkevych, Y. B. (2021) "Peculiarities in the design of the cutting apparatus for universal sowing of seeded and small-scale vegetable crops", *Mechanization and Electrification of Agriculture: Nationwide Collection*, Vol. 14, No. 113, pp. 105-112. ISSN 2603-3704.

[2] Agronews (2021) "*The largest importers of Ukrainian oils have been introduced*". [Online]. Available: https://agronews.ua/news/nazvano-najbilshyh-importeriv-ukrayinskyh-olij [Accessed: Jan 12, 2024].

[3] Akhtar, N. (2023) "Unlocking the Potential: The Impact of Innovative Capability on Process, Product, and Market Innovation and Firm Performance", *Marketing and Management of Innovations*, Vol. 14, No. 2, pp. 19-33. ISSN 2451-1668. DOI 10.21272/mmi.2023.2-03.

[4] Andriichuk, V. H. (2013) "Economics of enterprises of the agro-industrial complex", KNEU, Kyiv, 779 p. (In Ukrainian).

[5] Ansoff, H. I., Kipley, D., Lewis, A. O., Stevens, H. and Ansoff, R. (2019) "Implanting Strategic Management", Palgrave Macmillan, Cham, Switzerland, 592 p. ISBN 978-3-319-99598-4. DOI 10.1007/978-3-319-99599-1.

[6] Balanovska, T., Mykhailichenko, M., Holik, V., Dramaretska, K. and Troian, A. (2021) "Development management of agricultural enterprises", *Financial and Credit Activity: Problems of Theory and Practice*, Vol. 3, No. 38, pp. 134-143. E-ISSN 2310-8770, ISSN 2306-4994. DOI 10.18371/fcaptp.v3i38.237434.

[7] Blikhar, V., Kopytko, M., Patsula, O., Synenkyi, V. and Bulachek, V. (2022) "Management and legal aspects of economic security of enterprises in the process of innovation", *Financial and Credit Activity: Problems of Theory and Practice*, Vol. 6, No. 41, pp. 360-368. E-ISSN 2310-8770, ISSN 2306-4994. DOI 10.18371/fcaptp.v6i41.251445.

[8] Cherep, A., Beridze, T., Baranik, Z., Korenyev, V. and Dashko, I. (2021) "Assessment of the competitiveness of industrial enterprise activities", *Financial and Credit Activity: Problems of Theory and Practice*, Vol. 3, No. 38, pp. 272-280. E-ISSN 2310-8770, ISSN 2306-4994. DOI 10.18371/fcaptp.v3i38.237457.

[9] Faivishenko, D., Dubovyk, T., Savchuk, A. and Romanchenko, T. (2020) "Strategic impact of innovations on enterprises financial state", *Financial and Credit Activity: Problems of Theory and Practice*, Vol. 4, No. 35, pp. 411-417. E-ISSN 2310-8770, ISSN 2306-4994. DOI 10.18371/fcaptp.v4i35.222442.

[10] Ferreira, J., Coelho, A. and Moutinho, L. (2020) "Dynamic capabilities, creativity and innovation capability and their impact on competitive advantage and firm performance: The moderating role of entrepreneurial orientation", *Technovation*, Vol. 92, p. 102061. ISSN 0166-4972. DOI 10.1016/j.technovation.2018.11.004.

[11] Goodman, D. and Wilkinson, J. (2023) "Patterns of research and innovation in the modern agro-food system", In: *Technological Change and the Rural Environment*, 1st ed., Routledge, pp. 127-146. ISBN 9781003394624.

[12] Government Portal. (2024) "*Denys Shmyhal: Our priority is to support domestic producers*". [Online]. Available: https://www.kmu.gov.ua/en/news/denys-shmyhal-nash-priorytet-pidtrymka-vitchyznianoho-vyrobnyka [Accessed: Feb 10, 2024].

[13] Harbar, V. (2021) "The essence and structure of the innovative potential of the enterprise", In: *2020: Theoretical and methodological approaches to the formation of a modern system of national and international enterprises, organizations and institutions' development: Collective Scientific Monograph*, pp. 2-12. DOI 10.36074/tmafmseoid.ed-2.05.

[14] Harkema, S. (2003) "A complex adaptive perspective on learning within innovation projects", *The Learning Organization*, Vol. 10, No. 6, pp. 340-346. E-ISSN 1758-7905, ISSN 0969-6474. DOI 10.1108/09696470310497177.

[15] Heiets, V. M. (2009) "Society, state, economy: The phenomenology of interaction and development", Kyiv, 864 p.

[16] Hlubish, L. (2021) "Obstacles to the formation of competitive advantages in the sectors of food security of Ukraine", *Agricultural and Resource Economics: International Scientific E-Journal*, Vol. 7, No. 1, pp. 115-136. E-ISSN 2414-584X. DOI 10.51599/are.2021.07.01.07. (In Ukrainian).

[17] Hrosul, V., Kruhlova, O., Mkrtchyan, T., Zubkov, S. and Timchenko, O. (2021) "Enterprise integration and formation of cluster structures in the field of food sector", *Agricultural and Resource Economics: International Scientific E-Journal*, Vol. 7, No. 2, pp. 119-140. E-ISSN 2414-584X. DOI 10.51599/are.2021.07.02.07.

[18] Hryhoruk, P. M., Paionk, O. P., Savchuk, O. P. and Khrushch, V. O. (2020) "Characteristics of processes of formation and implementation of the innovative potential of small and medium enterprises", *Visnyk*, Vol. 6. pp. 54-62. ISSN 2414-987X. DOI 10.31891/2307-5740-2020-288-6-8. (In Ukrainian).

[19] Karnaushenko, A., Tanklevska, N., Povod, T., Kononenko, L. and Savchenko, V. (2023) "Implementation of blockchain technology in agriculture: fashionable trends or requirements of the modern economy", *Agricultural and Resource Economics: International Scientific E-Journal*, Vol. 9, No. 3, pp. 124-149. E-ISSN 2414-584X. DOI 10.51599/are.2023.09.03.06.

[20] Kovalyov, A., Babii, O. and Tymchenko, K. (2022) "Clustering of winegrowing and winemaking industry as an effective form of management", *Financial and Credit Activity: Problems of Theory and Practice*, Vol. 6, No. 47, pp. 480-490. E-ISSN 2310-8770. DOI 10.55643/fcaptp.6.47.2022.3870.

[21] Kychko, I., Parubets, O., Kholodnytska, A., Perminova, V. and Lytvyn, S. (2021) "Formation of managerial competencies of managers and their impact on the competitiveness of the firm and the labor market in Ukraine", *Financial and Credit Activity: Problems of Theory and Practice*, Vol. 4, No. 39, pp. 284-293. E-ISSN 2310-8770. DOI 10.18371/fcaptp.v4i39.241317.

[22] Kyrylov, Y., Hranovska, V., Savchenko, V., Kononenko, L., Gai, O. and Kononenko, S. (2024) "Sustainable Rural Development in the Context of the Implementation of Digital Technologies and Nanotechnology in Education and Business", *Nanotechnology Perceptions*, Vol. 20, No. S8, pp. 297-323. ISSN 1660-6795. DOI 10.62441/nano-ntp.v20iS8.25.

[23] Lavrenenko, V., Makhova, H. and Vostriakova, V. (2021) "Development of the enterprise's innovative potential on the basis of resource theory", *Financial and Credit Activity: Problems of Theory and Practice*, Vol. 3, No. 38, pp. 397-408. E-ISSN 2310-8770. DOI 10.18371/fcaptp.v3i38.237473.

[24] Lis, A. and Lis, A. (2021) "Relationships Between Geographical and Virtual Proximity in Cluster Organisations", *Studia Regionalne i Lokalne*, Vol. 3, No. 85, pp. 142-161. ISSN 1509-4995. DOI 10.7366/1509499538506.

[25] Ministry of Agrarian Policy and Food of Ukraine. (2022a) *"Concept of the State Target Economic Program for the Development of Domestic Machine Engineering for the Agro-Industrial Complex until 2020*". [Online]. Available: https://www.minagro.gov.ua [Accessed: Jan 12,2022].

[26] Ministry of Agrarian Policy and Food of Ukraine. (2022b) "*Overview of war damage in Ukraine agriculture. Indirect damage assessment*". [Online]. Available: https://minagro.gov.ua/storage/app/sites/1/uploaded-files/damagesreportissue2ua-1.pdf. [Accessed: Jan 12,2022].

[27] Mykytiuk, P. P. (Ed.) (2015) "Innovative development of enterprises: A textbook", Printer Inform, Ternopil, 224 p.

[28] NISS (2023) "*The agricultural sector of Ukraine in 2023: components of sustainability, problems and promising tasks*". [Online]. Available: https://niss.gov.ua/doslidzhennya/ekonomika/ahrarnyy-sektor-ukrayiny-u-2023-rotsi-skladovi-stiykosti-problemy-ta [Accessed: March 21, 2024].

[29] Petrova, I., Sysolina, N., Kononenko, L., Sysolina, I. and Savelenko, H. (2024) "Increasing the Innovative Potential of the Enterprises of the Agro-Industrial Complex of Ukraine: Fundamental Developments", *The International Journal of Multiphysics*, Vol. 18, No. 3, pp. 1320-1340. ISSN 1750-9548.

[30] Petrova, I. L., Shpylova, T. I. and Sysolina, N. P. (2010) "Innovative activity: Incentives and obstacles", In: Petrova, I. L. (ed.) "*Innovative activity",* Dorado, Kyiv, 320 p. (In Ukrainian).

[31] Piletska, S. T. and Tkachenko, Y. (2020) "Innovative potential of the enterprise in the anti-crisis management system", *Oblik i Finansi*, No. 87, pp. 178-184. e-ISSN 2518-1181. DOI 10.33146/2307-9878-2020-1(87)-178-184. (In Ukrainian).

[32] Puzyrova, P. V. (2020) "Main factors influencing the process of forming and developing the innovative potential of integrated business structures", *Formation of Market Relations in Ukraine*. E-ISSN 1728-662X. DOI 10.5281/zenodo.4415456. (In Ukrainian).

[33] Ragazou, K., Garefalakis, A., Zafeiriou, E. and Passas, I. (2022) "Agriculture 5.0: A new strategic management mode for a cut cost and an energy efficient agriculture sector", *Energies*, Vol. 15, No. 9, p. 3113. ISSN 1996-1073. DOI 10.3390/en15093113.

[34] Sabluk, P. T. (2008) "Problems of ensuring the profitability of agro-industrial production in Ukraine during the post-industrial period", *Economics of Agro-Industrial Complex*, pp. 19-37. E-ISSN 2413-2322.

[35] Saunila, M. (2020) "Innovation capability in SMEs: A systematic review of the literature", *Journal of Innovation & Knowledge*, Vol. 5, No. 4, pp. 260-265. E-ISSN 2444-569X. DOI 10.1016/j.jik.2019.11.002.

[36] Savytskyi, E. E. (2019) "Evaluation of the level of innovative potential of the enterprise", *Financial and Credit Activity: Problems of Theory and Practice*, Vol. 2, No. 29, pp. 204-211. E-ISSN 2310-8770. DOI 10.18371/fcaptp.v2i29.171779.

[37] Schumpeter, J. A. (2004) "*The Theory of Economic Development*", 10th ed., Transaction Publishers, New Brunswick, New Jersey.

[38] Shulhina, L. M., Shulhyna, L. M., Yukhymenko, V. V. and Yukhymenko, V. V. (2011) "The modern concept of strategic management of innovation development of enterprises", *Marketing and Management of Innovations*, Vol. 2, No. 3, pp. 79-84. E-ISSN 2227-6718.

[39] Shvets, V. I. and Dubiei, D. I. (2021) "Management of the innovative potential of Ukrainian industrial enterprises", *Economic Bulletin of Dnipro University of Technology,* Vol. 75, pp.106-113. ISSN 2709-6459. DOI 10.33271/ebdut/76.106.

[40] Skotsyk, V. I. (2017) "Organizational and economic mechanism for the formation and functioning of agricultural machinery in Ukraine", Ph.D. Thesis, Vinnytsia.

[41] Smulka, O. (2020) "Formation of the innovative potential of agricultural enterprises", *Agrarian Economy*, Vol. 13, No. 1-2, pp. 45-54. ISSN 2313-3627.

[42] Solohub, I. (2023) "*The impact of war on capital investments in Ukraine*", Economics. [Online]. Available at: https://voxukraine.org/vplyv-vijny-na-kapitalni-investytsiyi-v-ukrayini [Accessed: Sept 10,2025]. (In Ukrainian).

[43] State Statistics Service of Ukraine (n.d.) Statistical data. [Online]. Available: https://www.ukrstat.gov.ua. [Accessed: June 5,2025]. (In Ukrainian).

[44] Stræte, E. P., Vik, J., Fuglestad, E. M., Gjefsen, M. D., Melås, A. M. and Søraa, R. A. (2022) "Critical support for different stages of innovation in agriculture: What, when, how?", *Agricultural Systems*, Vol. 203, p. 103526. ISSN 0308-521X. DOI 10.1016/j.agsy.2022.103526.

[45] Sysolina, N. P., Savelenko, H. V. and Sysolina, I. P. (2018) "Problematic aspects and prospects of innovative development of agricultural machinery", *Central Ukrainian Scientific Bulletin. Economic Sciences*, Vol. 1, No. 34, pp. 280-287. ISSN 2663-1636. DOI 10.32515/2663-1636.2018.1(34).208-287. (In Ukrainian).

[46] Team Ensol (2024) "*Analysis of the effectiveness of the consolidation of agricultural enterprises. The working model*". [Online]. Available: https://economic-grygoriy.ensol.team/ [Accessed: June 5, 2025].

[47] Thompson, V. A. (1965) "Bureaucracy and Innovation", *Administrative Science Quarterly,* Vol. 10, No. 1, pp. 1-20. ISSN 0001-8392. DOI 10.2307/2391646.

[48] Tomashuk, I. (2023) "Competitiveness of agricultural enterprises in market conditions and ways of its increase", *Green, Blue and Digital Economy Journal*, Vol. 4, No. 1, pp. 64-81. E-ISSN 2661-5282. DOI 10.30525/2661-5169/2023-1-7.

[49] Trusova, N. V., Hryvkivska, O. V., Yavorska, T. I., Prystemskyi, O. S., Kepko, V. N. and Prus, Y. O. (2020) "Innovative development and competitiveness of agribusiness subjects in the system of ensuring of economic security of the regions of Ukraine", *Rivista di Studi sulla Sostenibilita*, Vol. 10, No. 2, pp. 141-156. ISSN: 2239-7221.

[50] Ulyanchenko, O., Vasyurenko, L., Litvinov, A., Utenkova, K., Filimonov, Y. and Kuksa, I. (2021) "Strategic management of resource potential as a measure to increase the competitiveness of the enterprise in the agricultural sector", *Financial and Credit Activity: Problems of Theory and Practice*, Vol. 4, No. 39, pp. 276-283. E-ISSN 2310-8770. DOI 10.18371/fcaptp.v4i39.241316.

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Fintech Integration into Business Processes of Financial and Agricultural Companies: A Strategic Paradigm for Stable Development in the Capital Market

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Abstract

The article examines the integration of the fintech sector into the business processes of financial institutions and agricultural companies as a strategic paradigm for stability and security in the capital market. The directions for implementing the data complementarity methodology within an integrated fintech model that unites the fintech sector and the banking ecosystem within the digitalised global space are outlined. This model proposes methods and mechanisms for delivering fast, secure fintech services to business clients on a three-level collaborative platform and digitising financial assets in the capital market. The adaptive market hypothesis is outlined, according to which the assessment of data complementarity in big data analytics in fintech may expand the scope of financial analysis, support risk assessment, and improve analytical accuracy in an unstable investment environment. The results suggest that the most effective pragmatic strategies for stability in the capital market tend to prevail, while investors' financial behaviour is adaptive during crises. The findings also indicate that the capital market reflects economic trends and risks when stock prices exhibit non-random behaviour and may be analysed using big data analytics in fintech. The scale of transactions, investment activity, and market capitalisation of fintech companies is assessed. The paper also presents the market capitalisation of the top 10 global stock exchanges, the dynamics of the PFTS and Ukrainian Exchange indices, initial public offering (IPO) results of public agricultural companies, and changes in the WIG-Ukraine Index.

Keywords

Fintech sector, Blockchain, technologies, strategy, digital services.

Satyr, L., Starostenko, D., Zadoia, Y., Salin, S. and Mykhalchuk, O. (2026) "Fintech Integration into Business Processes of Financial and Agricultural Companies: A Strategic Paradigm for Stable Development in the Capital Market", *AGRIS on-line Papers in Economics and Informatics*, Vol. 18, No. 1, pp. 83-93. ISSN 1804-1930. DOI 10.7160/aol.2026.180107.

Introduction

Fintech has become an important element of contemporary business strategies. Despite some progress in the field, key challenges remain in identifying fintech solutions that support company development and in integrating these solutions into business processes.

Ananzeh et al. (2025) showed that digital financial technology has contributed to changes in the global market through financial inclusion. Based on financial inclusion indicators (internet access, Automated Teller Machines, and bank branches) from 22 high-income countries in 2010-2021, fintech is associated with economic development and may help reduce disparities between middle- and low-income countries. Accordingly, countries are encouraged to promote financial inclusion as a driver of economic growth and sustainable development. Similar conclusions were reached by Harsono and Suprapti (2024), who examined fintech in terms of openness, security, inclusivity, operational efficiency, and user experience. They showed that its integration is associated with improved business performance through greater efficiency and enhanced access to financial services.

Fedyshyn et al. (2024) distinguished three stages of integrating fintech into the global financial

market – the emergence of telegraphic lines for communication and information transmission (1866-1967), the mass circulation of a plastic payment card (1967-2009), and the emergence of financial and outsourcing companies providing fintech services (2009-2024). As of 2024, Ukraine had more than 100 fintech companies, mostly payment service providers, as well as providers of online lending and infrastructure solutions. Urikova et al. (2025) report that despite challenging circumstances, the Ukrainian fintech segment demonstrates sustainable growth. The experts attributed this growth to the steady demand for digital financial services, the rise of innovative technologies, and integration into the global market. Zhurko and Shcherbak (2025) argued that in contrast to traditional commercial institutions, which are focused on established operational processes and regulated approaches to management, entities using fintech solutions were more flexible and therefore more competitive. This competitiveness is associated with the use of artificial intelligence, big data analytics, blockchain, cloud technologies, the Internet of Things, and biometric identification, which also enable faster data processing and reduce the risk of errors.

Alsmadi and Al-Okaily (2025) show that the integration of fintech solutions into business processes was associated with company competitiveness due to enhanced customer loyalty. However, the survey of 231 Jordan respondents made Alsmadi and Al-Okaily conclude that acceptance of fintech solutions depends on a range of culture-specific factors, meaning that the adoption of specific fintech tools may vary considerably across contexts. Similar results were reported by Kurniasari and Lestari (2024), who studied fintech adoption among 270 women entrepreneurs in Indonesia and found that financial literacy initiatives help address barriers to adoption.

While the general advantages of fintech are well documented, its integration into the business processes of financial and agricultural companies – particularly regarding efficiency, risk management, and access to finance – remains underexplored. This gap underscores the relevance of studying strategies for integrating fintech into specific sectors of the economy. The study aims to identify factors shaping fintech integration in financial and agricultural companies and to examine its role in their sustainable development.

Materials and methods

The study uses a dataset compiled from industry reports, open-source financial databases, and peer-reviewed sources. The contextual analysis covers the period from 2006 to 2025. The empirical analysis (conducted in June 2024 – June 2025) uses weekly stock prices of Ukrainian and international fintech companies for the 2022-2024 period, along with market capitalisation data and sector-specific financial indicators. Particular attention was given to the inclusion of key stock market indices, notably the PFTS Index and the Ukrainian Exchange Index (2025), to assess market performance across distinct sectors, including financial technology, agriculture, and banking. Data sources included Global Fintech (2024), Largest Agriculture Companies by Market Cap (2025), PFTS Index (2025), and WIG Ukraine (2025), supplemented by statistical insights from Statista (2025). The methodological approach was informed by previous studies, including those by Del Gaudio et al. (2024), Dovhan (2025), Karyani et al. (2024), and Maknickiene and Lapkovskaja (2024).

Several analytical methods were used to assess differences in financial performance across sectors. To quantify short-term dynamics, the percentage change between two consecutive time points in financial time series was calculated using the rate of change formula (1):

$$R_1 = \left(\frac{Ic_i}{Ic_{i-1}} - 1\right) \times 100\%, \quad (1)$$

where R_1 – first difference of the selected index for the period i; Ic_i and Ic_{i-1} – closing prices of the selected index for period i and the previous period, respectively. This formula was applied to weekly closing prices of company stocks and sectoral indices – specifically for the fintech, agribusiness, and banking sectors – over the 2022-2024 period. The resulting growth or decline rates served as input variables for subsequent comparative and regression analyses.

To evaluate the complementarity of the selected data sets, a linear regression model with a binary (dummy) variable was employed, as shown in equation (2):

$$R_l = a_0 + a_1 D_{1i} + \varepsilon_i, \quad (2)$$

where R_l – the average value of the first difference, i.e. the week-to-week change of the respective stock index over the observation period; $a0$ – mean

weekly change of the PFTS Index; a_1 – estimated coefficient for the dummy variable D1i, which takes the value 0 for observations from the PFTS Index and 1 for those from the Ukrainian Exchange Index.

The model was used to compare 52 weekly observations for each index, covering the period from January 2022 to December 2024. The statistical significance of the estimated coefficients was assessed using t-tests, with corresponding p-values reported to determine the strength of the estimated effect. Prior to model interpretation, standard diagnostic tests were conducted, including the Durbin-Watson test for autocorrelation and the Variance Inflation Factor to check for multicollinearity. These tests confirmed the absence of significant autocorrelation and multicollinearity, validating the robustness of the model.

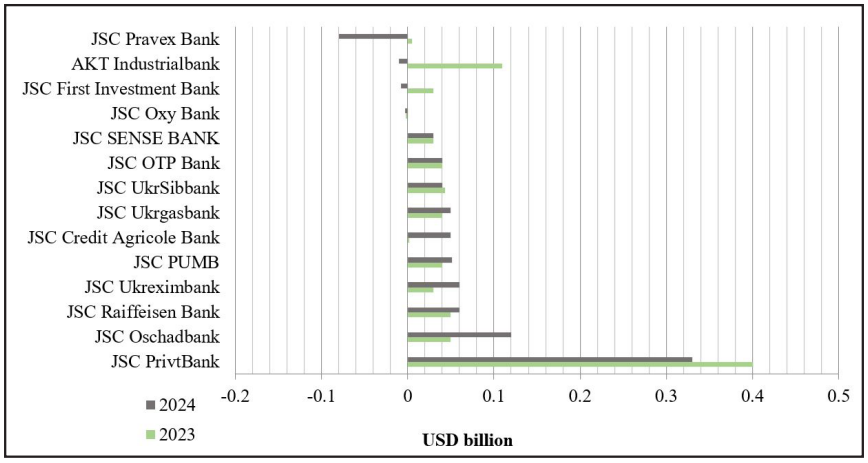
This model tests whether the two indices differ significantly in their dynamics. If the coefficient a1 was not significantly different from zero, it suggests that the average behaviour of the two series did not differ in a meaningful way, thereby indicating similarity in the short-term dynamics of the data sets. Conversely, a significant a_1 indicates divergence, suggesting that the indices are not interchangeable in further analysis.

Results and discussion

The collaboration between financial institutions and fintech companies is associated with positive profitability dynamics in the Ukrainian banking ecosystem. Under martial law and foreign policy instability, the focus on state ownership is associated with greater control over economic indicators. The total profit of financial institutions for the first quarter of 2024 amounted to USD 1.08 billion; 55 financial institutions reported a total profit of USD 1.50 billion, 13% of financial institutions (8 banks) reported losses of USD 2.72 million (OpenDataBot, 2025). Joint-stock company (JSC) Raiffeisen Bank remains among the leading banks in the ranking, as well as JSC UkrSibbank, which works exclusively with legal entities. JSC Pravex Bank demonstrated unprofitability in 2023-2024 (Figure 1).

The securities portfolio of JSC CB "Privatbank" for 2022-2024 had some significant changes in financial indicators. In particular, income from investment securities recognised through profit increased from USD 2.55 million in 2022 to USD 2.63 million in 2023. However, in 2024 this indicator decreased to USD 2.43 million, which may indicate a change in profitability or a change in the investment portfolio. It should be noted that other comprehensive income of the financial company – at fair value through other comprehensive income – decreased from USD 3.24 million in 2022 to USD 2.88 million in 2024. This decrease may reflect lower profitability in other segments or changes in financial management.

JSC CB "Privatbank" manages securities portfolios, conducts transactions with government securities, and works with investors' funds to improve liquidity and returns. In addition, the financial institution provides consultations on investment issues, offers information support on securities markets, and develops individual investment strategies taking into account financial goals (Hurani and Abdel-Haq, 2025; Shulyk, 2024). These actions are associated with relatively stable financial performance, supported by capital market and risk



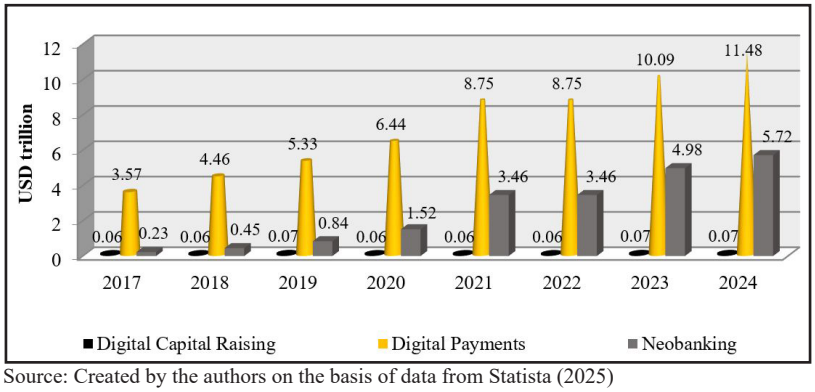
Source: Created by the authors on the basis of data from OpenDataBot (2025), Riabokin and Kotukh (2024)

Figure 1: Profitability of financial institutions of Ukraine for 2023-2024, USD billion.

analysis and collaboration with fintech companies and regulators. In the broader fintech context, digital payments dominate transaction volumes, while neobanking shows steady growth and capital raising remains relatively low (Figure 2).

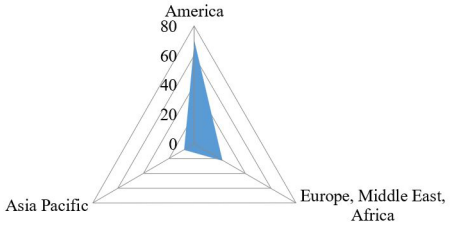
The total value of investments in fintech companies worldwide increased sharply in 2010-2019 and reached USD 216.8 billion. Since 2020, investments in fintech companies have decreased and amounted to less than USD 125 billion. The value of investments increased in 2021, exceeding USD 225 billion. For fintech companies, 2022 was a "slow" year: investments decreased by 13% compared to 2021 but remained above 2020 levels. The trend towards a decrease in investments continued in 2023-2024 – the global cost of financing decreased by 42.2% and 54%, respectively, compared to 2022. It is worth noting that investment activity in the fintech industry varies by region. The Americas attracted the largest share of investment, accounting for more than half of the total (Figure 3).

The global fintech sector is segmented by type of service, with each segment developing heterogeneously (Figure 4).



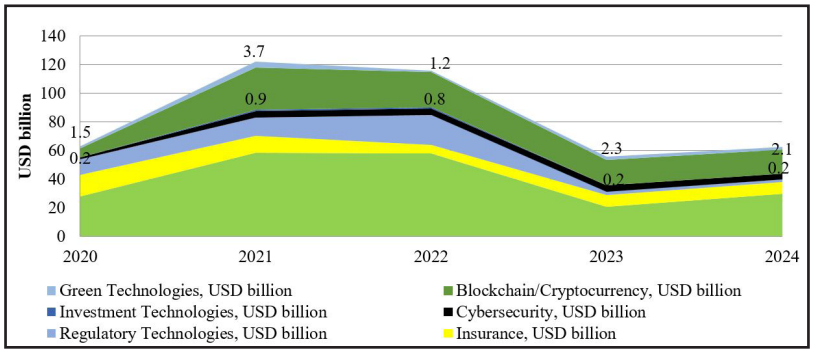
Source: Created by the authors on the basis of data from Statista (2025)

Figure 2: Transaction volume in fintech by direction in 2017-2024, USD trillion.



Source: Created by the authors on the basis of data from Del Gaudio et al. (2024), Global Fintech (2024), Karyani et al. (2024)

Figure 3: Structure of investments in the fintech sector by region in 2024, %.



Source: Created by the authors on the basis of data from Global Fintech (2024)

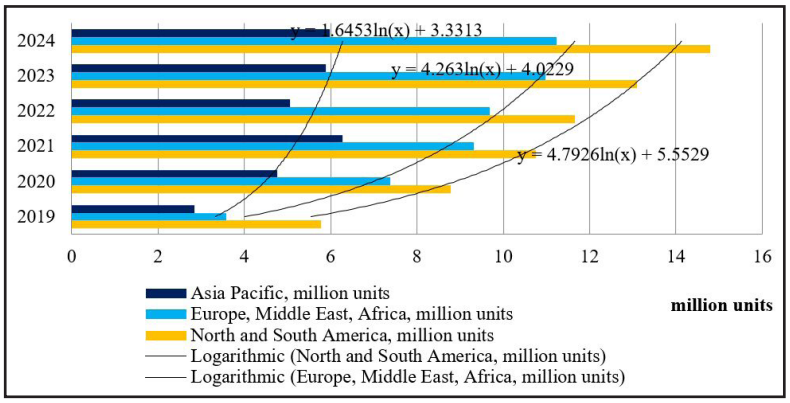
Figure 4: Investment activity of fintech companies by segments of the fintech sector in 2020-2024, USD billion.

In 2020-2024, the least active segment was investment technologies, while higher investment volumes were observed in several other segments, particularly insurance and blockchain-related activities (Figure 4). Most segments demonstrated a downward trend in 2023-2024 compared to earlier years. At the same time, certain segments, including Insurtech and ESG/Greentech, showed relative resilience despite the overall decline (Global Fintech, 2024).

The number of fintech companies is significantly higher in Europe, the Middle East and Africa compared to the Asia-Pacific region (Figure 5).

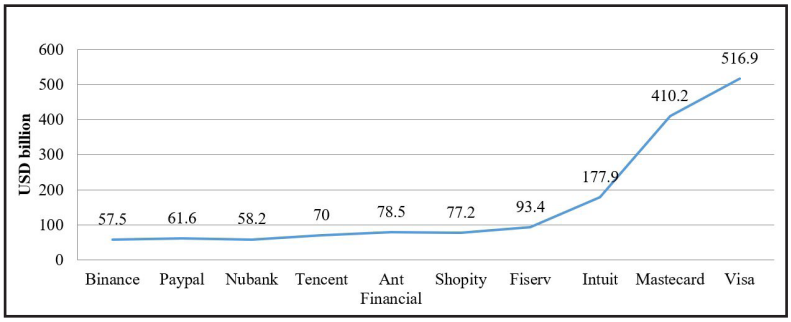
The largest fintech companies are concentrated in the United States and China. The highest market capitalisation is observed among global payment and financial technology providers, with companies such as Visa and Mastercard leading the sector (Figure 6). Overall, the market capitalisation of fintech companies demonstrates steady growth.

The financial landscape of countries is changing alongside the growth of financial technologies and their increasing revenues, which are associated with broader economic dynamics. The dynamics of fintech sector revenues are presented in Figure 7.



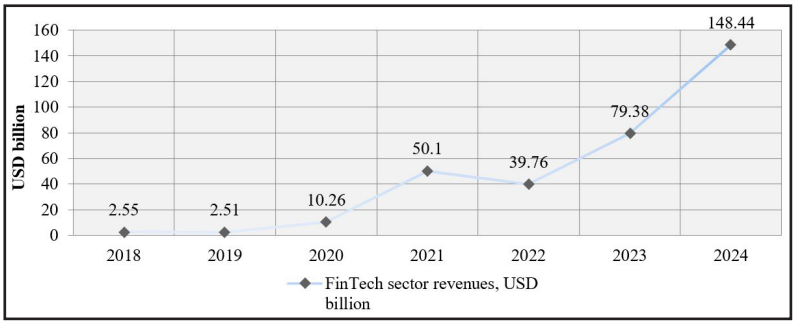
Source: Created by the authors on the basis of data from Global Fintech (2024)

Figure 5: Number of fintech companies in the regions of the world in 2019-2024, million units.



Source: Created by the authors on the basis of data from Global Fintech (2024)

Figure 6: Market capitalisation of the largest fintech companies in the world in 2024, USD billion.



Source: Created by the authors on the basis of data from Global Fintech (2024)

Figure 7: Revenues of the fintech sector in the global space for 2018-2024, USD billion.

Global fintech revenues continue to grow at a solid pace, despite some slowdown in 2022 due to macroeconomic factors. It is important to note that the fintech sector has initiated a transition to profitable growth, with Earnings Before Interest, Taxes, Depreciation, and Amortization margins improving by an average of 10.4 percentage points. Most of the 70 largest public fintechs are still operating below the threshold, which means their annual revenue growth and Earnings Before Interest, Taxes, Depreciation, and Amortization margins are less than 40%.

These global fintech trends are also reflected at the sectoral level, particularly in agriculture, where fintech tools are used to support access to capital markets and facilitate IPO processes. In this context, agricultural companies increasingly use fintech solutions to support IPOs, enabling them to raise capital on international stock exchanges and place shares for public trading (Pilyavoz et al., 2023). Agricultural companies can choose the exchange for IPO placement depending on listing costs (Table 1).

Figure 8 presents the market capitalisation of the top 10 global stock exchanges in 2022-2024. The New York Stock Exchange remains the largest by market capitalisation, followed by NASDAQ and major Asian exchanges, including the Shanghai, Tokyo, and Hong Kong stock exchanges. European exchanges, such as the London Stock Exchange, Euronext, and the Frankfurt Stock Exchange, also maintain significant positions in the global financial system (Figure 8).

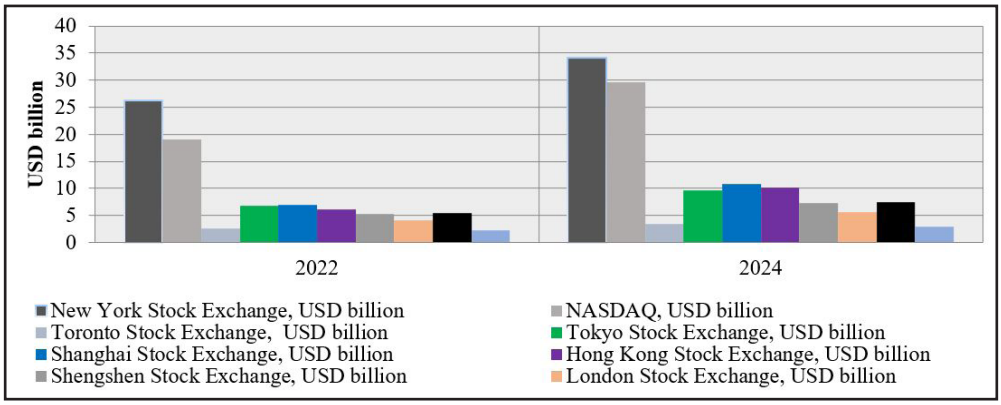
During 2016-2024, the market capitalisation of the top 10 global stock exchanges increased steadily, with particularly strong growth observed after 2021. Despite some fluctuations, the overall trend indicates a substantial expansion of capital market activity over the analysed period (Figure 9).

Based on big data analytics in fintech, the Ukrainian capital market was analysed using the PFTS Index and the Ukrainian Exchange Index. The Ukrainian Exchange Index includes the agricultural company MHP SE. The main role, as well as a significant number of shares in circulation, belongs to Raiffeisen Bank (61.50 billion shares). The absolute values of stock indices are less important than their dynamic characteristics. That is, the trend of indicators shows the direction of the capital market movement (growth or decline)

Placement exchange	First listing fee	Annual fee for maintaining the listing
New York Stock Exchange	From USD 150 thousand to USD 295 thousand	USD 0.00113 per share or USD 74 thousand (for large companies)
NASDAQ	From USD 55 thousand to USD 80 thousand	From USD 45 thousand to USD 81 thousand
London Stock Exchange	From GBX 118 thousand	From GBX 11,530
Euronext Exchange	1% of the nominal value of the securities placed	0.05% of the volume of transactions made during the period (146.45 EUR per share)
Warsaw Stock Exchange	0.03% (not less than PLN 8 thousand and not more than PLN 96 thousand)	0.02% of the volume of transactions (not less than PLN 9 thousand and not more than PLN 70 thousand)

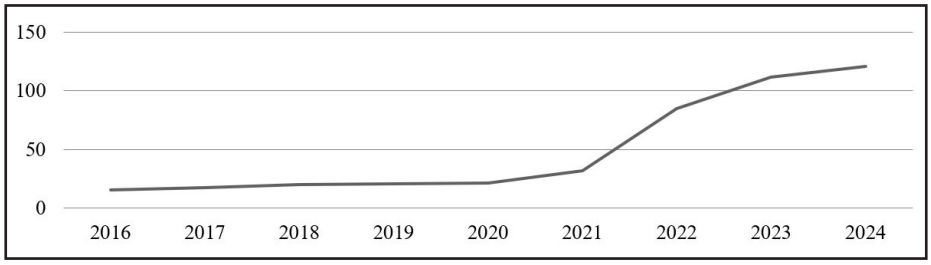
Source: Created by the authors

Table 1: Listing costs of the world's largest stock exchanges.



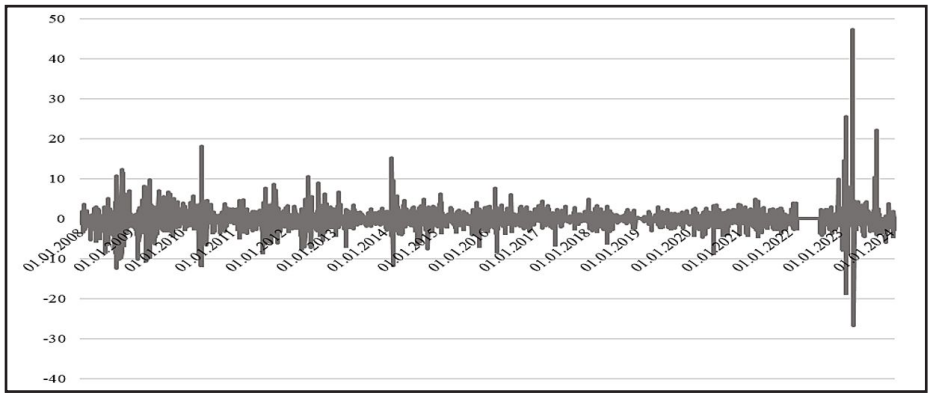
Source: Created by the authors

Figure 8: Market capitalisation of the TOP-10 stock exchanges of the world in 2022-2024, USD billion.



Source: Created by the authors on the basis of data from Alsmadi and Al-Okaily (2025)

Figure 9: Market capitalisation of the top 10 global stock exchanges, USD billion.



Source: Created by the authors on the basis of data from PFTS Index (2025), Ukrainian Exchange Index (2025)

Figure 10: Dynamics of the first differences (returns) of the PFTS Index on the Ukrainian capital market for 2006-2023.

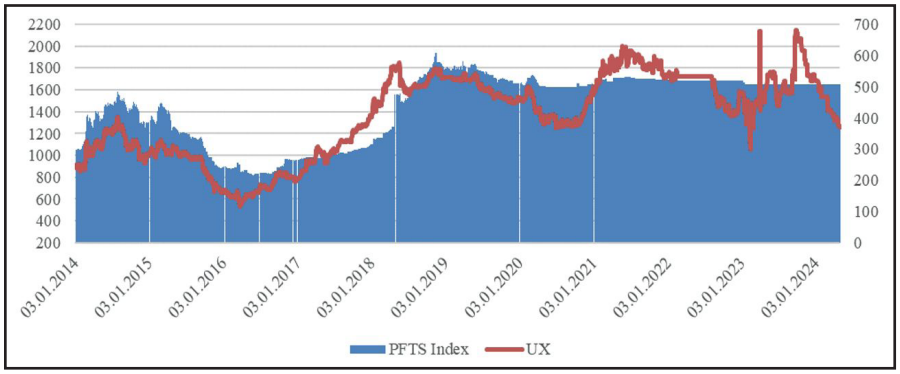
even in the case of multi-vector changes in stock prices. The dynamics of the first differences (returns) of the PFTS Index for 2006-2023, showing noticeable volatility spikes over time, is presented in Figure 10.

The overall dynamics of the Ukrainian Exchange Index growth rates reflect the complex and sensitive nature of the Ukrainian capital market to external and internal factors in 2014-2024. However, the PFTS Index demonstrates relatively more stable dynamics compared to the Ukrainian Exchange Index, despite fluctuations and sharp changes observed in 2020-2024 (Figure 11).

Based on fintech analytics, the performance of the world's top 10 public agricultural companies in 2024 shows notable variation in financial indicators related to IPO activity (Table 2). These differences may be associated with both traditional factors (economic, legal, and political) and external shocks, including the pandemic and the war, which have affected companies' financial performance and stability. The variation in profit indicators across companies reflects differences in firm size, market structure, and reporting practices rather than uniform performance patterns, which should be taken into account when interpreting the data.

To support large Ukrainian agribusiness, big data analytics in fintech enabled the Warsaw Stock Exchange to create a dedicated WIG-Ukraine index, which includes 10 agricultural companies traded on the platform. These are mainly agricultural holdings and food producers, in particular, Kernel, Astarta, IMC, Ovostar Union, KSG Agro. It should be noted that the WIG-Ukraine Index, which includes shares of Ukrainian agricultural companies listed on the Warsaw Stock Exchange, grew intensively in 2024, which may reflect increased investor interest in large agricultural businesses in Ukraine (Table 3 below).

According to Warsaw Stock Exchange data, the share price of the country's largest sugar producer "Astarta" decreased by 7.76%, agricultural companies "IMS" and "Agroton" with land fund located on the front line – by 3.30% and 7.48%, "Milkiland" – by 2.28%, "KSG-Agro" – by 0.32%. Only shares of the largest Ukrainian oil producer – the company "Kernel", which is not included in the index due to a small free-float, increased in price by 1.54% (WIG Ukraine, 2025).



Source: Created by the authors on the basis of data from PFTS Index (2025), Ukrainian Exchange Index (2025)

Figure 11: Change in the PFTS Index and the Ukrainian Exchange Index on the Ukrainian capital market in 2014-2024.

Agricultural company	Country	Market capitalisation, USD billion	Market price per share, USD	Profit, USD billion	IPO proceeds, USD billion	P/E ratio (market price of the share/ annual profit)	Dividends, %	Operating margin, %
Corveta	USA	48.03	70.41	1.8	16.83	42.9	0.95	10.72
The Andersons	USA	1.19	34.97	0.22	11.19	10.9	2.22	1.78
Kuala Lumpur Kepong	Malaysia	5.35	4.81	0.27	5.03	41.3	2.96	5.49
Sime Darby Plantation	Malaysia	7.62	1.1	0.81	4.59	13.2	3.52	17.68
Cal-Maine Foods	USA	4.63	95.52	1.28	3.79	4.55	7.04	33.69
Bayer Crop Science	India	2.98	66.5	0.062	0.59	48.2	2.21	12.88
BrasilAgro	Brazil	0.38	3.84	0.053	0.22	7.11	0	22.22
Limoneira	USA	0.28	15.69	0.006	0.18	47	1.93	7.48
Kaveri Seed	India	0.89	17.5	0.038	0.14	23.5	0.34	26.45
Al-Jouf Agricultural Development	S. Arabia	0.37	12.53	0.023	0.14	16	2.13	17.72

Note: Financial indicators are reported in billions of USD. Differences in scale reflect variations in company size and reporting practices across data sources.
Source: Created by the authors.

Table 2: Performance indicators from IPOs on stock exchanges for the TOP-10 global public agricultural companies in 2024.

Company	Stock price	Share price change since February 2022	Share price change for January 2024	Share price change for December 2024
IMC	9.38 PLN	-62.3	+3.3	+15.6
Kernel Holding	11.6 PLN	-78.6	+26.8	+14.6
KSG Agro	1.75 PLN	-42.6	+7.7	+12.6
WIG Ukraine	218.01 PLN	-62	+2.8	+8.6
MHP	3.55 GBX	-43.7	+15.6	+6.6
Astarta	28.05 PLN	-17.6	-2.26	+5.25
Ovostar Union	69.8 PLN	+22.5	-3.7	-0.3
WIG 20	2442 PLN	+14	+4.26	-4.4

Source: Created by the authors on the basis of data from Dovhan (2025), Largest Agriculture Companies by Market Cap (2025), Maknickiene and Lapkovskaja (2024), WIG Ukraine (2025)

Table 3: Dynamics of changes in the WIG-Ukraine Index for shares of Ukrainian public agricultural companies listed on the Warsaw Stock Exchange in 2022-2024.

The volatility of Ukrainian agricultural companies' shares on the Warsaw Stock Exchange at the end of May 2025 was much worse than the overall dynamics of the Warsaw Capital Market: the WIG index decreased by 0.95% per day, and the WIG40 – by 0.22%. Forecasts of improving relations between Ukraine and the US and the announcement of a temporary ceasefire coincided with an increase in the WIG-Ukraine index to 590 points. After the announcement of plans for negotiations in Istanbul and a possible longer-term ceasefire, the index rose to 625 points and then began to fall along with the fading optimism about the prospects for a quick end to the war.

Thus, the results suggest that the use of big data analytics in fintech is associated with the use of IPOs as a source of financing by domestic issuers to attract significant investment into the economy. Despite the fact that the fintech sector does not fully support the public placement of corporate rights of Ukrainian agricultural companies on international capital markets during the period of martial law, access to fintech services may still facilitate their participation in global exchanges. Access of Ukrainian agribusiness to fintech services to expand its presence on stock exchanges may serve as a potential factor of competitive advantage for the Ukrainian economy.

The findings also indicate between fintech use and profitability trends in the Ukrainian banking sector. Latiff et al. (2025) identify profitability, trust, and operational optimisation as key fintech trends in banking, which is consistent with the observed trends in this study. However, the present analysis does not directly assess trust or systemic risk, and these aspects should be interpreted with caution. The observed growth of fintech sector revenues despite declining investment partially contradicts the findings of Javeria and Abdus (2024), who noted the growing reliance on human advisors. The decline in investment activity observed here may indicate the coexistence of fintech and traditional banking during a transitional phase. In contrast to Hasan et al. (2024), who predicted resilient fintech investment, the decline in investment activity observed in this study coincided with periods of geopolitical instability and potential market saturation.

Conclusion

The fintech sector is transforming the financial system by blending technology and finance, accelerating its growth, especially during the pandemic. However, in 2022, investments in fintech slowed due to political instability and recession fears, prompting companies to focus on profitability rather than growth. In Ukraine, agricultural companies are increasingly adopting financial digitalisation, expanding the use of stock market instruments based on fintech technologies. Due to the ongoing war, companies are reluctant to sell shares, as low asset prices may lead to capital outflows.

The results suggest that fintech development is associated with changes in investment activity, transaction volumes, and capital market dynamics, including the behaviour of stock indices and IPO-related indicators. The findings also highlight the sensitivity of the Ukrainian capital market to external shocks and structural constraints under conditions of economic and geopolitical instability.

Overall, the study suggests that fintech tools may support the functioning of capital markets by enhancing data processing, facilitating access to financial instruments, and improving analytical capabilities within financial and agricultural sectors.

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References

[1] Alsmadi, A. A. and Al-Okaily, M. (2025) "Future Front of Finance: The Role of FinTech Strategies, Competitiveness Dynamics and Sustainable Solutions", *Competitiveness Review*. ISSN 1059-5422. DOI 10.1108/CR-11-2023-0298.

[2] Ananzeh, I. E., Khalaf, L. and Khalawi, D. (2025) "The Role of FinTech and Financial Inclusion in the Economic Development of Countries: A Comparative Analysis", *Banks and Bank Systems*, Vol. 20, No. 1, pp. 248-258. ISSN 1816-7403. DOI 10.21511/bbs.20(1).2025.20.

[3] Del Gaudio, B. L., Gallo, S. and Previtali, D. (2024) "Exploring the Drivers of Investment in FinTech: Board Composition and Home Bias in Banking", *Global Finance Journal*, Vol. 60, p.100944. ISSN 1044-0283. DOI 10.1016/j.gfj.2024.100944.

[4] Dovhan, O. (2025) "Analysis of the Development of Digital Innovations in the Financial Services Market in Ukraine in 2010-2024", *Economy and Society*, Vol. 71. ISSN 2524-0072. DOI 10.32782/2524-0072/2025-71-48.

[5] Fedyshyn, M. P., Zhurko, R. V. and Lobko, O. M. (2024) "The Role of FinTech in the Financial Market Development in Ukraine", *The Actual Problems of Regional Economy Development*, Vol. 2, No. 20, pp. 278-291. ISSN 2313-8246. DOI 10.15330/apred.2.20.278-291.

[6] Global Fintech. (2024) "*Prudence, Profits, and Growth", BCG Publications*", [Online]. Available: https://www.bcg.com/publications/2024/global-fintech-prudence-profits-and-growth [Accessed: March 4, 2026].

[7] Harsono, I. and Suprapti, I. A. (2024) "The Role of FinTech in Transforming Traditional Financial Services", *Accounting Studies and Tax Journal*, Vol. 1, No. 1, pp. 81-91. ISSN 3062-9204. DOI 10.62207/gfzvtd24.

[8] Hasan, M., Hoque, A., Abedin, M. Z. and Gasbarro, D. (2024) "FinTech and Sustainable Development: A Systematic Thematic Analysis Using Human- and Machine-Generated Processing", *International Review of Financial Analysis*, Vol. 95, p.103473. ISSN 1057-5219. DOI 10.1016/j.irfa.2024.103473.

[9] Hurani, J. and Abdel-Haq, M. K. (2025) "Factors Influencing FinTech Adoption among Bank Consumers in Palestine: An Extended Technology Acceptance Model Approach", *International Journal of Financial Studies*, Vol. 13, No. 1, p. 11. ISSN 2227-7072. DOI 10.3390/ijfs13010011.

[10] Javeria, A. and Abdus, S. (2024) "FinTech Revolutionizing the Banking Domain", *Premier Journal of Business and Management*, Vol. 1, p.100008. ISSN 3048-5016. DOI 10.70389/PJBM.100008.

[11] Karyani, T., Perdana, T., Sadeli, A. H., Utami, H. N. and Renaldi, E. (2024) "Leveraging Financial Technology for Sustainable Fresh Agricultural Products Financing in Indonesia", *Frontiers in Sustainable Food Systems*, Vol. 8, p. 1438263. ISSN 2571-581X. DOI 10.3389/fsufs.2024.1438263.

[12] Kurniasari, F. and Lestari, E. D. (2024) "Development of Financial Literacy and FinTech Adoption on Women SMEs Business Performance in Indonesia", *Eastern-European Journal of Enterprise Technologies*, Vol. 5, No. 13, pp. 67-75. ISSN 1729-3774. DOI 10.15587/1729-4061.2024.312613.

[13] Largest Agriculture Companies by Market Cap. (2025) "*Largest Agriculture Companies by Market Capitalization*", CompaniesMarketCap, [Online]. Available: https://companiesmarketcap.com/agriculture/largest-companies-by-market-cap/ [Accessed: March 4, 2026].

[14] Latiff, A. R., Alqudah, M. Z., Samara, H. and Alslaibi, N. (2025) "Empowering the Financial Sector: The Role of FinTech Research Development Trends", *Future Business Journal*, Vol. 11, p. 92. ISSN 2314-7210. DOI 10.1186/s43093-025-00512-y.

[15] Maknickiene, N. and Lapkovskaja, J. (2024) "An Exploratory Review of the FinTech Influence Field", *Journal of Infrastructure Policy and Development*, Vol. 8, No. 4, p. 3410. ISSN 2572-7923. DOI 10.24294/jipd.v8i4.3410.

[16] OpenDataBot. (2025) "*Profitability of the Ukrainian Banking System*", OpenDataBot, [Online]. Available at: https://opendatabot.ua/open/bank-ranking [Accessed: March 4, 2026].

[17] PFTS Index. (2025) "*PFTS Stock Index Information*", PFTS Stock Exchange, [Online]. Available: https://pfts.ua/trade-info/indexes/shares-indexes [Accessed: March 4, 2026].

[18] Pilyavoz, T. M., Glushchenko, L. D. and Koval, N. O. (2023) "Current State of the Corporate Securities Market in Ukraine", *Economy and Society,* Vol. 51. ISSN 2524-0072. DOI 10.32782/2524-0072/2023-51-56.

[19] Riabokin, M. and Kotukh, Y. (2024) "The Growing Role of Financial Technologies in the Context of Digital Economy Development", *Herald of Kyiv Institute of Business and Technology*, Vol. 50, No. 1, pp. 60-78. ISSN 2707-1820. DOI 10.37203/kibit.2024.50.06.

[20] Shulyk, Y. V. (2024) "State and Prospects for the Development of the Stock Market of Ukraine", *Scientific Notes of Ostroh Academy National University, Economics Series*, Vol. 61, No. 33, pp. 69-80. ISSN 2311-5149. DOI 10.25264/2311-5149-2024-33(61)-69-80.

[21] Statista. (2025) "*Payments - Worldwide*", Statista, [Online]. Available: https://www.statista.com/outlook/dmo/fintech/worldwide [Accessed: March 4, 2026].

[22] UkrAgroConsult (2025) "*Most Agricultural Holdings Saw a Decline in Capitalisation between 19 and 26 May*", UkrAgroConsult, [Online]. Available: https://ukragroconsult.com/news/ [Accessed: March 4, 2026].

[23] Ukrainian Exchange. (2025) "*Daily History of the Ukrainian Equity Index*", Ukrainian Exchange, [Online]. Available: https://www.ux.ua/ua/index/stat/dailyhistory.aspx?code=UX [Accessed: March 4, 2026].

[24] Urikova, O., Mysko, Y. and Karyy, O. (2025) "FinTech Industry of Ukraine: Prospects and Challenges", *Academic Journals and Conferences*, Vol. 9, No. 1, pp. 96-111. ISSN 2786-7102. DOI 10.23939/semi2025.01.096.

[25] WIG Ukraine (2025) "*WIG Ukraine Index*", [Online]. Available at: https://ru.investing.com/indices/wig-ukraine-chart [Accessed: March 4, 2026].

[26] Zhurko, R. and Shcherbak, Y. (2024) "Trends and Challenges of FinTech Development in the Banking Sector of Ukraine", *Scientific Bulletin of Polissya*, Vol. 29, No. 2, pp. 479-495. ISSN 2410-9576. DOI 10.25140/2410-9576-2024-2(29)-479-495.

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Assessing Climate Vulnerability and Its Linkages to Adaptation Strategies and Farm Resilience in Rice Farming Systems

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Abstract

Rice farming systems in swamp lowland ecosystems are highly vulnerable to climate change due to their dependence on hydrological conditions and limited adaptive resources. This study aims to examine the interaction between vulnerability, adaptation strategies, and farmer resilience to strengthen the sustainability of swamp-based rice farming. Using a mixed-methods approach that integrates Vulnerability and Capacity Assessment, SWOT analysis, and Structural Equation Modeling with data from 80 farmers selected through stratified random sampling, the research evaluates vulnerability components, identifies context-specific adaptive strategies, and tests causal relationships among key variables. The findings show that farmers face high vulnerability driven by strong exposure and sensitivity, while adaptive capacity remains limited. Although farmers possess experiential knowledge and social capital, technological gaps, low climate literacy, and financial constraints reduce adaptive readiness. The SEM results indicate that farmer characteristics significantly shape adaptation strategies, and both factors play a critical role in determining resilience. Overall, the study demonstrates that resilience emerges from the interaction between biophysical pressures and socioeconomic constraints, highlighting the importance of strengthening knowledge, technology access, and institutional support to enhance adaptive capacity and ensure the long-term sustainability of rice farming in vulnerable swamp ecosystems.

Keywords

Adaptation strategies, climate change, resilience, farmers, rice farming, Value Chain Analysis (VCA).

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Introduction

Climate change has emerged as a major challenge for the global agricultural sector, particularly for strategic food commodities such as rice, which serves as a primary pillar of food security in many developing countries. Global temperature surface during the decade of 2006-2015 was 0.87°C, and between 2030 and 2052 it has been predicted that temperature will be 1.5°C. Consequently, the risk of climate change to health is expected to be growing (Fatmawati and Sulistyawati, 2019). Climate change in Indonesia can be seen from the increasing of the temperature above average every year and the decreasing of annual rainfall in some regions. The South part of Indonesia tends to have less rain while the north has more rainfall, even it is always increasing. The temperature average in Indonesia during 1981-2010 was 27°C. However, in May 2019, it was detected that it was increasing up to 0,9°C (BMKG, 2019).

In Indonesia, the agricultural sector plays a vital role in national economic development (Nendissa et al., 2022; Salendu, 2021). However, this sector is confronted with numerous challenges, many of which are driven by climate change ((Maja and Ayano, 2021). Increasingly unpredictable climate variability including the rising frequency of floods, droughts, extreme weather anomalies, and shifts in planting seasons has direct implications for crop productivity, cultivation efficiency, and the income stability of farming households (Malhi et al., 2021; Saikanth et al., 2023). Farmers' vulnerability to climate change is further exacerbated by limited access to adaptive technologies, reliable climate information, and adequate agricultural infrastructure (Ogundeji et al., 2022).

The challenges posed by climate change affect not only agricultural production but also have broader implications for the sustainability of farmers' livelihoods and the stability of rural economies, particularly among smallholder farmers who face

significant limitations in accessing technology, information, and productive resources (Habib-ur-Rahman et al., 2022; Zenda, 2024). Studies by Maulu et al. (2021 and Yamin et al. (2025) highlight that the high dependence of smallholder farming systems on natural conditions makes them extremely sensitive to climatic disturbances such as drought and rainfall uncertainty. One of the regions most vulnerable to climate change is the lowland swamp agricultural area (Hashim et al., 2025). This ecosystem comprises three distinct types shallow swamp margin, intermediate swamp lowland, deep swamp lowland (Putra et al., 2025; Qurani and Lakitan, 2021), each exhibiting high susceptibility to climate-related impacts (Ratmini, 2021; Susilawati et al., 2025). Studies by Pathak et al. (2020) indicate that farmers operating within floodplain systems possess unique vulnerability characteristics due to their heavy dependence on water-level dynamics and the duration of inundation.

Research by Belay et al. (2022) further shows that smallholder farmers, who dominate agricultural structures in developing countries, represent the most vulnerable group due to limited formal education, insufficient access to information, and low capacity to comprehend rapidly changing climate dynamics. Low levels of education significantly hinder farmers' ability to identify climate risks and select appropriate adaptation measures when facing floods, droughts, and increasingly erratic planting seasons (Ahmad et al., 2022). Education level is one of the most decisive factors influencing the effectiveness of farmers' climate change adaptation, as it affects their capacity to interpret climate information and adopt adaptive technologies (Marie et al., 2020). These conditions create a deepening cycle of vulnerability, wherein limited adaptive capacity directly contributes to heightened risks of crop failure, declining productivity, and income instability among farming households (Abebaw, 2025).

However, to date, most research on climate change within the agricultural sector has predominantly focused on biophysical dimensions or merely described its impacts on crop production Piontek et al. (2021), In contrast, studies that comprehensively examine the interlinkages between farmers' vulnerability, adaptation strategies, and agricultural resilience remain limited (Kapitza). Previous studies have largely assessed vulnerability using conventional quantitative approaches, without integrating participatory perspectives capable of capturing the social ecological dynamics experienced by farmers at the local level (Alfie-Cohen and Garcia-Becerra, 2022). Moreover, holistic vulnerability assessment frameworks such as the Vulnerability and Capacity Assessment (VCA) remain rarely applied in research on rice farming systems in Indonesia, particularly in efforts to understand how the dimensions of exposure, sensitivity, and adaptive capacity interact to shape farmers' overall vulnerability. Earlier research has also tended to focus solely on vulnerability mapping, without further linking these assessments to the actual adaptation strategies implemented by farmers or to the resulting resilience outcomes (Kuchimanchi et al., 2021). Yet the connection between adaptation strategies and the level of resilience is essential for understanding the extent to which adaptive actions can reduce climate-related risks and enhance the long-term sustainability of farming systems (Loboguerrero et al., 2019).

Therefore, this study offers a methodological and conceptual contribution by pursuing three key objectives: (1) to conduct an in-depth assessment of rice farming vulnerability based on the three core dimensions of the Vulnerability and Capacity Assessment (VCA) exposure, sensitivity, and adaptive capacity; (2) to evaluate the adaptation strategies implemented by farmers in response to climate-related risks, not only descriptively but also in terms of their relevance and effectiveness; and (3) to examine the relationship between adaptation strategies and the level of resilience in rice farming systems, in order to understand how adaptive actions contribute to farmers' capacity to cope with and recover from climate-induced stresses. Integrating these three objectives provides a more comprehensive analytical framework and addresses the gaps identified in previous research, thereby generating a more holistic understanding of vulnerability, adaptation, and resilience.

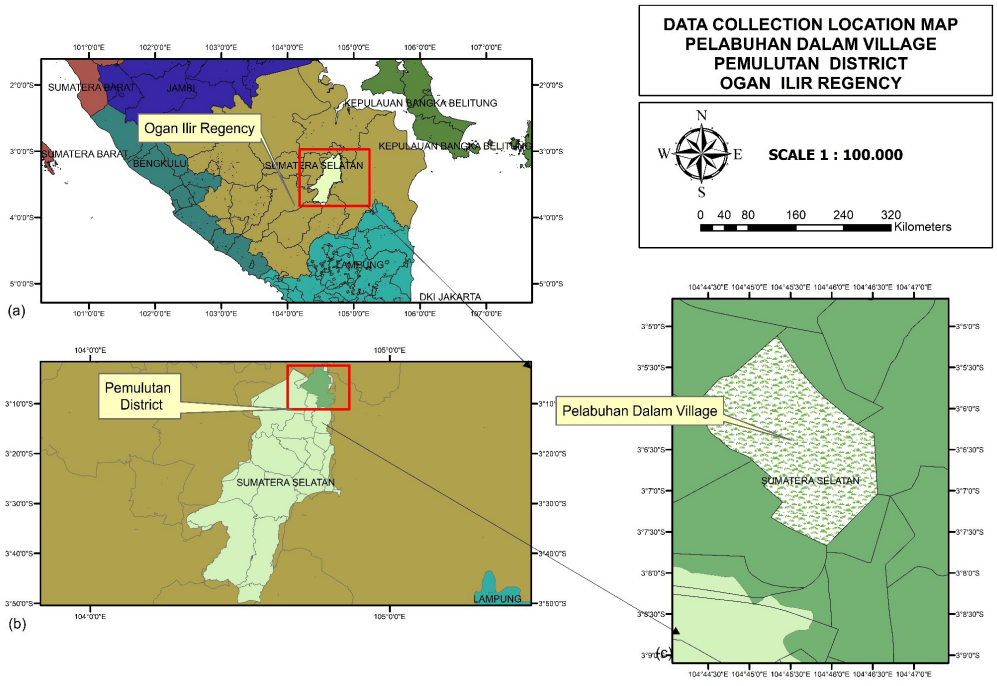
Materials and methods

The study was conducted in Pelabuhan Dalam Village, Pemulutan Subdistrict, Ogan Ilir Regency, an area characterized by swamp lowlands, which comprise three distinct types: shallow swamp margin, intermediate swamp lowland, and deep swamp lowland. The unique characteristics of these landscapes coupled with their high exposure to climate-related risks make farmers particularly vulnerable to the impacts of climate

change. Therefore, this research aims to assess the extent of farmers' vulnerability to climate change and to identify the adaptation strategies required for sustaining their agricultural activities. The detailed research location is presented in Figure 1 below.

This study employs a mixed-methods approach, integrating quantitative and qualitative analyses through the application of three analytical frameworks: VCA, SWOT, and SEM. These methods were selected to provide a comprehensive understanding of vulnerability, adaptation strategies, and resilience among rice farmers in lebak swamp lowland ecosystems. The VCA analysis is used to assess vulnerability based on the dimensions of exposure, sensitivity, and adaptive capacity (Nadeem et al., 2024), thereby offering empirical insights into farmers' levels of climate exposure and their capacity to adapt (Abdollahzadeh et al., 2023). The SWOT analysis complements these findings by identifying the strengths, weaknesses, opportunities, and threats that shape the formulation of realistic and context specific adaptation strategies for farmers (Magondu et al., 2025). Furthermore, the SEM approach is employed to examine the causal relationships among farmer characteristics, the adaptation strategies they implement, and the resulting levels of farming resilience. This enables a more holistic understanding of the key determinants influencing the sustainability of rice farming systems within swamp environments (Hidayat and Wulandari, 2022; Stoffels et al., 2023).

The population of this study consists of rice farmers cultivating swamp lowlands across the three land types in Pelabuhan Dalam Village, Pemulutan Subdistrict, Ogan Ilir Regency. A total of 80 farmers were selected as respondents using a random sampling technique stratified by land type, ensuring proportional representation of each swam category (Noor et al., 2022). Indicators used to identify internal factors including strengths and weaknesses and external factors including opportunities and threats were examined through a descriptive qualitative SWOT analysis. All items were measured using a five-point Likert scale ranging from "strongly disagree" to "strongly agree" (Zheng et al., 2024). Details of the research variables and indicators are presented in Table 1 and Table 2.



Source: Autors

Figure 1: Site study sampling: a) South Sumatra, b) Pemulutan Subdistrict, c) Pelabuhan Dalam Vilage.

Variable	Indicator	Measurement
Farmer Characteristics (X1)	Age	Years
	Education Level	Years
	Household Dependents	Persons
	Length of Farming Experience	Years
	Cultivated Land Area	Hectares
Adaptation Strategies (X2)	Adjustment of Planting Schedules	Likert Scale
	Climate-Tolerant Varieties	Likert Scale
	Farm Diversification	Likert Scale
	Adaptive Technologies	Likert Scale
	Access to Climate Information	Likert Scale
Resilience (Y)	*Absorptive Capacity*	Likert Scale
	Adaptive Capacity	Likert Scale
	Transformative Capacity	Likert Scale

Source: Autors

Table 1: Variables and indicators for SEM–PLS analysis.

Component	Fokus Indicator
Strengths	Farmers' Experience
	Local Knowledge
	Social Support
	Presence of Farmer Groups
Weaknesses	Limited Access to Technology
	Insufficient Capital
	Low Climate Literacy
Opportunities	Government Program
	Market Access
	Availability of Adaptive Agricultural Technologies
Threats	Extreme Climate Variability
	Price Fluctuations of Agricultural Products
	Natural Resource Degradation

Source: Autors

Table 2: Identification of SWOT Element.

Result and discussion

Socioeconomic and demographic characteristics of respondents

Table 1 summarizes the respondents' socioeconomic characteristics. Most farmers were mature adults, with 60% aged 31–45 and the rest above 46, a pattern consistent with rice-farming demographics reported in Vietnam (Tran et al., (2020). Over half had 10–20 years of farming experience, indicating strong practical knowledge of swamp rice systems. Education levels were generally low, as 62.5% had only basic schooling, which may limit access to modern technologies. Household size was moderate (4–7 members), providing family labor but also increasing economic responsibility. Farm sizes varied, with 53.75% cultivating less than one hectare and 33.75% managing more than two hectares, reflecting a mix of semi-subsistence and semi-commercial production.

Climate vulnerability of rice farmers

The vulnerability assessment conducted in the study area reveals that rice farmers experience a high level of climate-related vulnerability, as summarized in Tables 2 and 3. Table 2 shows that the vast majority of respondents (88.75%) fall into the very high vulnerability category, with only a small proportion categorized as high (6.25%), moderate (1.25%), or low (3.75%). Notably, no respondents were classified as having very low vulnerability, indicating that climate stressors

Category	Frequency	Percentage (%)	Standard Deviation
Age (years)			
15-30	0	0	6.9
31-45	48	60	
>46	32	40	
Farming Experience (years)			
1 - 10	17	21.25	8.9
10-20	41	51.25	
>20	22	27.5	
Years of Schooling			
6- 9	50	62.5	3.3
10 -12	29	36.25	
> 12	1	1.25	
Household Size			
1-3	30	37.5	1.3
4-7	48	60	
>7	2	2.5	
Farm Siza (ha)			
0-1	43	53.75	1.2
1-2	10	12.5	
>2	27	33.75	

Source : Primary data (2025)

Table 3: Socioeconomic and demographic characteristics of respondents.

Score Range	Frequency	Percentage (%)	Category
0 - 1	0	0	Very Low
1.1- 1.5	3	3.75	Low
1.6 - 2.5	1	1.25	Moderate
2.6 - 3	5	6.25	Hight
> 3.1	71	88.75	Very High
Total	80	100	Very High

Source: Primary data (2025)

Table 4: Vulnerability level data.

overwhelmingly affect all farmers in the region. This pattern is consistent with findings from flood-prone and hydrologically unstable rice ecosystems across Asia and Africa. Studies in Bangladesh Islam et al., (2022); and Jamal et al., (2023) similarly report that rice farmers are disproportionately vulnerable due to their strong dependence on climate-sensitive production systems and limited access to adaptive resources.

The component-level analysis (Table 5) shows that exposure (4.12) and sensitivity (4.11) are the dominant drivers of vulnerability. The high exposure score reflects farmers' continual interaction with climate hazards such as erratic rainfall, prolonged inundation, and fluctuating swamp water tables conditions that are widely acknowledged as major stressors in lowland rice production systems. Comparable results were reported by Mohammed and Favretto., (2025) in Nigeria's floodplain agriculture, where climate extremes directly undermine production stability and household food security. High sensitivity in this study further indicates the strong reliance of farmers on rice as their primary livelihood, which heightens the impact of climatic disturbances on income and welfare. This relationship has also been highlighted in (Gardezi et al., 2021), who observed that rice-dependent households are particularly vulnerable to seasonal hydrological shifts driven by climate change.

In contrast, the adaptive capacity index (3.32) is considerably lower than exposure and sensitivity, suggesting that the ability of farmers to adjust or mitigate climate impacts remains constrained. This finding aligns with Aqib et al., (2024), who reported that limited education, insufficient financial capital, and weak institutional support commonly restrict adaptive capacity in rural agricultural communities. Similar constraints have been identified in Southeast Asian rice systems, where access to climate information, improved seed varieties, and extension services remains uneven (Bell et al., 2018).

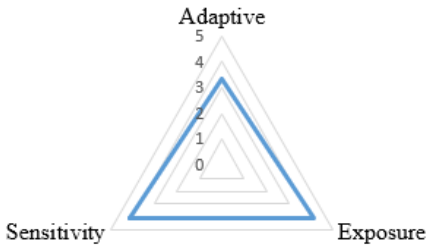
Component	Vulnerabillity Index
Adaptability	3.32
Sensitivity	4.11
Exposure	4.12

Source: Primary data analysis (2025)

Table 5: Key component of vulnerabillity index of area study.

Figure 2 further illustrates the imbalance among the three vulnerability components, with exposure and sensitivity extending more prominently than adaptive capacity. This triangular configuration highlights the structural and persistent nature of climate vulnerability in swamp-based rice farming systems. Such a pattern has similarly been reported in other coastal and inland wetland rice ecosystems, where farmers face simultaneous pressures from hydrological variability, extreme climatic events, and ecological fragility (Aalst et al., 2023) The convergence of high climatic exposure, elevated sensitivity, and constrained adaptive capacity reflects a vulnerability trap commonly found in lowland rice systems, particularly those dependent on highly climate-sensitive water regimes.

Overall, the findings indicate that rice farmers in the study area experience systemic and multi-dimensional climate vulnerability driven by both biophysical and socioeconomic constraints. These results are consistent with contemporary Scopus-indexed literature, which emphasizes that strengthening adaptive capacity through the adoption of climate-smart technologies, improved climate information services, livelihood diversification, and enhanced institutional support remains essential for building long-term climate resilience among smallholder rice farmers (Islam et al., 2022). The evidence therefore underscores the urgent need for integrated adaptation strategies tailored to the unique ecological conditions of swamp-based rice production.



Source: Primary data analysis (2025)

Figure 2: Triangle diagram of the vulnerability index.

Climate change adaptation strategies of rice farmers

The IFE and EFE matrices outline farmers' adaptive readiness and the external conditions shaping climate change adaptation (Table 6). An IFE score of 2.26 reflects moderate internal strength, mainly supported by long-term experience in swamp rice farming and strong farmer-group institutions. These findings align with studies showing that experiential knowledge, social capital, and community cohesion are central to rural climate resilience (Okolie et al., 2024). Farmer collaboration and active groups facilitate information sharing, peer learning, and coordinated action, reinforcing their role as key adaptation assets. Local wisdom in managing hydrological variability further strengthens adaptive capacity. Despite these strengths, notable weaknesses persist. Limited access to improved technologies, low financial capacity, and insufficient climate-risk awareness constrain farmers' ability to shift from traditional to more technical adaptation strategies. Such constraints mirror patterns observed in other developing-country rice systems where financial and informational barriers inhibit adoption of climate-resilient innovations (Khan et al., 2021). With a total weakness score of 1.00, these structural limitations continue to restrict farmers' adaptive flexibility.

The EFE results (Table 7) indicate an opportunity score of 1.08, showing that the external environment provides meaningful support for adaptation. Government agricultural programs represent the strongest opportunity (0.60), consistent with evidence that subsidies, credit, and extension services enhance adaptive capacity and technology adoption (Gardezi et al., 2021). Climate-oriented technologies (0.38) also offer potential, although limited market access (0.10) constrains broader benefits.

In contrast, the threat score of 1.25 reflects significant external pressures. Unpredictable weather (0.45)

Internal Factor	Rating	Weight	Score
Strengths			
Farmers experience in managing swamp land	4	0.15	0.60
Local wisdom that contributes to agricultural activities	4	0.13	0.53
Collaboration among farmers	4	0.11	0.45
Farmer groups activities	4	0.17	0.68
Total Score			**2.26**
Weakness			
Limited access to improved agricultural tools and technologies	1	0.17	0.17
Farmers' financial capacity	1	0.09	0.09
Farmers exhibit limited awareness regarding climate change and its implications for agricultural production	1	0.17	0.17
Total Score		**1.00**	**0.43**

Source: Primary data (2025)

Table 6: IFE Matrix.

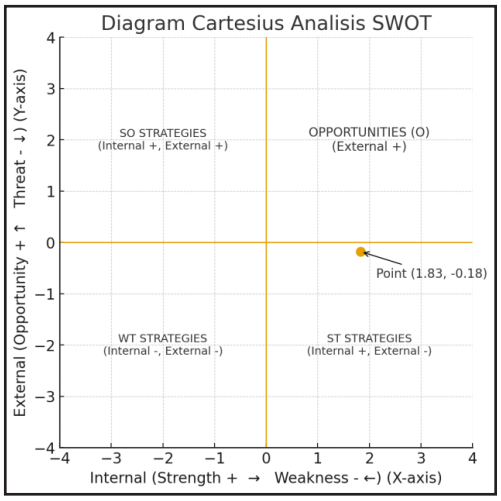
Exernal Factor	Rating	Weight	Score
Opportunities			
Government-supported programs provide assistance that strengthens agricultural activities	4	0.15	0.60
Harvested rice has market access beyond the local area	1	0.10	0.10
Availability of equipment and technologies designed to address climate-related challenges	3	0.13	0.38
Total Score			**1.08**
Threats			
Increasingly unpredictable weather patterns affect crop performance	2	0.23	0.45
Fluctuating and unstable paddy prices	2	0.20	0.40
Declining soil and water quality in rawa agricultural areas	2	0.20	0.40
Total Score		**1.00**	**1.25**

Source: Primary data (2025)

Table 7: EFAS Matrix.

poses the greatest threat, echoing patterns across Indonesia's swamp-based agricultural regions, where extreme hydrological fluctuations reduce planting windows and heighten crop failure risks (Das et al., 2025; Yuliantina et al., 2024). . Price volatility (0.40) and degradation of soil and water quality (0.40) further intensify vulnerability, similar to conditions in other floodplain and deltaic systems in Bangladesh, Myanmar, and Vietnam, where climate shocks and market stressors jointly increase livelihood risks (Ahmed et al., 2021; Tran et al., 2020).

The SWOT Cartesian diagram (Figure 3) positions the farming community in the Quadrant II (Weakness–Opportunity) strategic zone, with a coordinate of (1.83 – 0.18). This position indicates that although farmers possess access to external opportunities, internal limitations weaken their ability to fully utilize those opportunities.



Source: Primary data analysis (2025)

Figure 3: SWOT analysis.

Strategically, this suggests a WO strategy priority, emphasizing the need to address internal constraints (limited technology access, financial capacity, and climate awareness) by leveraging external supports such as government programs, emerging technologies, and institutional partnerships. This strategic orientation aligns with sustainability frameworks that view climate adaptation as a function of both endogenous capacity-building and exogenous resource mobilization.

Overall, the integrated IFE–EFE and SWOT assessment reveals that while farmers benefit from strong social structures and experiential knowledge, their adaptation is hindered by financial, technological, and informational constraints. Enhancing institutional support, improving farmer access to climate-smart technologies, and strengthening extension-based climate literacy emerge as central priorities for reducing vulnerability and enabling more robust and transformative adaptation pathways.

The adaptation strategies formulated in Table 8 demonstrate a coherent integration of farmers' internal capacities with the external opportunities and challenges shaping climate resilience in swamp-based rice systems. The SO strategies highlight the optimization of experiential knowledge, farmer-group collaboration, and local wisdom through alignment with government programs and climate-smart technologies. Recent studies confirm that strengthening endogenous capacities through institutional support significantly enhances adaptive responses in smallholder agriculture (Ishtiaque, 2021). The WO strategies address structural weaknesses limited technological access, insufficient financial resources, and low climate literacy by leveraging available institutional and technological opportunities. This approach is consistent with contemporary evidence showing that targeted external interventions, including microfinance, digital extension services, and climate-oriented innovations, are crucial for reducing capacity gaps in vulnerable farming

Internal Factor / **External Factor**	**Strengths (S)** 1. Farmers possess substantial experience in managing lowland swamp rice fields. 2. Local knowledge remains widely practiced and continues to support agricultural activities. 3. Strong mutual assistance exists among farmers in day-to-day farming operations. 4. Farmer groups are active and provide both technical and social support to their members.	**Weaknesses (W)** 1. Farmers have limited access to modern agricultural tools and technologies. 2. Financial capital among farmers remains insufficient 3. Knowledge of climate change and its agricultural impacts is still limited.
Opportunities (O) 1. Government programs and assistance schemes are available to support agricultural development. 2. Harvested rice can be marketed to external regions, offering wider market access. 3. Support for agricultural tools and climate-adaptive technologies is increasingly available.	**SO Strategies (Strength–Opportunity)** 1. Leverage farmers' experience and collaborative networks (S1, S3, S4) to maximize the benefits of government programs (O1) aimed at improving technologies for swamp-based rice cultivation. 2. Integrate local knowledge (S2) with available climate-adaptive technologies (O3) to enhance farmers' resilience without disregarding traditional practices. 3. Improve production and product quality (S1, S2) to meet external market demand (O2) by establishing cooperative-based marketing systems.	**WO Strategies (Weakness–Opportunity)** 1. Utilize government-supported agricultural technologies (O1, O3) to address farmers' limited technological capacity (W1). 2. Access government programs (O1) to obtain additional financial support (W2) through microfinance or rural credit institutions. 3. Involve farmers in climate-adaptation training initiatives (O3) to strengthen their knowledge and risk-management skills (W3).
Threats (T) 1. Increasingly unpredictable weather patterns negatively affect crop yields. 2. Rice grain prices fluctuate frequently and lack stability. 3. Soil and water quality in swamp-based farming areas show signs of deterioration.	***ST Strategies (Strength–Threat)*** 1. Mobilize farmer groups (S4) to improve coordination and collective action in responding to unpredictable weather conditions (T1). 2. Utilize farmer-to-farmer solidarity (S3) to establish minimum selling-price agreements that reduce the impact of price fluctuations (T2). 3. Maintain and promote local knowledge practices (S2) that help sustain soil and water quality in swamp ecosystems (T3).	**WT Strategies (Weakness–Threat)** 1. Develop partnerships with cooperatives or financial institutions (addressing W2) to strengthen farmers' resilience to grain-price volatility (T2). 2. Implement training programs on soil and water management (addressing W3) to mitigate declining land quality in swamp-based farming areas (T3). 3. Promote crop diversification (W1, T1) to reduce dependency on a single climate-sensitive commodity.

Source: Primary data analysis (2025)

Table 8: SWOT-derived adaptation strategies.

communities (Antwi-agyei et al., 2022). The ST strategies utilize farmers' social cohesion and local ecological knowledge to mitigate major threats such as weather unpredictability, market volatility, and environmental degradation. Recent literature underscores that community-based networks and farmer mechanisms improve adaptive behavior by enabling coordinated responses to climatic shocks (Osumba et al., 2021). Similarly, the continuation of local knowledge practices is recognized as a key factor in maintaining ecological stability in wetland agricultural systems (Barman et al., 2025).

Lastly, the WT strategies act as defensive measures aimed at minimizing climate-related risks by simultaneously addressing internal limitations and external threats. Strategies such as crop diversification, improved soil–water management, and financial partnerships align closely with recommended adaptive pathways for climate-sensitive rice ecosystems, particularly in hydrologically vulnerable landscapes (Tran et al., 2020). These strategies directly correspond to the high levels of vulnerability previously identified in the study area. Overall, the SWOT-derived adaptation strategies reflect a balanced and context-specific framework that reinforces the need for integrated, institutionally supported, and community-driven approaches to strengthen resilience in swamp-based rice farming systems.

Structural Equation Modeling (SEM)

Structural Equation Modeling (SEM) was employed to examine the structural relationships among farmer characteristics, adaptive strategies, and the resilience of rice farmers in floodplain (rawa lebak) areas (Faruk and Maharjan, 2022; Saleh et al., 2024). This method was selected for its ability to simultaneously evaluate complex causal relationships among latent variables. The construct model analysis focused on the interrelations between Farmer Characteristics, Adaptive Strategies, and Resilience, with results summarized in Table 9.

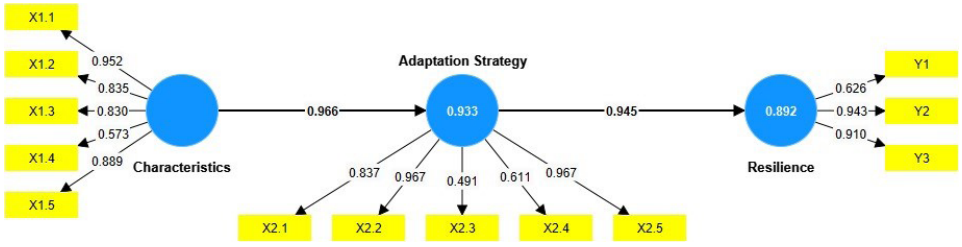
Variable	Outer loadings
X1.1 <- X1. Characteristics	0.952
X1.2 <- X1. Characteristics	0.835
X1.3 <- X1. Characteristics	0.830
X1.4 <- X1. Characteristics	0.573
X1.5 <- X1. Characteristics	0.889
X2.1 <- X2. Adaptive Strategies	0.837
X2.2 <- X2. Adaptive Strategies	0.967
X2.3 <- X2. Adaptive Strategies	0.491
X2.4 <- X2. Adaptive Strategies	0.611
X2.5 <- X2. Adaptive Strategies	0.967
Y1 <- X3. Resilience	0.626
Y2 <- X3. Resilience	0.943
Y3 <- X3. Resilience	0.910

Source: Primary data (2025)

Table 9: Factor loadings of latent constructs.

Outer loadings were used to assess the strength of the relationships between latent constructs and their manifest indicators, following the conventional threshold of 0.70 (Hair Jr. et al., 2020).

The low outer loading values indicate limited contributions of several indicators to their latent constructs. Farming Experience (0.573) shows weak association, reflecting that long experience does not necessarily support adaptation when farmers remain attached to traditional practices (Bouttes; de Boon). Adaptive Technologies (0.491) also has minimal influence due to low adoption driven by limited access, high perceived risks, and inadequate technical (Fyka et al., 2025). Access to Climate Information (0.611) contributes moderately, as climate data is not consistently transformed into adaptive decisions because of limited climate literacy and information barriers (Nugroho et al., 2025). Absorptive Capacity (0.626) further suggests restricted ability to internalize new knowledge. Overall, these results underscore the need to strengthen information access, technological readiness, and adaptive support to improve construct representation in the model (Figure 4).



Source: Primary data analysis (2025)

Figure 4: Results of data analysis (after reconstruction).

Hypotesis testing

Hypothesis testing in the SEM-PLS framework employed bootstrapping to obtain stable parameter estimates and reliable confidence intervals, using a 5% significance level and SmartPLS 4. This approach enabled a clearer evaluation of the causal pathways afnmong the latent constructs and strengthened the interpretation of how exogenous and mediating variables influence the endogenous variables within the model (Table 10).

The SEM analysis indicates that the structural relationships among the variables exert a highly significant and robust influence in explaining the dynamics of adaptive strategies and the resilience of rice farmers to climate change. The magnitude of the path coefficients, combined with substantial t-statistics and highly significant p-values, confirms the reliability and validity of the estimated structural model. The path linking farmer characteristics (X1) to adaptive strategies (X2) exhibits a coefficient of 0.966, demonstrating that individual attributes constitute a primary determinant of adaptive decision-making. Factors such as educational attainment, farming experience, managerial competency, and access to agricultural information significantly enhance farmers' capacity to respond effectively to climatic stressors, emphasizing the pivotal role of human capital in shaping adaptation outcomes.

The relationship between farmer characteristics (X1) and resilience (X3) yields a coefficient of 0.912, suggesting that resilience is influenced not only by the implementation of adaptive strategies but also by the intrinsic socio-economic and personal capacities of the farmers. Stronger characteristics enable more effective risk management, recovery from extreme climate events, maintenance of production stability, and preservation of income streams (Lawrence et al., 2020). These results underscore the critical importance of personal and socio-economic capacity in fostering long-term farm-level resilience. The linkage between adaptive strategies (X2) and resilience (X3) shows a coefficient of 0.945 (t = 113.435; p = 0.000), confirming that adaptation strategies represent a central mechanism directly determining resilience outcomes. Strategies such as adjustments to planting calendars, adoption of climate-resilient varieties, water-efficient technologies, livelihood diversification, and utilization of climate information substantially enhance farmers' ability to cope with climatic variability and extreme events (Gowdhaman, 2024; Malhi et al., 2021; Amaka et al., 2025). Improvements in these strategies are reflected in increased production capacity, income stability, and recovery potential. the estimated SEM model indicates that farm resilience is primarily shaped by two interrelated pillars: the inherent capacities embedded in farmers' socio-economic and personal characteristics, and the effectiveness of the adaptation strategies they implement (Mirzaei et al., 2022). Stronger characteristics facilitate the selection and adoption of appropriate adaptive measures, while effective strategies directly enhance resilience. These findings highlight the necessity of policy interventions focused on human capital development, knowledge dissemination, and the provision of accessible adaptive technologies to strengthen resilience in climate-vulnerable rice-farming system.

Conclusion

This study demonstrates that rice farming systems in swamp lowland areas face substantial vulnerability due to high exposure to climatic stressors, strong sensitivity to environmental disturbances, and limited adaptive capacity. Through the integration of VCA, SWOT, and SEM analyses, the research reveals that farmers' characteristics, the adaptation strategies they adopt, and the resilience they achieve are closely interconnected. In essence, the sustainability of rice farming is shaped not only by ecological

Variable	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
X1. Characteristics> X2. Adaptive Strategies	0.966	0.968	0.007	131.256	0
X1. Characteristics> X3. Resilience	0.912	0.916	0.013	71.222	0
X2. Adaptive Strategies > X3. Resilience	0.945	0.946	0.008	113.435	0

Source: Primary data (2025)

Table 10: Path analysis.

conditions but also by the quality of human capital and the effectiveness of adaptive actions undertaken by farmers. The findings indicate that farmers possess valuable experiential knowledge and social capital, yet constraints related to technology access, climate information, and financial resources reduce their ability to fully capitalize on available adaptation opportunities. This creates a clear causal pathway: limited adaptive capacity leads to suboptimal adaptation strategies, which in turn restrict the development of resilience. Conversely, stronger personal attributes and more appropriate adaptation strategies enable farmers to reduce risks and recover more effectively from climate-related disturbances. Overall, this study emphasizes that strengthening resilience in swamp-based rice farming systems requires continuous enhancement of farmers' adaptive capacity through improved knowledge, technological support, and institutional reinforcement that aligns with local needs. Such efforts are essential to ensure that farmers are not only able to withstand climatic pressures but also capable of advancing within an increasingly dynamic and uncertain agricultural landscape. The research concludes that resilience is not an inherent condition but a product of deliberate, integrated, and sustained adaptation processes.

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References

[1] Aalst, M. A., Koomen, E. and de Groot, H. L. F. (2023) "Vulnerability and resilience to drought and saltwater intrusion of rice farming households in the Mekong delta, Vietnam", *Economics of Disasters and Climate Change*, Vol. 7, No. 3, pp. 407-430. E-ISSN 2511-1299, ISSN 2511-1280. DOI 10.1007/s41885-023-00133-1.

[2] Abdollahzadeh, G., Sharifzadeh, M. S., Sklenička, P. and Azadi, H. (2023) "Adaptive capacity of farming systems to climate change in Iran: Application of composite index approach", *Agricultural Systems*, Vol. 204, p. 103537. ISSN 0308-521X. DOI 10.1016/j.agsy.2022.103537..

[3] Abebaw, S. E. (2025) "A global review of the impacts of climate change and variability on agricultural productivity and farmers' adaptation strategies", *Food Science & Nutrition*, Vol. 13, No. 5, pp. e70260. ISSN 2048-7177. DOI 10.1002/fsn3.70260.

[4] Ahmad, M. M., Yaseen, M. and Saqib, S. E. (2022) "Climate change impacts of drought on the livelihood of dryland smallholders: Implications of adaptation challenges", *International Journal of Disaster Risk Reduction*, Vol. 80, p. 103210. ISSN 2212-4209. DOI 10.1016/j.ijdrr.2022.103210.

[5] Ahmed, Z., Guha, G. S., Shew, A. M. and Alam, G. M. M. (2021) "Climate change risk perceptions and agricultural adaptation strategies in vulnerable riverine char islands of Bangladesh", *Land Use Policy*, Vol. 103, p. 105295. ISSN 1873-5754. DOI 10.1016/j.landusepol.2021.105295.

[6] Alfie-Cohen, M. and Garcia-Becerra, F. Y. (2022) "A multi-stakeholder participatory methodology to facilitate socio-ecological climate change vulnerability-adaptation-resilience strategies: application of the Q Method", *Mitigation and Adaptation Strategies for Global Change*, Vol. 27, p. 14. E-ISSN 1573-1596, ISSN 1381-2386. DOI 10.1007/s11027-021-09988-9.

[7] Amaka, C., Okeke, G., Ndubuisi, Cletus, E., Agbakhamen, C., Abubakar, S., Fnse, G. and Okeke, N. G. (2025) "Climate Change and Agriculture: Exploring Climate- Resilient Farming Practices. *International Journal of Innovative Finance and Economics Research*, Vol. 13, No. 2, pp. 266-280. ISSN 2360-896X. DOI 10.5281/zenodo.15571344.

[8] Antwi-Agyei, P., Mawuli, E., John, A. and Baffour-ata, F. (2022) "Motivations, enablers and barriers to the adoption of climate-smart agricultural practices by smallholder farmers: Evidence from the transitional and savannah agroecological zones of Ghana", *Regional Sustainability*, Vol. 2, No. 4, pp. 375-386. ISSN 2097-0129. DOI 10.1016/j.regsus.2022.01.005.

[9] Aqib, S., Seraj, M., Ozdeser, H., Khalid, S., Raza, M. H. and Ahmad, T. (2024) "Assessing adaptive capacity of climate-vulnerable farming communities in flood-prone areas: Insights from a household survey in South Punjab, Pakistan", *Climate Services*, Vol. 33, pp. 100444. ISSN 2405-8807. DOI 10.1016/j.cliser.2023.100444.

[10] Barman, A., Rajak, F. and Jha, R. (2025) "Integrating traditional knowledge systems for wetland conservation and management : a critical analysis", *Nature Environment & Pollution Technology*, Vol. 24, No.1, pp. 1-16. ISSN 0972-6268. DOI 10.46488/NEPT.2025.v24i01.B4212.

[11] Belay, A., Oludhe, C., Mirzabaev, A., Recha, J. W., Berhane, Z., Osano, P. M., Demissie, T., Olaka, L. A. and Solomon, D. (2022) "Knowledge of climate change and adaptation by smallholder farmers: evidence from Southern Ethiopia", *Heliyon*, Vol. 8, No. 12, p. e12089. E-ISSN 2405-8440. DOI 10.1016/j.heliyon.2022.e12089.

[12] Bell, J. E., Brown, C. L., Conlon, K., Herring, S., Kunkel, K. E., Lawrimore, J., Luber, G., Schreck, C., Smith, A. and Uejio, C. (2018) "Changes in extreme events and the potential impacts on human health", *Journal of the Air & Waste Management Association*, Vol. 68, No. 4, pp. 265-287. ISSN : 2162-2906. DOI 10.1080/10962247.2017.1401017.

[13] BMKG. (2019) "*Climate Change Extremes*", Indonesian Agency for Meteorology, Climatology, and Geophysics [Online]. Available: http://wis.bmkg.go.id/index.php?lang=en. [Accessed: Sept 11, 2025].

[14] Das, S. R., Chatterjee, D., Saha, S., Sarkar, D., Alam, R., Dey, S., Ghosh, S., Nayak, B. K., Smith, P. and Pathak, H. (2025) "Enhancing carbon sequestration potential of lowland rice agroecosystems for environmentally clean production system: A review", *Climate Smart Agriculture*, Vol. 2, No. 2, p. 100054. ISSN 2456-6632. DOI 10.1016/j.csag.2025.100054.

[15] Faruk, M. O. and Maharjan, K. L. (2022) "Factors affecting farmers' adoption of flood adaptation strategies using structural equation modeling", *Water*, Vol. 14, No. 19, p. 3080. ISSN 1816-7950. DOI 10.3390/w14193080.

[16] Fatmawati, F. and Sulistyawati, S. (2019) "Climate change and dengue in Indonesia: a systematic review", *Epidemiology and Society Health Review*, Vol. 1, No. 1, pp. 29-40. ISSN 2656-1107.

[17] Fyka, S. A., Rianse, U., Yunus, L. and Limi, M. A. (2025) "The existing analysis of rice-fish integration farming on lebak swamp land in terms of social economic and institutional dimensions", *Jurnal Ilmiah Membangun Desa Dan Pertanian*, Vol. 10, No. 3, pp. 252-265. E-ISSN 2527-2748. DOI 10.37149/JIMDP.v10i3.2065.

[18] Gardezi, M., Semhar Michael, R. S., Vij, S., Ogunyiola, A. and Ishtiaque, A. (2021) "Prioritizing climate-smart agriculture: An organizational and temporal review", *WIREs Climate Change*, Vol. 3, No. 15, p. e755. ISSN 1757-7780. DOI 10.1002/wcc.755.

[19] Gowdhaman, P. (2024) "Adaptation to progressive climate change, technology development, agricultural practices", In: Jayasudha, J, Patel, P. N., Manobharathi, K, Aparna Jayan, R. and Chaudhary, K. L. (eds.) "*Innovative Agricultural Extension Approach",* Chapter 14, pp. 207-255. ISBN 9789361356995. DOI 10.22271/ed.book.2567.

[20] Habib-ur-Rahman, M., Ahmad, A., Raza, A., Hasnain, M. U., Alharby, H. F., Alzahrani, Y. M., Bamagoos, A. A., Hakeem, K. R., Ahmad, S. and Nasim, W. (2022) "Impact of climate change on agricultural production; Issues, challenges, and opportunities in Asia", *Frontiers in Plant Science*, Vol. 13, p. 925548. E-ISSN 1664-462X. DOI 10.3389/fpls.2022.925548.

[21] Hair Jr., J. F., Howard, M. C. and Nitzl, C. (2020) "Assessing measurement model quality in PLS-SEM using confirmatory composite analysis", *Journal of Business Research*, Vol. 109, pp. 101-110. ISSN 0148-2963. DOI 10.1016/j.jbusres.2019.11.069.

[22] Hashim, B. M., Alnaemi, A. N. A., Sultan, M. A., Alraheem, E. A., Abduljabbar, S. A., Halder, B., Shahid, S. and Yaseen, Z. M. (2025) "Impact of climate change on land use and relationship with land surface temperature: representative case study in Iraq", *Acta Geophysica*, Vol. 73, No. 3, pp. 3025-3043. E-ISSN 1895-7455. DOI 10.1007/s11600-024-01514-0.

[23] Hidayat, R. and Wulandari, P. (2022) "Data analysis procedures with structural equation modelling (SEM): Narrative literature review", *Open Access Indonesia Journal of Social Sciences*, Vol. 5, No. 6, pp. 859-865. E-ISSN 2723-777X. DOI 10.37275/oaijss.v5i6.142.

[24] Ishtiaque, A. (2021) "Multilevel governance in climate change adaptation: Conceptual clarification and future outlook", In: Ali, F. (ed.) "*Climate Change and Extreme Events"*, Chapter 10, pp. 171-185. ISBN 9780128227008. DOI 10.1016/B978-0-12-822700-8.00009-3.

[25] Islam, F., Alam, G. M. M., Begum, R., Sarker, M. N. I. and Bhandari, H. (2022) "Farm level adaptation to climate change: insight from rice farmers in the coastal region of Bangladesh", *Local Environment*, Vol. 27, No, 6, pp. 671-681. ISSN 1354-9839. DOI 10.1080/13549839.2022.2068139.

[26] Jamal, M. R., Kristiansen, P., Kabir, M. J. and Lobry de Bruyn, L. (2023) "Challenges and adaptations for resilient rice production under changing environments in Bangladesh", *Land*, Vol. 12, No. 6, p. 1217. ISSN 2073-445X. DOI 10.3390/land12061217.

[27] Khan, P. A., Johl, S. K. and Johl, S. K. (2021) "Does adoption of ISO 56002-2019 and green innovation reporting enhance the firm sustainable development goal performance? An emerging paradigm", *Business Strategy and the Environment*, Vol. 30, No. 7, pp. 2922-2936. ISSN 1099-0836. DOI 10.1002/bse.2779.

[28] Kuchimanchi, B. R., van Paassen, A. and Oosting, S. J. (2021) "Understanding the vulnerability, farming strategies and development pathways of smallholder farming systems in Telangana, India", *Climate Risk Management*, Vol. 31, p. 100275. ISSN 2212-0963. DOI 10.1016/j.crm.2021.100275.

[29] Lawrence, J., Blackett, P. and Cradock-Henry, N. A. (2020) "Cascading climate change impacts and implications", *Climate Risk Management*, Vol. 29, p. 100234. ISSN 2212-0963. DOI 10.1016/j.crm.2020.100234.

[30] Loboguerrero, A. M., Campbell, B. M., Cooper, P. J. M., Hansen, J. W., Rosenstock, T. and Wollenberg, E. (2019) "Food and earth systems: priorities for climate change adaptation and mitigation for agriculture and food systems", *Sustainability*, Vol. 11, No. 5, p. 1372. ISSN 2071-1050. DOI 10.3390/su11051372.

[31] Magondu, E., Njogu, L., Ouko, K., Mboya, J. B., Muthoka, M., Yossa, R., Munguti, J., Opiyo, M. A., Meenakshisundaram, M. and Tanga, C. M. (2025) "A PESTEL-SWOT matrix analysis of sustainable aquafeed sector: a case of Kenya's fish feed sector", *Reviews in Aquaculture*, Vol. 17, No. 4, p. e70081. E-ISSN 1753-5131, ISSN 1753-5123. DOI 10.1111/raq.70081.

[32] Maja, M. M. and Ayano, S. F. (2021) "The impact of population growth on natural resources and farmers' capacity to adapt to climate change in low-income countries", *Earth Systems and Environment*, Vol. 5, No. 2, pp. 271-283. E-ISSN 2509-9434, ISSN 2509-9426. DOI 10.1007/s41748-021-00209-6.

[33] Malhi, G. S., Kaur, M. and Kaushik, P. (2021) "Impact of climate change on agriculture and its mitigation strategies: A review", Sustainability, Vol. 13, No. 3, p. 1318. SSN 2071-1050. DOI 10.3390/su13031318.

[34] Marie, M., Yirga, F., Haile, M. and Tquabo, F. (2020) "Farmers' choices and factors affecting adoption of climate change adaptation strategies: evidence from northwestern Ethiopia", *Heliyon*, Vol. 6, No. 4., p. 03867. E-ISSN 2405-8440. DOI 10.1016/j.heliyon.2020.e03867.

[35] Maulu, S., Hasimuna, O. J., Haambiya, L. H., Monde, C., Musuka, C. G., Makorwa, T. H., Munganga, B. P., Phiri, K. J. and Nsekanabo, J. D. (2021) "Climate change effects on aquaculture production: sustainability implications, mitigation, and adaptations", *Frontiers in Sustainable Food Systems*, Vol. 5, pp. 609097. ISSN 2571-581X. DOI 10.3389/fsufs.2021.60909

[36] Mirzaei, A., Azarm, H., Yazdanpanah, M. and Najafabadi, M. M. (2022) "Socio-economic, social-capital, and psychological characteristics and climate change adaptive behavior of farmers in Iran", *Climate Research*, Vol. 87, pp. 1-12. ISSN 1616-1572. DOI 10.3354/cr01683.

[37] Mohammed, U. K. and Favretto, N. (2025) "Livelihood diversification among women farmers in Nigeria's flood-resilient drylands", *Climate Risk Management*, Vol. 48, pp.100708. ISSN 2212-0963. DOI 10.1016/j.crm.2025.100708.

[38] Nadeem, F., Jacobs, B. and Cordell, D. (2024) "Adapting to climate change in vulnerable areas: farmers' perceptions in the Punjab, Pakistan", *Climate*, Vol. 12, No. 5, pp.58. ISSN 2225-1154. DOI 10.3390/cli12050058.

[39] Nendissa, D. R., Iriany, A., Sui, J. M., Khoiriyah, N., Suphattanakul, O. and Wisetsri, W. (2022) "The role of renewable and nonrenewable energy on agricultural economics in Indonesia", *International Journal of Energy Economics and Policy*, Vol. 12, No. 3, pp. 352-360. ISSN 2146-4553. DOI 10.32479/ijeep.13036.

[40] Noor, S., Tajik, O. and Golzar, J. (2022) "Simple random sampling", *International Journal of Education & Language Studies*, Vol. 1, No. 2, pp. 78-82. ISSN 2767-4851. DOI 10.22034/ijels.2022.162982.

[41] Nugroho, H. Y. S. H., Wahyuningrum, N., Basuki, T. M., Supangat, A. B., Auliyani, D., Indrajaya, Y., Lisnawati, Y. and Samawandana, G. (2025) "Sustainable Resilience for Integrated Watersheds Management Under Climate Change: Lesson Learned from Indonesia", In: Pal, S.C., Chatterjee, U., Saha, A., Ruidas, D. (eds) "*Climate Change: Conflict and Resilience in the Age of Anthropocene"*. Springer. pp. 303-327. ISBN 978-3-031-85358-6 DOI 10.1007/978-3-031-85359-3_13.

[42] Ogundeji, A. A., Danso-Abbeam, G. and Jooste, A. (2022) "Climate information pathways and farmers' adaptive capacity: Insights from South Africa", *Environmental Development.* Vol. 44, pp.100743. ISSN 2211-4645. DOI 10.1016/j.envdev.2022.100743.

[43] Okolie, C. C., Ogunleye, O. T., Danso-Abbeam, G., Ogundeji, A. A. and Restás, Á. (2024) "Smallholder farmers' coping and adaptation strategies to climate change: Evidence from a bibliometric analysis", *Environmental and Sustainability Indicators*, Vol.23, pp. 100451. ISSN 2665-9727. DOI 10.1016/j.indic.2024.100451.

[44] Osumba, J. J. L., Recha, J. W. and Oroma, G. W. (2021) "Transforming Agricultural Extension Service Delivery through Innovative Bottom-Up Climate-Resilient Agribusiness Farmer Field Schools", *Sustainability,* Vol.13, No. 7. pp. 3938. ISSN 2071-1050. DOI 10.3390/su13073938.

[45] Pathak, S., Panta, H. K., Bhandari, T. and Paudel, K. P. (2020) "Flood vulnerability and its influencing factors", *Natural Hazards*, Vol. 104, No. 3, pp. 2175-2196. ISSN 1573-0840. DOI 10.1007/s11069-020-04267-3.

[46] Piontek, F., Drouet, L., Emmerling, J., Kompas, T., Méjean, A., Otto, C., Rising, J., Soergel, B., Taconet, N. and Tavoni, M. (2021) "Integrated perspective on translating biophysical to economic impacts of climate change", *Nature Climate Change*, Vol. 11, No.7, pp.563-572. ISSN 1758-6798. DOI 10.1038/s41558-021-01065-y.

[47] Putra, D. E., Jambak, M. I. and Nawawi, Z. (2025) "Clustering of swamp land types against soil resistivity and grounding resistance", *TELKOMNIKA (Telecommunication Computing Electronics and Control)*, Vol. 23, No. 3, pp. 781-788. ISSN 1693-6930. DOI 10.12928/telkomnika.v23i3.26647.

[48] Qurani, I. Z. and Lakitan, B. (2021) "Inland swamp agriculture: Opportunities and challenges", *TJF Brief,* Figshare*,* Vol.18, No. 5, pp. 1-6. DOI 10.6084/m9.figshare.14608230.

[49] Ratmini, N. P. S. (2021) "The characteristics of swampland rice farming in South Sumatra: local wisdom for climate change mitigation", *IOP Conference Series: Earth and Environmental Science*, Vol. 724, No.1, pp 12033. ISBN 1755-1315. DOI 10.1088/1755-1315/724/1/012033.

[50] Saikanth, D. R. K., Kumar, S., Rani, M., Sharma, A., Srivastava, S., Vyas, D., Singh, G. A. and Kumar, S. (2023) "A comprehensive review on climate change adaptation strategies and challenges in agriculture", *International Journal of Environment and Climate Change*, Vol. 13, No.11, pp. 10-19. ISSN 2581-8627. DOI 10.9734/ijecc/2023/v13i113138.

[51] Saleh, K., Wibowo, A. S., Sulaeni, A. B. and Bukhari, A. (2024) "Characteristics and Managerial Capacity of Rice Farmers Impacting Family Welfare in Tangerang Banten District", *Jurnal Agrinika: Jurnal Agroteknologi Dan Agribisnis*, Vol. 8, No. 1. ISSN 2579-3659. DOI 10.30737/agrinika.v8i1.5089.

[52] Salendu, S. (2021) "The productivity of the agricultural sector and industrial sector as a driving force of economic growth and community welfare in Indonesia", *Benchmarking: An International Journal*, Vol. 28, No. 7, pp. 2216-2231. ISSN 14635771. DOI 10.1108/BIJ-07-2019-0349.

[53] Stoffels, M., Torre, D. M., Sturgis, P., Koster, A. S., Westein, M. P. D. and Kusurkar, R. A. (2023) "Steps and decisions involved when conducting structural equation modeling (SEM) analysis", *Medical Teacher*, Vol. 45, No. 12, pp. 1343-1345. ISSN 1466187X. DOI 10.1080/0142159X.2023.2263233.

[54] Susilawati, A., Izhar, L. and Sustama, A. A. S. (2025) "Land Management of Tidal Swamp Type B with Surjan System as Climate Change Anticipation", *Agromet*, Vol. 39, No.1, pp. 8-20. ISSN 0126-3633. DOI 10.29244/j.agromet.39.1.8-20.

[55] Tran, D. D., Quang, C. N. X., Tien, P. D., Tran, ham G., Long, P. K., Hoa, H. Van, Giang, N. N. H. and Ha, L. T. T. (2020) "Livelihood Vulnerability and Adaptation Capacity of Rice Farmers under Climate Change and Environmental Pressure on the Vietnam Mekong", *Water,* Vol.12, No. 11, pp.3282. ISSN 20734441. DOI 10.3390/w12113282.

[56] Yamin, M., Putri, T. W. S., Saputri, S. D., Tafarini, M. F., Sulastri, M. A., Damayanthy, D. and Andelia, S. R. (2025) "Analysis of Climate-Smart Agriculture (CSA) Adoption Level on Tidal Land and Its Effect on Household Food Security", *Research on World Agricultural Economy*, Vol. 6, No. 2, pp. 499-513. ISSN 27374785. DOI 10.36956/rwae.v6i2.1736.

[57] Yuliantina, N., Mulyana, A., Wildayana, E., Lionardo, A. and Septiana, B. (2024) "Analysis of Policy Strategies to Control the Conversion of Wetland Rice Land to Non- Agricultural Land Use in Palembang City South Sumatra", *Sriwijaya Journal of Environment*, Vol. 9, No.2, pp. 100-107. ISSN 25274961. DOI 10.22135/sje.2024.9.2.100-107.

[58] Zenda, M. (2024) "A systematic literature review on the impact of climate change on the livelihoods of smallholder farmers in South Africa", *Heliyon*, Vol.10, No.18, pp. 38162. ISSN 24058440. DOI 10.1016/j.heliyon.2024.e38162.

[59] Zheng, H., Ma, W. and He, Q. (2024) "Climate-smart agricultural practices for enhanced farm productivity, income, resilience, and greenhouse gas mitigation: a comprehensive review", *Mitigation and Adaptation Strategies for Global Change*, Vol.29, No.4, pp. 28. ISSN 15731596. DOI 10.1007/s11027-024-10124-6.

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Standardized Data Infrastructures for Plant Phenomics: A Review of MIAPPE and BrAPI Integration within High-Performance

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Abstract

The increasing complexity and volume of plant phenotypic data have driven the emergence of new computational and standardization frameworks to enable data integration, reproducibility, and reuse. This systematic literature review examines the current state of software tools, data models, and interoperability standards in plant phenomics, focusing on the implementation of the FAIR (Findable, Accessible, Interoperable, Reusable) principles. Using a structured PRISMA-based methodology, we analyze two major community driven initiatives MIAPPE and BrAPI as representative solutions for standardized data description and exchange. Furthermore, the study evaluates the role of High-Performance Computing (HPC) and deep learning in addressing computational challenges associated with large-scale datasets, including multi-sensor and 3D capture technologies. Special consideration is given to data governance, encompassing secure access, ethical use, and GDPR compliance within expanding phenomics ecosystems. The synthesis identifies persistent gaps in data harmonization and semantic alignment, proposing future research directions toward more integrated, secure, and scalable infrastructures. This review emphasizes that the success of plant phenomics depends on bridging the gap between standard definitions and their practical implementation within high-performance workflows.

Keywords

MIAPPE, BrAPI, plant phenomics, high-performance computing (HPC), FAIR principles, data management, ontology, data governance, interoperability, open science.

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Introduction

The proliferation of digital technologies and high-throughput data acquisition platforms has transformed plant science into a data intensive discipline. Modern phenomics, defined as the systematic study of plant traits through the integration of imaging, sensor technologies, and computational analytics, plays a crucial role in understanding genotype environment interactions. As the scale and complexity of data grows, ensuring that phenomics datasets are interoperable, reproducible, and reusable has become a central challenge for the research community.

A significant barrier to progress in this domain lies in the lack of standardized data models and exchange protocols. Phenotypic data are often stored in heterogeneous formats, annotated inconsistently, and distributed across numerous databases. This fragmentation hinders comparative analyses and limits the potential of integrative approaches that link phenotypic, genomic, and environmental data. To address these issues, international initiatives such as MIAPPE and BrAPI have been established to promote standardization and interoperability in phenomics research.

The MIAPPE standard defines a structured metadata schema to describe plant phenotyping experiments, covering elements such as experimental design, plant material, environmental conditions, and observed traits (Papoutsoglou et al., 2020). The accompanying data model enables harmonization and improves data discoverability across platforms. Complementarily, the BrAPI framework provides a web service specification that facilitates programmatic communication between breeding and phenotyping databases (Shelby

et al., 2019). Together, MIAPPE and BrAPI serve as key enablers of FAIR data management, enhancing transparency, re-producibility, and collaborative data sharing across institutions.

Alongside these standardization efforts, advances in computational infrastructure notably High-Performance Computing (HPC) and machine learning have significantly expanded analytical capacities in phenomics. HPC enables large-scale processing of multispectral images, time-series data, and multi-omics datasets, thereby supporting complex modeling and predictive breeding applications (Wallace et al., 2018; Abdul Hamid & Singh, 2024). These computational approaches not only accelerate scientific discovery but also contribute to the development of decision-support tools in precision agriculture and crop improvement.

As phenomics data ecosystems evolve, data governance and security emerge as equally critical dimensions. Responsible data management requires embedding ethical, legal, and technical safeguards such as role-based access control, data anonymization, and GDPR compliance into data infrastructures (Umbach, 2024). Ensuring security-by-design and adherence to open science principles strengthens public trust, encourages collaboration, and enhances the societal impact of research (Wilkinson et al., 2016, Papoutsoglou et al., 2020).

This review provides a systematic synthesis of current literature on software tools, data standards, and computational infrastructures in plant phenomics. It identifies key technological developments, evaluates the degree of interoperability achieved, and highlights emerging challenges related to scalability, ethical stewardship, and cross-domain data integration.

Breeding APIs and the evolution of BrAPI standards

In recent times, there has been a notable higher volume in the scale of datasets, leading to their dispersal across multiple platforms. As the demand for analyses requiring the interoperability of data from various origins rises, bridging the gap between disparate systems poses a considerable challenge. In addressing this challenge, was introduced the public plant Breeding Application Programming Interface (BrAPI), was introduced to enhance interoperability among breeding applications. BrAPI stands as a standardized web service API specification, conceived through collaborative efforts within a global community. The emergence of BrAPI enabled applications, known as BrAPPs, demonstrates the practical utility of this standard in aggregating datasets from diverse sources. This is further complemented by regional initiatives that integrate high-throughput measurements into high-performance computing infrastructures for agricultural research (Stočes et al., 2025). Acknowledged as a pivotal technology for various significant breeding system initiatives, the development of such a standard has gained recognition. The inaugural version of the API primarily focuses on furnishing services for system integration and the retrieval of fundamental breeding data encompassing germplasm, study, observation, and marker data. Several applications leveraging BrAPI compatibility, termed BrAPPs, have already been developed, capitalizing on the increasing adoption of BrAPI across numerous databases (Selby et al., 2019).

The introduction of BrAPI v2 marks a significant evolution of the standard, transitioning to a modular architecture that includes Core, Phenotyping, Genotyping, and Germplasm modules. This update enables more robust real-world applications for data integration and facilitates collaboration across diverse breeding and genetics communities, effectively addressing the challenges of managing large-scale, fragmented datasets in modern plant science (Selby et al., 2025). Specifically, for phenomics, BrAPI v2 provides enhanced support for high-throughput imaging data and complex phenotypic observations, allowing for more efficient programmatic exchange between large-scale phenotyping platforms and downstream analytical tools.

High-Performance Computing frameworks in phenomics

With the increasing complexity of data structures, the growing volume of multispectral imagery, time-series data, and integrated omics layers (e.g., the combination of phenomics and genomic data), the computational demands of phenomics research have risen substantially. In this context, High-Performance Computing (HPC) plays a crucial role. HPC provides the infrastructure necessary to process massive datasets in parallel, train large-scale machine learning models, and perform simulations that would be unfeasible or extremely time-consuming on conventional computing systems (Sterling et al., 2024, Choudhary at al., 2020).

HPC enables researchers to perform tasks more efficiently, such as automated seg-mentation of plant images, extraction of phenotypic traits, or yield prediction based on field-derived data. To ensure the FAIRness of HPC workflows, the use of standardized software containers and distributions like Bioconda is essential for reproducibility across different high-performance infrastructures (Georgiou et al., 2020, Grüning et al., 2018). For instance, the use of deep neural networks to process hyperspectral imagery facilitates accurate wheat yield estimations, an undertaking that would be nearly impossible without access to high-performance computational resources. Reflecting on the first decade of this development, deep learning has emerged as the dominant technique in plant phenotyping (Kartal et al., 2025), shifting the focus from traditional image analysis to high-capacity pipelines that extract high-level agronomic phenotypes (Ubbens et al., 2025). This evolution underscores the critical role of HPC in handling the "explosion" of multi-modal data from diverse sensors and 3D capture technologies (Ubbens et al., 2025).

In combination with standardized interfaces such as BrAPI, HPC not only accelerates computational workflows but also enhances the scalability and reproducibility of scientific experiments. Modern Breeding APIs are increasingly being linked to high-capacity pipelines, such as TASSEL-GBS, that leverage HPC clusters to perform genome-wide associations directly on integrated phenomics datasets (Glaubitz et al., 2014). This is critical for achieving robust, reproducible scientific outcomes and for enabling the integration of heterogeneous datasets from multiple sources.

HPC is particularly indispensable in the domain of predictive breeding, where historical and current phenotypic data are integrated with genotypic profiles to develop robust models with practical applications in agriculture and food security. The integration of genomic, phenomics, and environmental data through advanced computational techniques allows for more accurate predictions and more efficient selection of resilient and high-yielding cultivars (Yunbi et al., 2022).

Thus, the application of high-performance computing in phenomics not only accelerates scientific progress but also paves the way toward more efficient and sustainable approaches to plant production.

Aim of the review and anticipated research gaps

1. Gap in understanding how MIAPPE guidelines, BrAPI standards, and ontologies can be effectively combined to achieve better data harmonization. There is a lack of studies investigating the effectiveness of various methods in achieving this goal. This includes the application of retrospective harmonization and the impact of data transformation strategies on the quality of harmonized data.
2. Limited research on the selection of appropriate software tools for data harmonization, despite the increasing trend towards open science and FAIR principles. This includes tools that support the use of MIAPPE, BrAPI, and ontologies.
3. Gap in integrating standardized data workflows with High-Performance Computing (HPC) infrastructure. While HPC is essential for large-scale phenomics, there is insufficient research on how to maintain data standards (MIAPPE/BrAPI) throughout the automated processing and analysis in HPC environments.
4. Gap in understanding the practical challenges and opportunities in implementing these principles in real-world scenarios, although there has been progress in promoting data sharing and reusability. This includes issues related to data management, interoperability, and the use of tools like PHIS.

Materials and methods

The methodology of this study follows the PRISMA-ScR (Preferred Reporting Items for Systematic reviews and Meta-Analyses extension for Scoping Reviews) guidelines (Tricco et al., 2018) to ensure transparency and reproducibility. A scoping review approach was selected as particularly suited for mapping evidence in a rapidly evolving field, identifying main concepts, and uncovering knowledge gaps within a heterogeneous body of literature (Tricco et al., 2018). The primary objective was to map the current landscape of standardized data infrastructures, focusing on the integration of MIAPPE, BrAPI, and High-Performance Computing (HPC) frameworks in plant phenomics.

Research Questions (RQ)

To guide the literature search and synthesis, we formulated three key research questions:

- RQ1: What is the current state of data sharing (interoperability) and data harmonization in plant biology?
- RQ2: Which types of data and data models are utilized for phenotypic data harmonization?
- RQ3: Do tools and standards for data management and harmonization currently exist to support large-scale phenomics?

Search strategy and data source

The literature search was conducted across two primary databases: Web of Science (WoS) and Scopus, covering the period from 1990 to 2025. The selection was limited to original research papers and reviews with a focus on plant biology, agriculture, and in-formation technology. To ensure the quality of the synthesized evidence, only peer-reviewed articles and indexed conference proceedings were considered for inclusion. The search was performed using a combination of keywords and Boolean operators, following a strategy of sorting terms from generic to specific to capture the most relevant literature at the intersection of phenomics and data science.

Search Queries (SQ) and analysis

The systematic search was executed using a multi-layered approach, employing eleven distinct search queries (SQ1–SQ11) designed to capture the intersection of data standards, semantic technologies, and computational infrastructure. The strategy followed a progression from broad thematic areas to highly specific technical combinations involving MIAPPE, BrAPI, and High-Performance Computing (HPC). The full search strings used for both Web of Science (WoS) and Scopus are detailed in the list below:

- SQ1: TS=("Ontology" OR "Data management" OR "Fair Principles" OR "Open science").
- SQ2: TS=("Ontology" OR "Data management" OR "FAIR principles" OR "Open science" OR "Data sharing" OR "BrAPI").
- SQ3: TS=("Ontology" OR "Data management" OR "Fair Principles" OR "Open science" OR "Data sharing" OR "BrAPI" OR "Miappe" OR "Phenomics Databases" OR "Phenomics Platforms" OR "PHIS").
- SQ4: TS=("Ontology" OR "Data management" OR "Fair Principles" OR "Open science" OR "Data sharing" OR "BrAPI" OR "Miappe" AND "Phenomics Databases" AND "Phenomics Platforms" AND "PHIS").
- SQ5: TS=("Ontology" OR "Data management" OR "Fair Principles" OR "Open science" OR "Data sharing" AND "BrAPI" AND "Miappe" AND "Phenomics Databases" AND "Phenomics Platforms" AND "PHIS").
- SQ6: TS=("Ontology" OR "Data management" OR "Fair Principles" AND "Open science" AND "Data sharing" AND "BrAPI" AND "Miappe" AND "Phenomics Databases" AND "Phenomics Platforms" AND "PHIS").
- SQ7: TS=("Ontology" OR "Data management" AND "Fair Principles" AND "Open science" AND "Data sharing" AND "BrAPI" AND "Miappe" AND "Phenomics Databases" AND "Phenomics Platforms" AND "PHIS").
- SQ8: TS=("HPC").
- SQ9: TS=("HPC" OR "supercomputing" OR "high-performance" OR "parallel computing" OR "cluster computing").
- SQ10: TS=("HPC" OR "supercomputing" OR "high-performance" OR "parallel computing" OR "cluster computing" OR "Ontology" OR "Data management" OR "Fair Principles" OR "Open science" OR "Data sharing" OR "BrAPI" OR "Miappe" OR "Phenomics Databases" OR "Phenomics Platforms" OR "PHIS").
- SQ11: TS=("HPC" OR "supercomputing" OR "high-performance" OR "parallel computing" OR "cluster computing" AND "Ontology" AND "Data management" AND "Fair Principles").

To quantify the research landscape, we performed a bibliometric analysis of the results obtained from Web of Science (WoS) and Scopus. This analysis focused on the volume of reviews versus original research articles, publication trends over time, and the impact of the top cited publications within each query. The specific parameters and the resulting document count for each query are summarized in Table 1.

Search ID	Reviews (WoS)	Original Article (WoS)	Peak Publication Year	WoS (Fielded Search)	WoS (Query Builder)	Scopus (All Fields)
SQ1	5,629	109,885	2022: 12,263	3,465,450	163,794	2,762,160
SQ2	6,995	121,924	2024: 14,596	3,794,765	183,749	255,093
SQ3	7,082	123,043	2024: 14,701	3,952,857	185,134	25,705
SQ4	6,991	121,828	2024: 14,586	3,794,765	183,634	7
SQ5	5,629	109,885	2022: 12,263	3,465,450	163,794	2
SQ6	4,032	104,956	2022: 11,225	1,942,388	155,498	2
SQ7	2,332	86,560	2022: 9,015	133,883	121,931	2
SQ8	459	14,003	2024: 1,781	88,830	24,383	108,478
SQ9	27,187	532,548	2024: 53,682	1,399,556	671,897	1,520,993
SQ10	34,253	654,883	2024: 68,223	5,225,105	855,486	7,545
SQ11	27,179	531,948	2024: 53,657	754,312	670,578	690

Source: Own processing

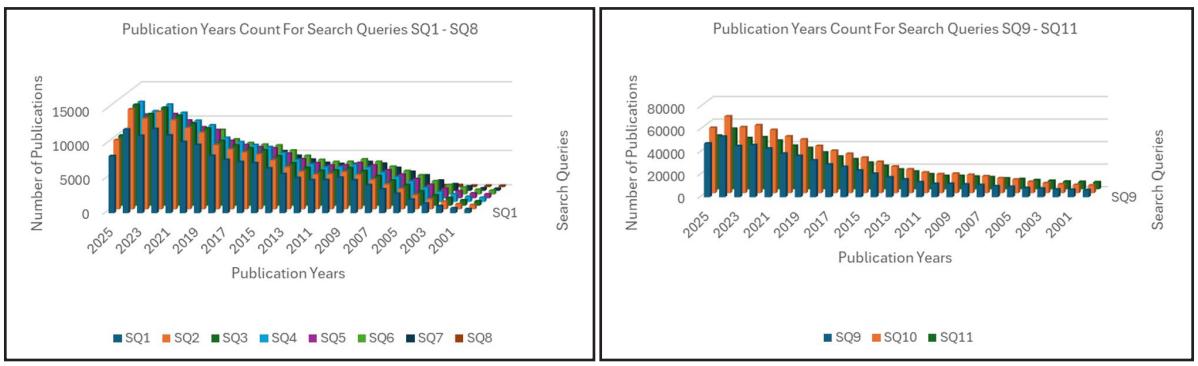
Table 1: Summary of systematic search queries and document retrieval counts across Web of Science (WoS) and Scopus databases.

The quantitative evolution of the research landscape was visualized by analyzing publication frequency over time for each search query. Due to the significant variance in retrieval volume where broad thematic searches yielded hundreds of thousands of records compared to hundreds in specialized queries the longitudinal analysis was divided into two comparative visualizations focusing on the peak development period from 2000 to 2025.

Figure 1(a) illustrates the annual publication trends for queries SQ1 through SQ8, representing the foundational growth of data stewardship, FAIR principles, and basic HPC concepts. Figure 1(b) focuses on the high-volume datasets retrieved in SQ9 through SQ11, reflecting the massive scale of research in supercomputing and parallel architecture. Both figures demonstrate a sharp exponential increase in scientific output, particularly following the global push for data interoperability after 2010 and the formalization of the FAIR principles in 2016.

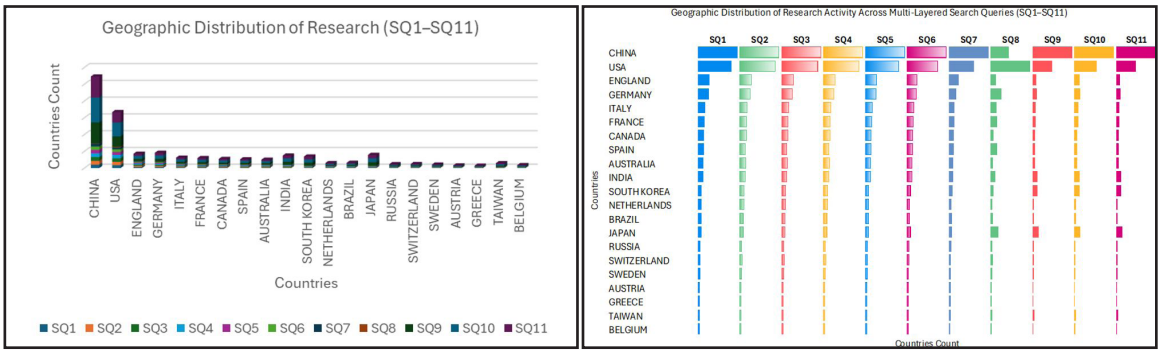
In addition to temporal trends, the geographic distribution of research activity was assessed to identify global hubs of expertise. This spatial analysis provides insights into the regional prioritization of high-performance computing (HPC) infrastructures and their application in data-driven life sciences.

Figure 2 presents a synthesized overview of the global contribution across all search queries. Figure 2(a) utilizes a comparative matrix format (heat map) to visualize the publication density for the top 21 countries, highlighting how research leadership scales with complexity. Complementary to this, Figure 2(b) employs a stacked bar chart to illustrate the cumulative research output of these nations across the entire query spectrum (SQ1–SQ11). This visualization allows for a direct



Source: Own processing

Figure 1: Comparative analysis of annual publication trends (2000–2025) derived from Web of Science: (a-left) Longitudinal growth of foundational topics represented by search queries SQ1–SQ8; (b-right) Evolution of high-volume research areas associated with supercomputing and large-scale data integration in SQ9–SQ11.



Source: Own processing

Figure 2: Geographic distribution of research activity across search queries (SQ1–SQ11): (a-left) Comparative matrix (heat map) of publication density for the top 21 countries; (b-right) Stacked bar chart illustrating the cumulative research output by country, categorized by search queries SQ1 through SQ11, highlighting the total volume and internal distribution of thematic focus.

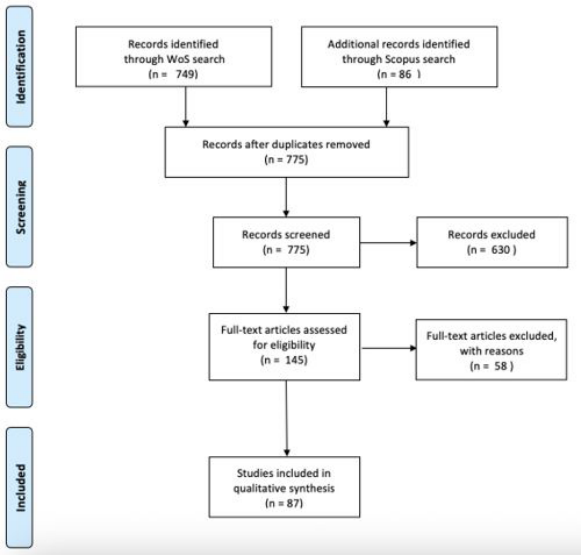
comparison of total volume while maintaining the visibility of individual query contributions per country.

To ensure full transparency while maintaining conciseness in the main text, the complete set of bibliometric analyses for all eleven search queries including individual annual growth charts and detailed geographic distribution maps for the top 10 countries is pro-vided in Appendix A (Figures A1–A22).

Study selection (PRISMA flowchart)

The systematic screening process followed the multi-stage approach defined by the PRISMA-ScR guidelines. The initial identification phase across WoS and Scopus yielded 835 records. Following the removal of duplicates, 775 unique records were screened based on titles and abstracts, resulting in the exclusion of 630 articles that did not meet thematic focus on plant phenomics or standardized metadata.

The remaining 145 articles underwent full-text assessment for eligibility. Of these, 58 were excluded due to a lack of technical detail regarding infrastructure implementation or insufficient alignment with MIAPPE/BrAPI standards. Ultimately, 87 studies were selected for qualitative synthesis and inclusion in this review. The complete selection workflow is visualized in the PRISMA flow diagram (Figure 3).



Source: Own processing

Figure 3: PRISMA flow diagram of the study selection process, illustrating the stages of identification, screening, eligibility, and final inclusion of the 87 selected studies focusing on plant phenomics data standards and HPC integration.

Results and discussion

This section synthesizes the findings from the literature review, categorizing the current state of the art into the data paradigm, security frameworks, phenotyping infrastructures, and semantic standards.

The development of phenomics marks the transition from individual trait observation to large-scale, technology assisted quantification of phenotypes. Phenomics can be defined as the systematic acquisition and analysis of phenotypic traits using automated sensor networks, imaging systems, robotics, and computational tools (Tardieu et al., 2017).

The field emerged as a distinct area of inquiry around 2010, stimulated by technological innovations introduced by companies such as Lemna-Tec and by collaborative initiatives including the International Plant Phenotyping Network (IPPN), which has since sought to establish phenomics as a fully recognized scientific discipline (Poorter et al., 2023).

Phenomics extends the classical concept of plant phenotyping by integrating multi-dimensional data streams describing plant structure, function, and temporal dynamics under diverse environmental conditions. These datasets enable the systematic linking of genotype × environment interactions to plant performance, thereby bridging molecular biology, physiology, and ecology within a unified experimental and computational framework (Tardieu et al., 2017).

The data paradigm: from acquisition to wisdom

Much of the recent progress in science and society is fundamentally driven by advances in data centered disciplines and the development of technologies that facilitate large-scale data acquisition, processing, and interpretation. The exponential growth of data collection technologies, such as high throughput sensors, Internet of Things (IoT) devices, imaging systems, and automated data loggers, has drastically transformed the landscape of research and innovation (Nicore et al., 2020, Wilkinson et al., 2016). Simultaneously, advances in data analytics and computational infrastructure, particularly High-Performance Computing (HPC) and cloud-based systems, have enabled the efficient processing of increasingly complex datasets. These technological shifts underpin the broader movement toward data intensive science, in which data are not merely by products of experimentation but central assets that drive discovery.

Evolution of the data paradigm

Over the past two decades, the philosophy of data management has evolved through several distinct paradigms. The Open Data movement, emerging in the early 2010s, advocated for unrestricted access to scientific data, encouraging researchers to make their data publicly available to promote transparency and reuse. However, as data volumes and heterogeneity grew, it became clear that openness alone was insufficient to ensure meaningful reuse and interoperability.

This realization led to the formulation of the FAIR Guiding Principles (Findable, Accessible, Interoperable, Reusable) in 2016, which provided a structured framework for responsible data stewardship (Wilkinson et al., 2016). The FAIR paradigm emphasized machine readability, persistent identifiers, and standardized metadata essential elements for ensuring that data can be discovered, understood, and reused by both humans and computational systems. In parallel, the introduction of the General Data Protection Regulation (GDPR) in 2018 established a legal framework for the ethical handling of personal and sensitive data, further reinforcing accountability and privacy in data-driven research.

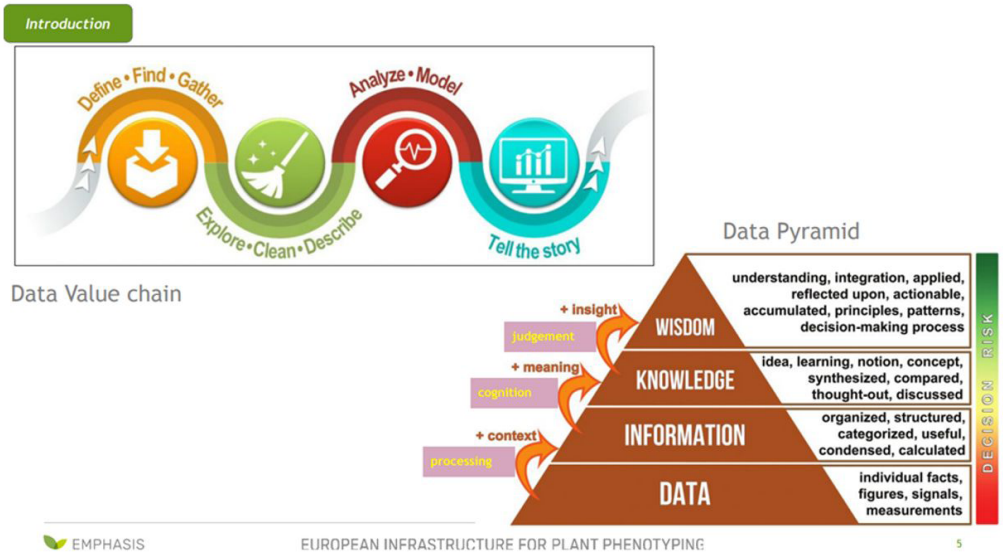
More recently, the concept of Digital Responsibility Goals (DRGs) has been proposed as a next stage in this evolution (Meier et al., 2021). The DRG framework extends beyond FAIR-ness and compliance by emphasizing digital literacy, algorithmic transparency, and trustworthy data use. It recognizes that for data to deliver societal value, users must not only have access to quality data but also possess the competencies and ethical awareness required to use it responsibly. In this view, the emphasis shifts from mere data availability to data quality, interpretability, and societal impact.

From data to wisdom: the knowledge hierarchy

This progression aligns with the widely accepted DIKW (Data Information Knowledge Wisdom) hierarchy, which conceptualizes the transformation of raw data into actionable insight (Ackoff, 1989). The transformation process from raw phenotypic observations to actionable wisdom is illustrated in (Figure 4). Within this framework:

- Data represents raw observations or measurements.
- Information emerges when data is structured and contextualized.
- Knowledge is derived through interpretation, linking information to understanding.
- Wisdom reflects the capacity to apply knowledge judiciously for decision-making and societal benefit.

In the context of phenomics, this paradigm is particularly relevant. Phenomics re-search produces vast amounts of heterogeneous data ranging from sensor readings and imaging data to environmental and genetic metadata. Transforming these diverse datasets into knowledge requires robust data management pipelines, interoperability standards (e.g., MIAPPE and BrAPI), and computational models



Source: Based on the Data–Information–Knowledge–Wisdom (DIKW) model (Ackoff, 1989; Rowley, 2007)

Figure 4: The DIKW hierarchy represents the transformation from raw phenotypic data to actionable wisdom.

capable of extracting biologically meaningful patterns. Ultimately, achieving "data-to-wisdom" in phenomics de-pends not only on data collection but also on the responsible, transparent, and collaborative use of data across the research ecosystem.

Data and end-users in phenomics

The primary users of phenomics data include plant biologists, geneticists, breeders, agronomists, and data scientists. Their needs vary from fundamental understanding of plant environment interactions to applied goals such as yield prediction, stress tolerance improvement, and resource efficient cultivation. For these stakeholders, standardized, high-quality data is essential to ensure comparability and reproducibility across experiments, institutions, and technological platforms.

Thus, the data paradigm in phenomics extends beyond scientific methodology: it encompasses ethical, technical, and educational dimensions that collectively determine the field's ability to generate not only data and information but actionable knowledge and wisdom for sustainable agriculture and food security.

Phenotyping data serves a dual purpose within the life sciences. From a fundamental research perspective, they provide an empirical basis for understanding how genetic variation translates into phenotypic diversity and environmental adaptability. High-resolution phenotypic datasets support the study of plant responses to abiotic and biotic stresses, photosynthetic efficiency, and biomass accumulation, contributing to predictive modeling of plant performance (Fiorani et al., 2013).

From an applied perspective, phenomics data underpin agricultural innovation and crop improvement. They facilitate data driven breeding strategies by enabling the identification and selection of genotypes with desirable agronomic traits such as enhanced drought tolerance, improved nutrient use efficiency, and increased yield stability. The integration of phenomics datasets into breeding pipelines accelerates the evaluation of genotype × environment × management interactions and informs decision making in precision agriculture and resource optimization (Ghanem et al., 2015). Beyond breeding, phenomics analyses are also instrumental in agronomy, agrochemical testing, crop nutrition research, and post-harvest quality characterization.

Data security and digital ethics in phenomics

Within the current data paradigm, it is essential to consider data security and digital ethics. As the volume and complexity of phenomics data increase, so do the risks of misuse, unauthorized access, data manipulation, or loss of integrity. Modern data management therefore encompasses not only standards such as FAIR, but also security-by-design principles, which assume the integration of security mechanisms directly into the design of data systems (Arend et al., 2022, Aksenova et al., 2024). Key tools include

role-based access control (RBAC) based on user roles and permissions, authentication and authorization protocols such as OAuth2 or OpenID Connect, data transmission encryption (TLS/SSL), and anonymization or pseudonymization of sensitive records (UK Data Service, 2025). In the context of phenomics, it is also crucial to implement audit logs and system monitoring, which enable retrospective tracking of data access and manipulation (Aksenova et al., 2024). These principles are particularly critical when data are related to proprietary breeding projects or hosted on cloud platforms with open access policies (Minssen et al., 2020).

From an ethical and legal perspective, it is now essential to consider European and international data protection frameworks, particularly the General Data Protection Regulation (GDPR) (European Commission, 2025, GDPR-info.eu, 2024, European Union, 2018). Although phenomics data is not inherently personal, their combination with metadata (e.g., geolocation, timestamps, or sensor data linked to specific operators) can lead to the identification of individuals or locations, thereby triggering regulatory obligations (OECD, 2022, Wong et al., 2021). Research infrastructures must therefore ensure not only technical data security, but also clear rules for access control, data retention, classification of data categories, and the management of consent for data use (OECD, 2022, Wong et al., 2021). Responsible data stewardship in this context not only protects the rights of users and research participants but also fosters trust among stakeholders within open and federated data ecosystems, where the trustworthiness of data is as crucial as its technical quality and interoperability (Prifti et al., 2023).

Phenotyping infrastructure, repositories, and data types

Phenotyping represents a fundamental component of contemporary biological and agricultural research, providing quantitative descriptions of an organism's observable characteristics that arise from the interaction between its genotype and the environment. The concept of phenotyping originated in the 1960s, initially referring to the morphological and physiological characterization of organisms through direct observation and measurement. With the advent of advanced sensing technologies, imaging, and automation, phenotyping has evolved into a high-throughput, data-driven scientific activity that enables systematic and reproducible quantification of complex biological traits (Fiorani et al., 2013).

High-Throughput platforms and HPC integration

The lack of common standards for describing phenotypic data has long hindered efficient data exchange and reuse, leading to the formulation of the MIAPPE (Minimum In-formation About a Plant Phenotyping Experiment) recommendations. This initiative de-fines the necessary scope of metadata and utilizes the ISA-Tab format for the practical organization of experimental data, thereby directly supporting the replicability and comparability of results (Ćwiek-Kupczyńska et al., 2016).

Ground-based robotic phenotyping platforms have emerged as a high-throughput solution for capturing multi-dimensional plant traits, yet they generate massive volumes of sensor data that challenge traditional processing capabilities. The integration of these robotic systems with High-Performance Computing (HPC) is essential for real-time data analytics, image reconstruction, and the management of heterogeneous datasets in field conditions (Rui and Changying, 2022; Yuan et al., 2023).;

Taxonomy of phenotyping data and 3D analysis

Phenotyping data encompasses a wide spectrum of measurements that collectively describe plant form, function, and response to the environment. Common categories of data include morphological, physiological, biochemical, environmental, and temporal data, each contributing distinct insights into plant behavior (Bosilj et al., 2018).

- Morphological data describe physical attributes such as plant size, shape, leaf area, color, and architecture, typically derived from 2D or 3D imaging systems, laser scanning, or structured light sensors.
- Physiological data capture biological processes such as transpiration, photosynthesis, chlorophyll fluorescence, or stomatal conductance, often obtained through hyperspectral or thermal imaging.
- Biochemical and molecular data include metabolite, protein, and enzyme profiles obtained from analytical platforms such as mass spectrometry or NMR, linking molecular variation to observed traits.

- Environmental data document growth conditions including light, temperature, humidity, and soil composition, which are crucial for interpreting genotype environment interactions.
- Temporal data represent longitudinal measurements that track develop-mental or stress related changes in plants across time.

Recent developments in 3D imaging and point cloud analysis have expanded the ability to capture complex plant geometries and canopy architectures. Such techniques have reached advanced levels in disciplines such as geospatial science, robotics, and industrial computer vision, where 3D object reconstruction, LiDAR-based mapping, and AI-driven image segmentation are standard. These approaches are increasingly being adapted for biological research, offering transferable solutions for data storage formats, spatial annotation, and metadata integration that could accelerate progress in plant phenotyping.

Data models and repository infrastructures

The increasing complexity of phenotypic datasets has stimulated efforts to formalize data models capable of ensuring structural consistency, semantic clarity, and interoperability. Traditional relational databases have proven insufficient for handling multimodal and temporal data typical of phenotyping workflows. Consequently, hybrid data architecture combining object relational, NoSQL, and graph-based models have emerged as more suitable options, supporting flexible schema definitions and efficient storage of large-scale sensors and imaging data.

Several open data repositories and infrastructure projects support phenotyping data storage and sharing, including PHIS (Plant Phenomics Information System), e!DAL-PGP (Plant Genomics and Phenomics Research Data Repository), and institutional databases integrated into ELIXIR or EMPHASIS networks. These repositories facilitate data deposition, versioning, and long-term accessibility in accordance with FAIR principles (Findable, Accessible, Interoperable, Reusable). The PGP (Plant Genomics and Phenomics Research Data Repository) serves as a key infrastructure for the publication of complex phenomics and genomic data, utilizing the e!DAL software framework. This system enables the assignment of persistent identifiers (DOIs) and automates the data submission process, thereby fulfilling FAIR principles even for voluminous datasets, such as phenotyping im-age collections or mass spectrometry data (Arend et al., 2016).

Case study: The TERRA-REF project and HPC

The TERRA-REF project demonstrates the necessity of high-performance computing (HPC) environments for processing open access reference datasets generated by high-resolution field scanners. This infrastructure supports the integration of hyperspectral imagery, 3D structures, and environmental measurements, providing an open-source computational pipeline that enables the calibration of algorithms for extracting plot-level phenotypes from massive datasets (Xu et al., 2022).

Phenomics inherently produces high-dimensional and heterogeneous data, and the processing of such data requires advanced information and communication technologies (ICT) and HPC to ensure reproducibility (Tardieu et al., 2017).

Despite rapid technological advancement, phenotypic traits remain inherently multifactorial, which complicates the development of robust models and remains a key obstacle to data comparability (Tardieu et al., 2017, Poorter et al., 2023).

Semantic standards: harmonization through ontologies

The field of plant phenotyping has rapidly evolved over the past two decades, driven by the increasing integration of sensor technologies, automation, and computational analysis. This development has led to the generation of diverse and complex datasets that capture structural, functional, and environmental aspects of plant performance. However, this heterogeneity also creates major challenges in data modeling, storage, harmonization, and interoperability across platforms and research infrastructures.

Given the diversity of experimental setups and data formats, data harmonization has become a critical focus area. The processing and interpretation of high-dimensional and heterogeneous data typically comprising multispectral imagery, 3D structural reconstructions, and sensor based temporal measurements require standardized data management frameworks capable of ensuring data interoperability and reproducibility. The establishment of community standards reflects ongoing efforts to promote harmonization and facilitate data exchange across phenotyping platforms and research infrastructures.

Metadata frameworks and MIAPPE

The most widely adopted community driven standard is MIAPPE (Minimum Information About a Plant Phenotyping Experiment), which defines a structured metadata schema describing experimental context, environmental conditions, biological material, and measured traits. MIAPPE is maintained as an open-source specification with its documentation and schema hosted on GitHub (MIAPPE Contributors, 2024). This standard is open community server accessible on GitHub, where there are available latest changes and documentation (MIAPPE Contributors, 2024). For practical implementation, this initiative utilizes the ISA-Tab format for the organization of experimental data, thereby directly supporting the replicability and comparability of results.

Programmatic interoperability: The breeding API (BrAPI)

To complement MIAPPE, the Breeding API (BrAPI) provides a web service interface for accessing, querying, and exchanging phenotypic and genotypic data across systems. Together, these standards support interoperability between databases, enabling efficient data integration, visualization, and computational analysis across research infrastructures. The practical integration of these standards is demonstrated in the proposed connection between institutional platforms and the BrAPI module, where client applications manage ontologies and data flows between phenotyping platforms (e.g., PSI, Phenospex) and centralized repositories. Such systems must ensure that metadata is generic and ex-tensible to allow for future mapping to diverse data consumers (Stočes et al., 2023). BrAPI serves as a standardized web service API specification, conceived through collaborative efforts within a global community, which is essential for transforming raw phenotypic observations into actionable biological and agronomic knowledge.

Semantic integration and reference ontologies

Bridging the gap between phenotypic and genotypic data requires validated trait names and measurement scales, a task addressed by the Crop Ontology (CO). The CO supports the harmonization of data annotation through synchronized trait dictionaries, allowing for automatic annotation of field observations and direct cross-referencing with other standards like the Plant Ontology (Matteis et al., 2012).

- The Planteome project: Provides a centralized suite of reference ontologies, such as the Plant Ontology and Plant Trait Ontology, which serve as common standards for the semantic integration of genomics and phenomics da-ta. By providing annotations for 95 plant taxa, this resource enables the linking of gene function and expression to specific phenotypes, thereby facilitating data discovery and reuse across diverse research communities (Cooper et al., 2018).
- Semantic tagging: The complexity of omics datasets necessitates the use of ontologies for semantic tagging, which significantly increases data interoperability and understanding of experimental conditions (Dumschott et al., 2023).
- Practical application: These principles are demonstrated in the GnpIS repository, which utilizes a generic, ontology-driven data model integrated with MIAPPE and BrAPI standards to ensure long-term access and cutability of phenotypic datasets across diverse species (Pommier et al., 2019).

From data interoperability to data wisdom

Beyond technical interoperability, the responsible and meaningful use of phenotyping data by end users is central to achieving what has been termed data wisdom the transformation of raw data into actionable biological understanding and informed decision-making. This requires not only robust data infrastructures but also the adoption of open science practices, transparent metadata documentation, and reproducible analytical workflows. In this context, the convergence of phenomics with computational biology, artificial intelligence, and systems modeling is expected to enhance data reusability and accelerate scientific discovery in plant research and agriculture.

In summary, phenomics constitutes a rapidly developing interdisciplinary domain that integrates plant biology, engineering, and data science to quantify the complexity of plant behavior under real world conditions. Phenotyping data not only enables the mechanistic understanding of genotype environment interactions but also support translational applications in breeding and sustainable agriculture. Given the scale and heterogeneity of phenomics datasets, future progress depends on continued advancements in computational infrastructure and the adoption

of standardized, interoperable data models such as MIAPPE and BrAPI, which are essential for transforming raw phenotypic observations into actionable biological and agronomic knowledge.

Discussion

This systematic literature review provides a comprehensive overview of the current landscape of data management and interoperability in plant phenomics, highlighting both achievements and remaining challenges. The adoption of standards such as MIAPPE and BrAPI, together with adherence to FAIR principles, has markedly improved the transparency, discoverability, and reusability of phenotyping data. Yet, the translation of these principles into operational practices remains fragmented and often limited to well-funded infrastructures.

Summary of main findings

This systematic review identified and synthesized the key developments in data standardization, interoperability, and computational infrastructure for plant phenomics. The analysis of available literature focused primarily on MIAPPE, BrAPI, and related FAIR data principles revealed significant progress in establishing community driven frameworks for standardized data management. These frameworks represent major milestones toward making plant phenotyping data Findable, Accessible, Interoperable, and Reusable (FAIR), facilitating cross platform integration and reuse.

Despite these advances, the adoption of standards across the research community remains uneven. While MIAPPE provides a robust metadata schema for describing experimental context, its implementation varies between institutions and platforms, often due to limited awareness, technical capacity, or resource constraints. Similarly, although BrAPI has gained recognition as a key interoperability layer between phenotyping and breeding databases, its deployment is still concentrated within a few leading infrastructures.

Furthermore, the review confirmed persistent gaps in data harmonization and se-mantic alignment. The integration of MIAPPE compliant metadata with ontologies and BrAPI endpoints remains an ongoing challenge, particularly when linking heterogeneous datasets across species or experimental designs. The lack of harmonized trait ontologies and incomplete mapping between existing vocabularies (e.g., Crop Ontology, Plant Ontology, and Environment Ontology) constrain automated interoperability and limit the reusability of data in downstream computational analyses.

From a technological standpoint, High-Performance Computing (HPC) and cloud infrastructures have become indispensable for managing the increasing complexity of phenomics data. However, the current state of the field indicates that while the theoretical framework for FAIR and interoperable phenomics data is well established, the practical realization of this vision remains fragmented. Modern phenotype monitoring systems often lack unified development standards across sensors, communication, and data analysis modules, which limit their scalability. Furthermore, due to current computational and algorithmic constraints, much of the data processing still occurs offline (Yuan et al., 2023). Despite the theoretical benefits, significant struggles remain in the practical 'FAIRification' of existing datasets (Papoutsoglou at al., 2023). Implementing FAIR principles requires a systematic approach that ad-dresses data organization, metadata standards, and secure access protocols (Krisnawijaya et al., 2024).

Future vision

Based on the findings of this review, several key research directions and open questions emerge that should guide future work in the plant phenomics data community:

1. Bridging the gap between standard definition and implementation: Although MIAPPE and BrAPI provide clear frameworks for describing and exchanging data, many research infrastructures have yet to implement them fully. Future work should focus on developing lightweight tools, APIs, and templates that simplify adoption without requiring extensive technical expertise. The integration of MIAPPE into popular data management platforms or laboratory information systems could serve as a practical accelerator.
2. Semantic harmonization through ontology alignment: Ontologies are the backbone of interoperability, yet inconsistencies in trait naming and semantic structure still impede data integration. Efforts should concentrate on cross-linking domain ontologies (e.g., Plant Ontology, Crop Ontology, and Environment Ontology) and align them with MIAPPE metadata schemas to facilitate automatic data discovery and integration across repositories. However,

as noted in recent research, most agricultural ontologies currently lack explicit evaluation procedures. To address this, a structured evaluation framework focusing on criteria such as clarity, coherence, and completeness is essential for matching specific evaluation methods to the intended purpose, whether for decision support or system interoperability (Goldstein et al., 2021).

3. Integration of HPC and AI-based data analytics: The increasing scale of phenomics datasets demands tighter coupling between standard compliant data infrastructures and HPC/AI pipelines. Research should focus on establishing modular, reusable workflows for image analysis, time series modeling, and genotype phenotype association studies that are strictly compatible with FAIR data principles.
4. Advancing data ethics and digital responsibility: As phenomics expands into open and federated data ecosystems, the community must address issues of data security, intellectual property, and equitable access. Future infra-structures should incorporate digital responsibility goals (Meier et al., 2021), ensuring that users are digitally literate, that algorithms are transparent, and that data is trustworthy and ethically managed.
5. Reframing the research questions: A critical reflection raised by Vincent Vadez ("Got all the answers! But what was the question?") (Varshney et al., 2018) underscores that progress in phenomics is often limited not by data availability, but by the lack of well formulated research questions. Future research should move beyond mere data accumulation to focus on hypothesis driven, integrative studies that translate data into actionable biological knowledge and agronomic innovation.
6. Towards an ecosystem of interoperable wisdom: The goal of the data paradigm transforming data into knowledge nd wisdom requires a shift from technological readiness to community maturity. This includes the establishment of governance models, training programs, and incentive structures that reward FAIR and open data practices while ensuring data quality, re-producibility, and trust.

Conclusion

This systematic literature review has provided a comprehensive synthesis of the current state of data management and interoperability in plant phenomics. The findings demonstrate that while the adoption of standards such as MIAPPE and BrAPI, alongside the FAIR principles, has significantly enhanced the transparency and discoverability of phenotypic datasets, a gap persists between theoretical frameworks and their operational implementation.

The synthesis identified three critical areas requiring urgent attention: the inconsistent integration of existing standards across diverse research platforms, the insufficient alignment of semantic frameworks and ontologies, and the need for more robust data governance mechanisms to address emerging ethical and security concerns. Overcoming these obstacles will necessitate coordinated community efforts, institutional support for long term data stewardship, and closer collaboration between data scientists, biologists, and infrastructure developers.

Ultimately, the integration of High-Performance Computing (HPC), artificial intelligence, and standardized APIs are essential for achieving scalable and reproducible phenomics research. However, technological readiness must be matched by community maturity. By fostering a culture of openness, semantic harmonization, and digital responsibility, the field can transition toward a mature data ecosystem. Such an ecosystem will be capable of transforming complex, high dimensional datasets into the actionable wisdom required to address global challenges in sustainable agriculture and food security.

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References

[1] Abdul Hamid, N. A. W. and Singh, B. (2024) "High-Performance Computing Based Operating Systems, Software Dependencies and IoT Integration", In: K. A. Ahmad, K. A., Abdul Hamid, N. A. W., Jawaid, M., Khan, T. and Singh, B. (eds.) "*High Performance Computing in Biomimetics*", pp. 175-204, Series in BioEngineering. Springer, Singapore. E-ISBN 978-981-97-1017-1, ISSN 2196-8861. DOI 10.1007/978-981-97-1017-1_8.

[2] Ackoff, R. L. (1989) "From data to wisdom", *Journal of Applied Systems Analysis*, Vol. 16, pp. 3-9. ISSN 0308-9541.

[3] Aksenova, A., Johny, A., Adams, T., Gribbon, P., Jacobs, M. and Hofmann-Apitius, M. (2024) "Current state of data stewardship tools in life science", *Frontiers in Big Data*, Vol. 7, p. 1428568. E-ISSN 2624-909X. DOI 10.3389/fdata.2024.1428568.

[4] Arend, D., Junker, A., Scholz, U., Schüler, D. and Selbig, J. (2022) "From data to knowledge - big data needs stewardship, a plant phenomics perspective", *The Plant Journal*, Vol. 110, No. 1, pp. 12-28. E-ISSN 1365-313X, ISSN 0960-7412. DOI 10.1111/tpj.15804.

[5] Arend, D., Junker, A., Scholz, U., Schüler, D., Wylie, J. and Lange, M. (2016) "PGP repository: a plant phenomics and genomics data publication infrastructure", *Database (Oxford)*, Vol. 2016, p. baw033. ISSN 1758-0463. DOI 10.1093/database/baw033.

[6] Bosilj, P., Duckett, T. and Cielniak, G. (2018) "Connected attribute morphology for unified vegetation segmentation and classification in precision agriculture", *Computers in Industry*, Vol. 98, pp. 226-240. ISSN 0166-3615. DOI 10.1016/j.compind.2018.02.003.

[7] Bosilj, P., Duckett, T., Cielniak, G. and Pearson, S. (2018) "Quantitative phenotyping of plants using three-dimensional imaging and machine vision", *Computers and Electronics in Agriculture*, Vol. 153, pp. 69-79. ISSN 1872-7107.

[8] Cooper, L., Meier, A., Laporte, M. A., Elser, J. L., Mungall, C., Sinn, B. T., Cavaliere, D., Carbon, S., Dunn, N. A., Smith, B., Qu, B., Preece, J., Zhang, E., Todorovic, S., Gkoutos, G., Doonan, J. H., Stevenson, D. W., Arnaud, E. and Jaiswal, P. (2018) "The Planteome database: an integrated resource for reference ontologies, plant genomics and phenomics", *Nucleic Acids Research*, Vol. 46, No. D1, pp. D1168 - D1180. E-ISSN 1362-4962. DOI 10.1093/nar/gkx1152.

[9] Ćwiek-Kupczyńska, H., Altmann, T., Arend, D., Arnaud, E., Chen, D., Cornut, G., Fiorani, F., Frohmberg, W., Junker, A., Klukas, C., Lange, M., Mazurek, C., Nafissi, A., Neveu, P., van Oeveren, J., Pommier, C., Poorter, H., Rocca-Serra, P., Sansone, S.A., Scholz, U., van Schriek, M., Seren, Ü., Usadel, B., Weise, S., Kersey, P. and Krajewski, P. (2016) "Measures for interoperability of phenotypic data: minimum information requirements and formatting", *Plant Methods*, Vol. 12, No. 44. E-ISSN 1746-4811. DOI 10.1186/s13007-016-0144-4.

[10] Dumschott, K., Dörpholz, H., Laporte, M. A., Brilhaus, D., Schrader, A., Usadel, B., Neumann, S., Arnaud, E. and Kranz, A. (2023) "Ontologies for increasing the FAIRness of plant research data", *Frontiers in Plant Science*, Vol. 14, p. 1279694. E-ISSN 1664-462X. DOI 10.3389/fpls.2023.1279694.

[11] European Commission. (2025) "*Legal framework of EU data protection*". [Online]. Available: https://commission.europa.eu/law/law-topic/data-protection/legal-framework-eu-data-protection_en [Accessed: Dec. 15, 2025].

[12] European Union. (2018) "General Data Protection Regulation (GDPR)", *Official Journal of the European Union*, L119, pp. 1-88. E-ISSN 1725-2423.

[13] Fiorani, F. and Schurr, U. (2013) "Future scenarios for plant phenotyping", *Annual Review of Plant Biology*, Vol. 64, pp. 267-291. ISSN 1545-2123. DOI 10.1146/annurev-arplant-050312-120137.

[14] Frontiers in Plant Science. (2023) "*Phenomics as an emerging research discipline*". [Online]. Available: https://www.frontiersin.org/articles/10.3389/fpls.2023.1233794/full [Accessed: Sept 21, 2025].

[15] GDPR-info.eu. (2024) "*General Data Protection Regulation (GDPR) - Legal Text*". [Online]. Available: https://gdpr-info.eu [Accessed: Sept 21, 2025].

[16] Georgiou, Y., Zhou, N., Zhong, L., Hoppe, D., Pospieszny, M., Papadopoulou, N., Nikas, K., Nikolos, O. L., Kranas, P., Karagiorgou, S., Pascolo, E., Mercier, M. and Velho, P. (2020) "Converging HPC, Big Data and Cloud Technologies for Precision Agriculture Data Analytics on Supercomputers", In: Jagode, H., Anzt, H., Juckeland, G., Ltaief, H. (eds) *High Performance Computing. ISC High Performance 2020*. Lecture Notes in Computer Science, Vol. 12321, Springer, Cham. E-ISBN 978-3-030-59851-8. DOI 10.1007/978-3-030-59851-8_25.

[17] Ghanem, M. E., Marrou, H. and Sinclair, T. R. (2015) "Physiological phenotyping and its application to the breeding of drought-tolerant crops", *Frontiers in Physiology*, Vol. 6, 362. E-ISSN 1664-042X. DOI 10.3389/fphys.2015.00362.

[18] Glaubitz, J. C., Casstevens, T. M., Lu, F., Harriman, J., Elshire, R. J., Sun, Q. and Buckler, E. S. (2014) "TASSEL-GBS: a high capacity genotyping by sequencing analysis pipeline", *PLoS One*, Vol. 9, No. 2, p. e90346. ISSN 1932-6203. DOI 10.1371/journal.pone.0090346.

[19] Goldstein, A., Fink, L. and Ravid, G. (2021) "A Framework for Evaluating Agricultural Ontologies", *Sustainability*, Vol. 13, No. 11, p. 6387. ISSN 2071-1050. DOI 10.3390/su13116387.

[20] Grüning, B. Dale, R., Sjödin, A., Chapman, B. A., Rowe, J., Tomkins-Tinch C. H., Valieris, R., Köster, J. and Biocomda Team (2018) "Bioconda: sustainable and comprehensive software distribution for the life sciences", *Nature Methods*, Vol. 15, No. 7, pp. 475-476. ISSN 1548-7105. DOI 10.1038/s41592-018-0046-7.

[21] Kartal, S., Choudhary, S., Stočes, M., Šimek, P., Vokoun, T. and Novák, V. (2020) "Segmentation of Bean-Plants Using Clustering Algorithms", *AGRIS on-line Papers in Economics and Informatics*, Vol. 12, No. 3, pp. 36-43. ISSN 1804-1930. DOI 10.7160/aol.2020.120304.

[22] Kartal, S., Masner, J., Kholová, J., Galba, A., Murugesan, T., Baddam, R., Mikes, V. and Kánská, E. (2025) "AI-Driven Background Segmentation for High-Throughput 3D Plant Scans", *IEEE Access*, Vol. 13, pp. 136027-136037. DOI 10.1109/ACCESS.2025.3594406. ISSN 2169-3536.

[23] Krisnawijaya, N. N. K., Tekinerdogan, B., Catal, C., van der Tol, R. and Herdiyeni, Y. (2025) "Implementing FAIR principles in data management systems: A multi-case study in precision farming", *Computers and Electronics in Agriculture*, Vol. 230, p. 109855. ISSN 0168-1699. DOI 10.1016/j.compag.2024.109855.

[24] LeBauer, D., Maxwell, B., Demieville, J., Fahlgren, N., French, A., Garnett, R., Hu, Z., Huynh, K., Kooper, R., Li, Z., Maimaitijiang, M., Mao, J., Mockler, T., Morris, G., Newcomb, M., Ottman, M., Ozersky, P., Paheding, S., Pauli, D., Pless, R., Quin, W., Riemer, K., Rohde, G., Rooney, W., Sagan, V., Shakoor, N., Stylianou, A., Thorp, K., Ward, R., White, J., Willis, C. and Zender, C. (2020) "*Data From: TERRA-REF, An open reference data set from high resolution genomics, phenomics, and imaging sensors*", [Dataset], Dryad. DOI 10.5061/dryad.4b8gtht99.

[25] Matteis, L., Skofic, M., Portugal, A., Mclaren, G., Hyman, G. and Arnaud, E. (2012) "Bridging the phenotypic and genetic data useful for integrated breeding through a data annotation using the Crop Ontology developed by the crop communities of practice", *Frontiers in Physiology*, Vol. 3, p. 326. E-ISSN 1664-042X. DOI 10.3389/fphys.2012.00326.

[26] Meier, P., Deksnyte, G. and Winter, R. (2021) "Digital Responsibility Goals: A Framework for the Responsible Use of Data and Algorithms", *Business & Information Systems Engineering*, Vol. 63, No. 6, pp. 665-678. ISSN 1867-0202. DOI 10.3233/SHTI220377.

[27] MIAPPE Contributors. (2024) "*Minimum Information About a Plant Phenotyping Experiment (MIAPPE) Specification, Version 1.2*". [Online]. Available: https://github.com/MIAPPE [Accessed: Oct 25, 2025].

[28] Minssen, T., Rutz, B. and van Zimmeren, E. (2020) "Clinical trial data transparency and GDPR compliance", *Science and Public Policy,* Vol. 47, No. 2, pp. 228-238. ISSN 1471-5430. DOI 10.1093/scipol/scaa014.

[29] Nicora, G., Vitali, F., Dagliati, A., Geifman, N. and Bellazzi, R. (2020) "Integrated Multi-Omics Analyses in Oncology: A Review of Machine Learning Methods and Tools", *Frontiers in Oncology*. Vol. 10. E-ISSN. 2234-943X. DOI 10.3389/fonc.2020.01030.

[30] OECD. (2022) "*Responding to societal challenges with data: Access, sharing, stewardship and control*", OECD Publishing. [Online]. Available: https://www.oecd.org/en/publications/responding-to-societal-challenges-with-data_2182ce9f-en.html [Accessed: Oct 25, 2025].

[31] Papoutsoglou, E. A., Farian D., Arend, D., Arnaud, E., Athanasiadis, I. N., Chaves, I., Coppens, F., Cornut, G., ...Pommier, C. (2020) "Enabling reusability of plant phenomic datasets with MIAPPE 1.1", *New Phytologist*, Vol. 227, No. 1, pp. 260-273. E-ISSN 1469-8137. DOI 10.1111/nph.16544.

[32] Papoutsoglou, E. A., Athanasiadis, I., Visser, R. and Finkers, R. (2023) "The benefits and struggles of FAIR data: the case of reusing plant phenotyping data", *Scientific Data*, Vol. 10. E-ISSN 2052-4463. DOI 10.1038/s41597-023-02364-z.

[33] Pommier, C., Michotey, C., Cornut, G., Roumet, P., Duchêne, E., Flores, R., Lebreton, A., Alaux, M., Durand, S., Kimmel, E., Letellier, T., Merceron, G., Laine, M., Guerche, C., Loaec, M., Steinbach, D., Laporte, M. A., Arnaud, E., Quesneville, H. and Adam-Blondon, A. F. (2019) "Applying FAIR Principles to Plant Phenotypic Data Management in GnpIS", *Plant Phenomics*, Vol. 2019, p. 1671403. ISSN 2643-6515. DOI 10.34133/2019/1671403.

[34] Prifti, K., Krijger, J., Thuis, T. and Stamhuis, E. (2023) "From Bilateral to Ecosystemic Transparency: Aligning GDPR's Transparency Obligations with the European Digital Ecosystem of Trust", In: Kuhlmann, S., De Gregorio, F., Fertmann, M., Ofterdinger, H. and Sefkow, A. (eds.) *Transparency or Opacity : A Legal Analysis of the Organization of Information in the Digital World*, 1st ed., pp. 115, Nomos. ISBN 978-3-7560-0027-2. DOI 10.5771/9783748936060-115.

[35] Rowley, J. (2007) "The wisdom hierarchy: representations of the DIKW hierarchy", *Journal of Information Science*, Vol. 33, No. 2, pp. 163-180. E-ISSN 1741-6485. DOI 10.1177/0165551506070706.

[36] Selby, P., Abbeloos, R., Backlund, J. E., Basterrechea Salido, M., Bauchet, G., Benites-Alfaro, O. E., Birkett, C., Calaminos, V. C., Carceller, P., Cornut, G. ... The BrAPI consortium (2019) "BrAPI - an application programming interface for plant breeding applications", *Bioinformatics*, Vol. 35, pp. 4147-4155. ISSN 1367-4811. DOI 10.1093/bioinformatics/btz190.

[37] Selby, P., Abbeloos, R., Adam-Blondon, A.F., Agosto-Pérez, F. J., Alaux, M., Alic, I., Al-Shamaa, K., Aparicio, ... BrAPI Consortium. (2025) "BrAPI v2: real-world applications for data integration and collaboration in the breeding and genetics community", *Database*, Vol. 2025, p. baaf048. ISSN 1758-0463. DOI 10.1093/database/baaf048.

[38] Sterling, T., Anderson, M. and Brodowicz, M. (2024) "*High performance computing: Modern systems and practices*", 2nd ed., Elsevier. ISBN 9780128230350. DOI 10.1016/C2013-0-09704-6.

[39] Stočes, M., Jarolímek, J., Anderle, M., Kholová, J., Pavlík, J., Masner, J., Spichal, L. and Klimes, P. (2025) "*Plant Phenotyping Network: Data Standards*". Poster, National EOSC CZ Conference 2025, Ostrava, Czech Republic. [Online]. Available: https://www.eosc.cz/media/4054734/stoces_a1_height-poster-stoces.pdf [Accessed: Dec. 12, 2025].

[40] Stočes, M., Vaněk, J., Jarolímek, J., Novák, V., Masner, J., Šimek, P., Kánská, E., Havránek, M., Kubata, K. and Voral, V. (2023) "Agriculture Data Platform - Institutional Data Repository - Selected Aspects", *AGRIS on-line Papers in Economics and Informatics*, Vol. 15, No. 4, pp. 127-133. DOI 10.7160/aol.2023.150409.

[41] Tardieu, F., Cabrera-Bosquet, L., Pridmore, T. and Bennett, M. (2017) "Plant phenomics, from sensors to knowledge", *Current Biology*, Vol. 27, No. 15, pp. R770 - R783. E-ISSN 0960-9822. DOI 10.1016/j.cub.2017.05.055.

[42] Tricco, A. C., Lillie, E., Zarin, W., O´Brien, K. K., ColQuhoun, H., Levac., D., Moher, D., Peters, M. D. J...Straus, S. E. (2018) "PRISMA Extension for Scoping Reviews (PRISMA-ScR): Checklist and Explanation", *Annals of Internal Medicine*, Vol. 169, No. 7, pp. 467-473. E-ISSN 1539-3704. DOI 10.7326/M18-0850.

[43] Ubbens, J., Stavness, I., Pound, M.P. and Wei Guo. (2025) "Deep learning in plant phenotyping: the first ten years", *Plant Phenomics*, Vol. 7, No. 4, p. 100062. ISSN 2643-6515. DOI 10.1016/j.plaphe.2025.100062.

[44] UK Data Service. (2025) "FAIR data principles". [Online]. Available: https://ukdataservice.ac.uk/learning-hub/research-data-management/plan-to-share/fair-data-principles/ [Accessed: Sept. 22, 2025].

[45] Umbach, G. (2024) "Open Science and the impact of Open Access, Open Data, and FAIR publishing principles on data-driven academic research: Towards ever more transparent, accessible, and reproducible academic output?", *Statistical Journal of the IAOS*, Vol. 40, No. 1, pp. 59-70. ISSN 1875-9254. DOI 10.3233/SJI-240021.

[46] Varshney, R. K., Thudi, M., Pandey, M. K., Tardieu, F., Ojiewo, C., Vadez, V., Whitbread, A. M., Siddiwue, K. H. M., Nguyen, H. T., Carberry, P. S. and Bergvinson, D. (2018) "Accelerating genetic gains in legumes for the development of prosperous smallholder agriculture: integrating genomics, phenotyping, systems modelling and agronomy", *Journal of Experimental Botany*, Vol. 69, No. 13, pp. 3293-3312. ISSN 0022-0957. DOI 10.1093/jxb/ery088.

[47] Wilkinson, M. D., Dumontier, M., Aalbersberg, I., Appleton, G., Axton, M., Baak, A., Blomebrg, N, Boiten, J.-W...Mons, B. (2016) "The FAIR Guiding Principles for scientific data management and stewardship", *Scientific Data*, Vol. 3, p. 160018. E-ISSN 2052-4463. DOI 10.1038/sdata.2016.18.

[48] Wong, J., Henderson, T. and Ball, K. (2021) "Data protection for the common good: Developing a framework for a data protection-focused data commons", *Data & Policy*, Vol. 3, p. e41. E-ISSN 2632-3249. DOI 10.1017/dap.2021.40.

[49] Xu, R. and Li, C. (2022) "A Review of High-Throughput Field Phenotyping Systems: Focusing on Ground Robots", *Plant Phenomics*, Vol. 2022, pp. 1-20. ISSN 2643-6515. DOI 10.34133/2022/9760269.

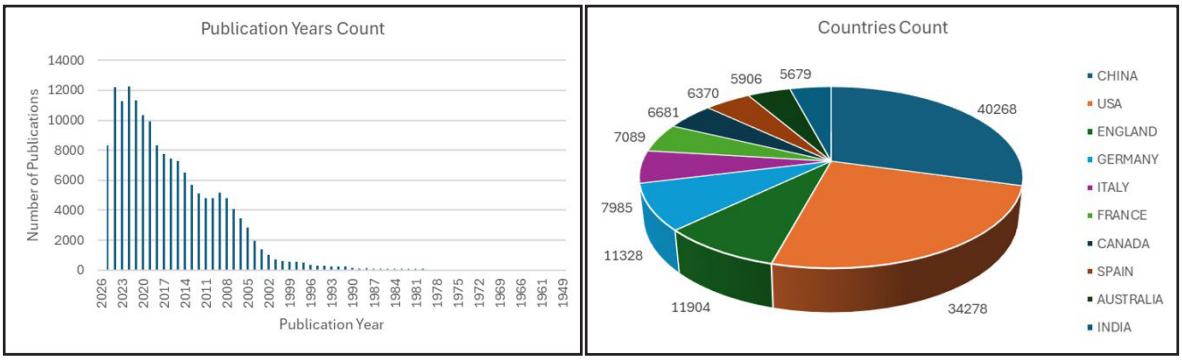
[50] Xu, Y., Zhang, X., Li, H., Zheng, H., Zhang, J., Olsen, M. S., Varshney, R. K., Prasanna, B. M. and Qian, Q. (2022) "Smart breeding driven by big data, artificial intelligence, and integrated genomic-enviromic prediction", *Molecular Plant*, Vol. 15, No. 11, pp. 1664-1695. ISSN 1674-2052. DOI 10.1016/j.molp.2022.09.001.

[51] Yuan, H., Song, M., Liu, Y., Xie, Q., Cao, W., Zhu, Y. and Ni, J. (2023) "Field Phenotyping Monitoring Systems for High-Throughput: A Survey of Enabling Technologies, Equipment, and Research Challenges", *Agronomy*, Vol. 13, No. 11, 2832. ISSN 2073-4395. DOI 10.3390/agronomy13112832.

Appendix A: Detailed bibliometric analysis per Search Query

This appendix presents a detailed breakdown of the bibliometric data for each of the eleven search queries (SQ1–SQ11). For each query, the annual publication growth and the geographic distribution of the top 10 contributing countries are provided.

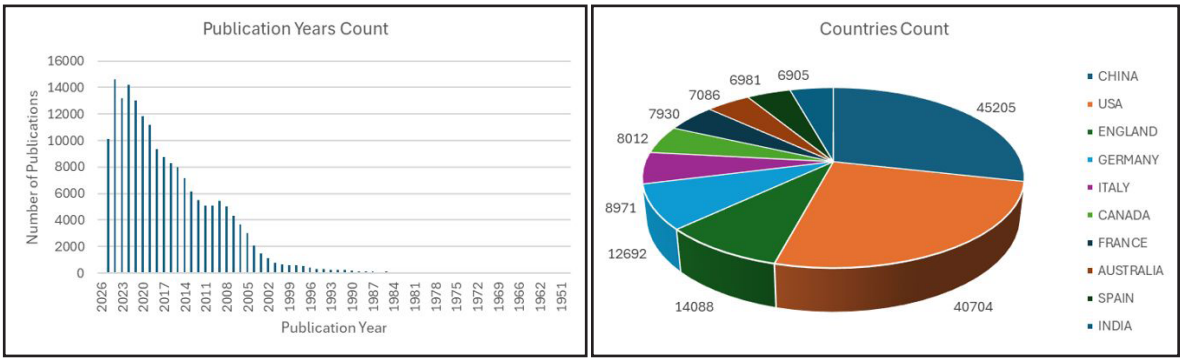
Search Query 1 (SQ1)



Source: Own processing

Figure A1: Bibliometric profile for SQ1: (a-left) Annual publication trends (1949–2025); (b-right) Geographic distribution of the top 10 most active countries.

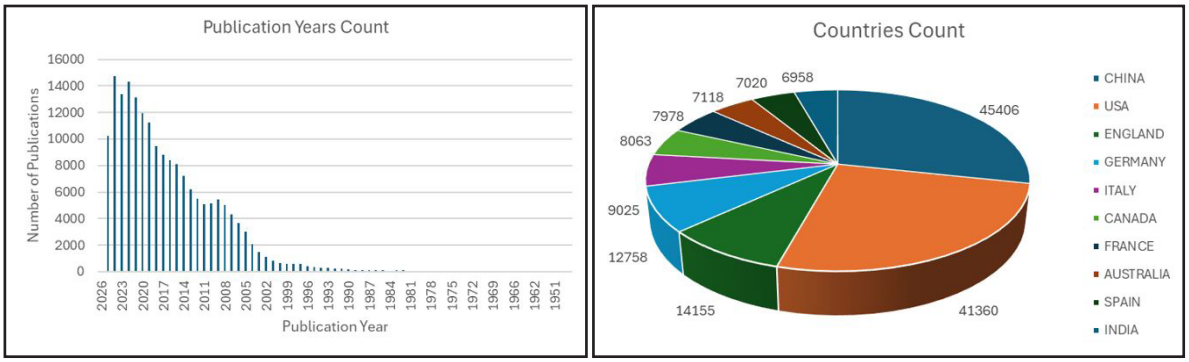
Search Query 2 (SQ2)



Source: Own processing

Figure A2: Bibliometric profile for SQ2: (a-left) Annual publication trends (1949–2025); (b-right) Geographic distribution of the top 10 most active countries.

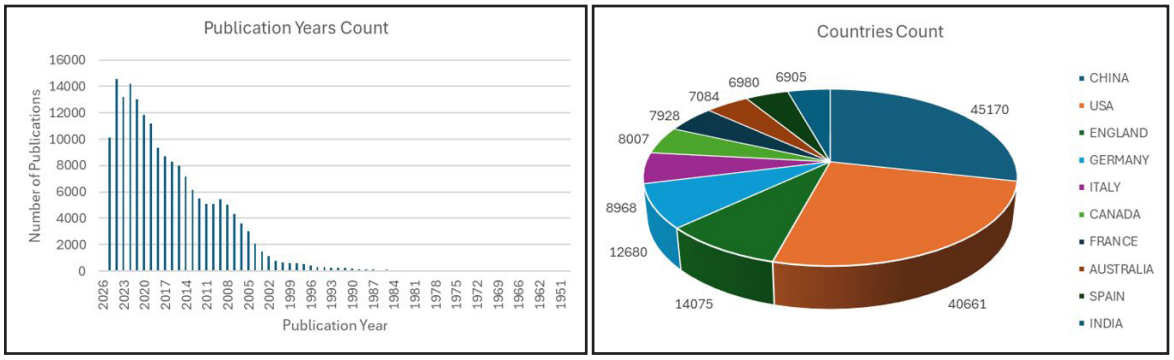
Search Query 3 (SQ3)



Source: Own processing

Figure A3: Bibliometric profile for SQ3: (a-left) Annual publication trends (1949–2025); (b-right) Geographic distribution of the top 10 most active countries.

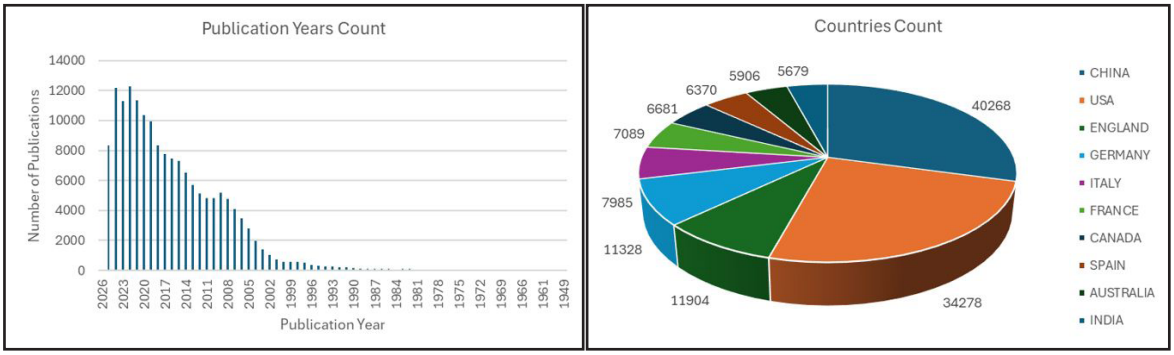
Search Query 4 (SQ4)



Source: Own processing

Figure A4: Bibliometric profile for SQ4: (a-left) Annual publication trends (1949–2025); (b-right) Geographic distribution of the top 10 most active countries.

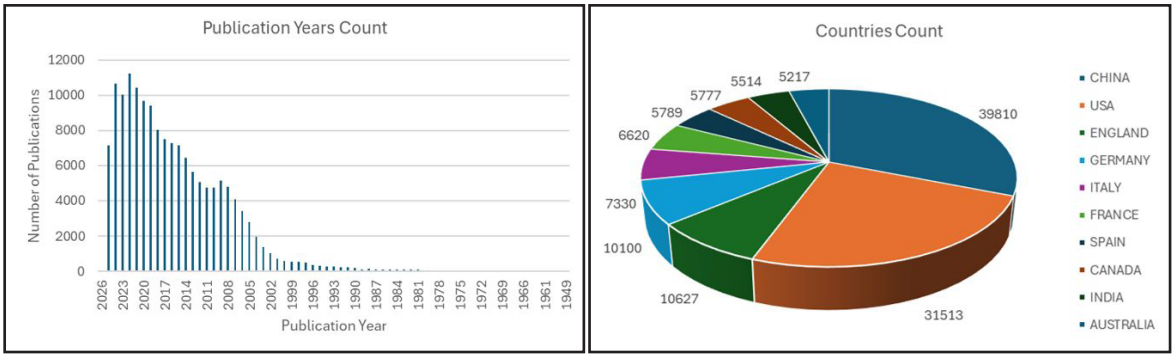
Search Query 5 (SQ5)



Source: Own processing

Figure A5: Bibliometric profile for SQ5: (a-left) Annual publication trends (1949–2025); (b-right) Geographic distribution of the top 10 most active countries.

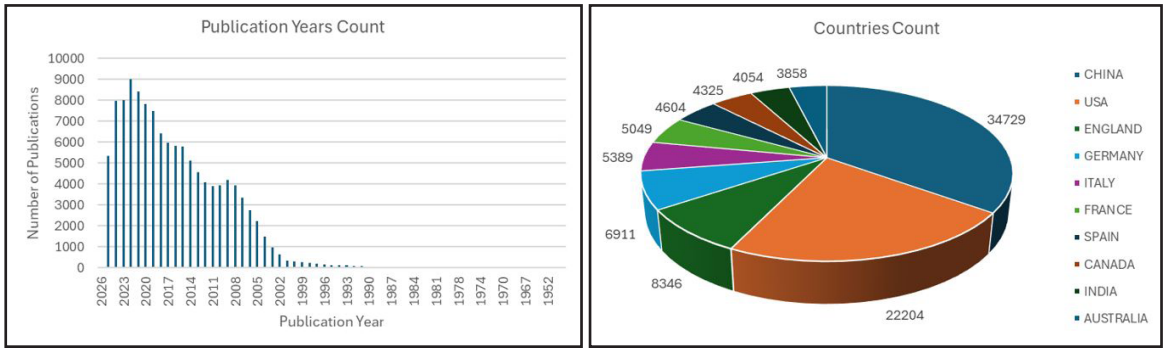
Search Query 6 (SQ6)



Source: Own processing

Figure A6: Bibliometric profile for SQ6: (a-left) Annual publication trends (1949–2025); (b-right) Geographic distribution of the top 10 most active countries.

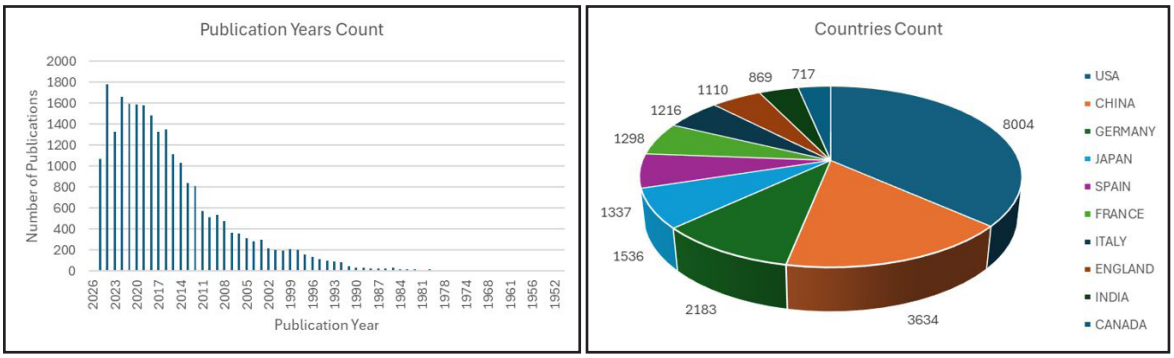
Search Query 7 (SQ7)



Source: Own processing

Figure A7: Bibliometric profile for SQ7: (a-left) Annual publication trends (1949–2025); (b-right) Geographic distribution of the top 10 most active countries.

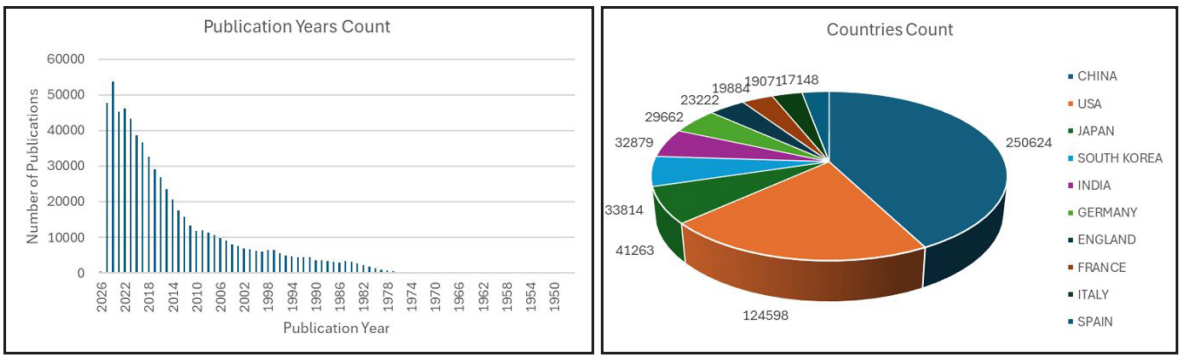
Search Query 8 (SQ8)



Source: Own processing

Figure A8: Bibliometric profile for SQ8: (a-left) Annual publication trends (1949–2025); (b-right) Geographic distribution of the top 10 most active countries.

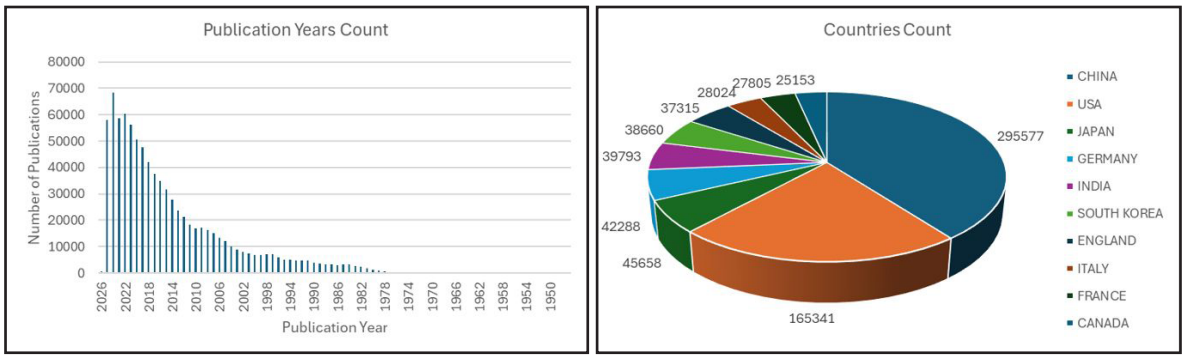
Search Query 9 (SQ9)



Source: Own processing

Figure A9: Bibliometric profile for SQ9: (a-left) Annual publication trends (1949–2025); (b-right) Geographic distribution of the top 10 most active countries.

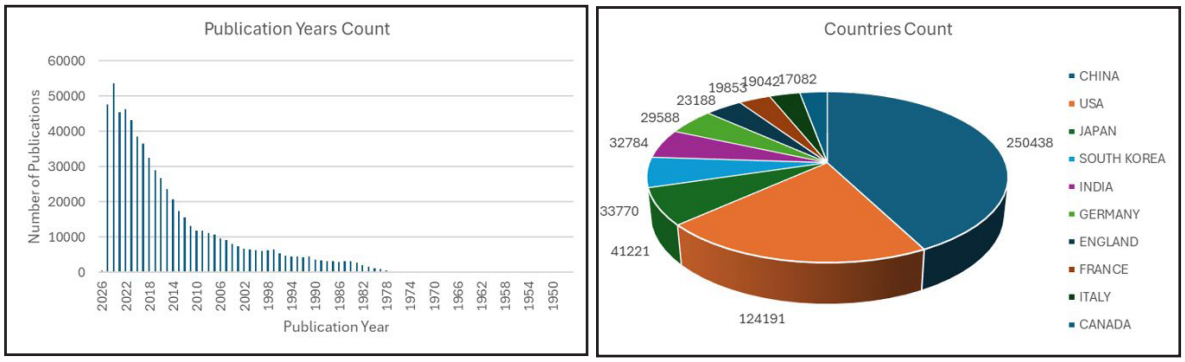
Search Query 10 (SQ10)



Source: Own processing

Figure A10: Bibliometric profile for SQ10: (a-left) Annual publication trends (1949–2025); (b-right) Geographic distribution of the top 10 most active countries.

Search Query 11 (SQ11)



Source: Own processing

Figure A11: Bibliometric profile for SQ11: (a-left) Annual publication trends (1949–2025); (b-right) Geographic distribution of the top 10 most active countries.

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Assessing and Forecasting the Competitiveness of Indonesian Downstream Coffee Industry

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Abstract

This study aims to identify the factors influencing the competitiveness of the Indonesian downstream coffee industry and provide a forecast through 2030. This study uses Revealed Symmetric Comparative Advantage (RSCA) and the Autoregressive Distributed Lag (ARDL) model, based on the Porter Diamond model, to identify the position and determinants of competitiveness in Indonesia's downstream coffee industry. In developing the forecasting model, this study employs three approaches: ARIMA, HP-Filter, and ARDL forecasting, utilising data from 1990 to 2023. The study indicates that Indonesia's downstream coffee industry has comparative advantages, as reflected in the continuous increase of RSCA values over the past two decades. The Porter Diamond model shows that GDP, manufacturing value-added, and foreign direct investment are key drivers of competitiveness. Coffee prices negatively affect both the short and long term, while domestic consumption negatively affects competitiveness only in the short term. Land area, however, does not show a significant effect. The forecasting results show that the competitiveness of the downstream coffee industry in Indonesia is projected to experience continued growth from 2024 to 2030.

Keywords

Business analytics, coffee industry, competitiveness, downstream, Porter Diamond Model.

Yusuf, M., Suroso, A. I., Sumarwan, U., Suhendi. and Haryono, A. (2026) "Assessing and Forecasting the Competitiveness of Indonesian Downstream Coffee Industry", *AGRIS on-line Papers in Economics and Informatics*, Vol. 18, No. 1, pp. 133-148. ISSN 1804-1930. DOI 10.7160/aol.2026.180110.

Introduction

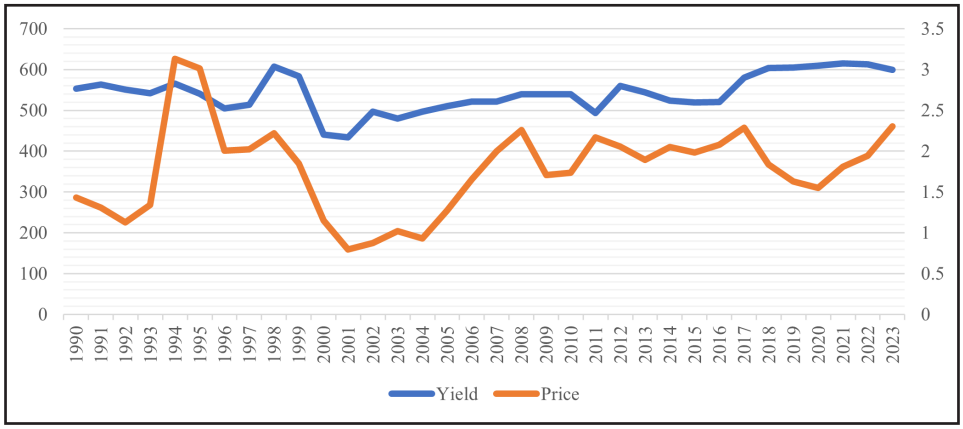
Coffee is a strategic plantation commodity for Indonesia, as this commodity serves as a smallholder farmers' income, provides industrial raw materials, plays a crucial role in rural development for sustainable agriculture, and contributes significantly to export earnings (Suryana et al., 2024). Coffee is one of the most traded agricultural commodities and has become a source of livelihood for millions of smallholders worldwide. Indonesia is the fourth-largest coffee producer in the world, with a total production of 717,000 tons (ICO, 2022). The coffee industry is a significant component of the Indonesian economy. In 2023, the Republic of Indonesia produced 774,000 tons of coffee beans, generating income for 1.89 million smallholder households (Kementerian Pertanian, 2023). As one of the world's coffee production centres, Indonesian coffee cultivation is mostly managed by smallholder farmers, covering approximately 95.71% of the total plantation area and approximately 1.23 million hectares. Indonesia has become Asia's second-largest coffee producer, and various types of high-quality coffee beans are grown across the Indonesian archipelago. Coffee has also been a prestigious commodity in Indonesia since the Dutch colonial period; at that time, coffees from Indonesia were sought in the European market (Hoffman, 2014). Along with changes in coffee drinking trends, the Indonesian coffee industry has changed its approach by developing many different types of coffee products, such as instant coffee products that are usually premixed with sugar and milk powder, in addition to regular pre-ground coffees (Ashardiono and Trihartono, 2024). Because of these changes, Sunarharum et al. (2021) underline that coffee drinks are enjoyed by people in all sectors of Indonesian society, ranging from rural to urban areas.

As the coffee market expands, Indonesian coffee producers are no longer solely focused on production for the international market; some are also starting to target the domestic market. As in countries with high coffee consumption, coffee has become an integral part of Indonesian life. This was true even before the café lifestyle trend emerged in Indonesia. For some, drinking coffee has become a morning

ritual before starting work; the day feels incomplete without a cup. With increasing demand for high-quality speciality coffee in the international market, the Indonesian government has slowly pushed for an increase in coffee production and processing in recent years. Coffee reaches around 400 billion cups annually, making it a highly valued beverage and a significant global trade commodity (Sachs et al., 2019). Export competitiveness defined as the ability of a product to enter foreign markets successfully. The strength of a nation's competitiveness is determined, among other things, by its capability to employ its superior resources to reinforce its position in world competition (Innayatuhibbah, Rahayu and Ferichani, 2024). Porter's theory of competitiveness outlines four key factors that influence the competitiveness of companies and industries within a nation. These factors include the availability of production factors, both basic and advanced, demand and quality requirements from end consumers, supporting industries in the supply chain, as well as strategy, market structure, and business rivalry in the industry (Porter, 1991).

The coffee industry in Indonesia has a strategic role in driving national economic growth. However, the competitiveness of Indonesian coffee, especially in the downstream sector, still presents various challenges. According to Tampubolon et al. (2023), the competitiveness of the downstream sector of the Indonesian coffee industry remains weak, as evidenced by an export structure dominated by raw coffee beans, low processing innovation, and limited penetration into premium markets that prioritise quality and added value. The dependence on Robusta commodities with minimal processing also exacerbates Indonesia's position as a raw material supplier for developed countries that dominate the market for high-value processed products (Rosiana et al., 2018). The absence of a downstream policy makes it difficult for small businesses to meet global requirements such as certification, quality consistency, and product origin tracking. Fragmentation between subsystems in the agribusiness chain, weak quality standardisation, and the lack of strong local brands also became significant obstacles to strengthening downstream competitiveness in the international market (Widyantini, 2019). Figure 1 shows that the Indonesian coffee industry's upstream and downstream sectors face high volatility. Sharp price fluctuations from year to year reflect downstream market instability, while upstream productivity volatility indicates suboptimal management and innovation in value-added creation. Instability on both sides suggests that the Indonesian coffee industry lacks resilience and strong competitiveness, particularly on the downstream side of the industry.

In the globalisation era, competition is increasingly fierce, with each country opening its markets to the other. The development of diverse processed coffee products holds a strategic position because they have the potential to become superior commodities with high competitiveness in the international market (Purwawangsa, Irfany and Haq, 2024). Indonesia, as a tropical country, has a significant opportunity to develop diversified processed coffee products and has the potential to build a speciality coffee processing industry. These products have distinctive flavours, such as Toraja Coffee and Kintamani Coffee, which can become a competitive advantage (Rahardjo et al., 2020). Previous studies found that Indonesian coffee has a comparative advantage in the global



Source: FAO Statistics & World Bank, 2024

Figure 1: Trends in coffee yield and price volatility in Indonesia from 1990 to 2023.

market, comparable to coffee from Brazil, Vietnam, and Colombia (Innayatuhibbah et al., 2024; Nasution et al., 2024; Suryana et al., 2024). However, research focusing on the downstream competitiveness remains limited, especially in major global coffee-producing countries like Indonesia. Changing global consumer preferences for convenient, ready-to-consume products create opportunities and a strategic position for processed coffee products to compete worldwide. Unfortunately, the contribution of downstream products to Indonesian coffee exports remains very limited. This is despite other producing countries, such as Brazil and Vietnam, having demonstrated success in making downstream products a significant source of foreign exchange. This indicates that Indonesia has not fully utilised its economic potential in the downstream processed coffee trade.

This study aims to determine the position and prospects of the Indonesian downstream coffee industry's competitiveness and identify its determinants. This study offers novelty by providing a more comprehensive perspective on determining the competitive position of the downstream sector, a relatively rare approach, using the Porter Diamond model. This study is expected to provide a more comprehensive and nuanced understanding of the position and evolving dynamics of the Indonesian downstream coffee industry's competitiveness in the international market, encompassing an analysis of its comparative standing against key global competitors, as well as the emerging opportunities and challenges that influence its long-term growth and sustainability.

Materials and methods

This research utilises two groups of data in accordance with the objectives to be achieved. The first objective is to estimate and forecast the competitive position of the Indonesian downstream coffee industry. The second objective is to analyse the factors influencing industry competitiveness based on the Porter Diamond Model. This study defines the downstream coffee industry as the segment of the coffee value chain engaged in post-harvest processing, value-added transformation, and product diversification beyond raw bean production, primarily encompassing processed and export-oriented coffee products. The first group of data analysed in this study is international trade data for downstream coffee in Indonesia obtained from UN Comtrade. The commodity group data analysed in this study is determined based on the aggregate value of the 6-digit HS code that represents processed coffee products as a representation of the downstream industry's capabilities. This study investigates the performance of Indonesia's downstream coffee industry by analysing export data corresponding to HS codes 210110, 210111, 210112, and 210130, which collectively encompass a broad spectrum of processed coffee products. Specifically, HS 210110 (coffee extracts, essences, concentrates, and preparations), HS 210111 (extracts, essences, and concentrates of coffee, and preparations based on these components), HS 210112 (preparations with a basis of coffee extracts, essences, or concentrates), and HS 210130 (roasted coffee substitutes such as chicory, including their extracts, essences, and concentrates) are included in the analysis. HS 210120 (tea or mate-based extracts, essences, and preparations) is excluded from this study, as it does not fall within the scope of coffee-related commodities. The export data, therefore, reflect the aggregate value of Indonesia's processed and value-added coffee products that constitute its downstream industry.

Furthermore, determinants of the downstream coffee industry were estimated using time series data from 1990 to 2023. The dependent variable of this study is the revealed symmetric comparative advantage of the Indonesian downstream coffee industry. The following independent variables are considered: coffee harvested area, GDP, manufacturing value-added, domestic consumption, FDI inflows, and price. The selection of independent variables in this study is based on the Porter Diamond model indicators developed by Tsai et al. (2021), by selecting several proxies that represent all aspects of the Porter Diamond model, including: factor conditions, demand conditions, firm strategy and rivalry, related and supporting industries, and government and chance. Table 1 presents the aspect, notation, definition, unit and source of variable used.

To estimate the competitive position of the downstream coffee industry, this study uses the Revealed Symmetric Comparative Advantage (RSCA). The RSCA is a symmetrical form of the RCA index developed by Balassa (1965) to measure a commodity relative comparative advantage compared to the global trade structure (Pascucci, 2018; Manalu et al., 2019; Jalata, 2021; Tandra et al., 2022; Wang et al., 2022; Suryana et al., 2024). The RSCA ranges from −1 to +1, where positive number shows comparative advantage, while negative number shows

Aspect	Notation	Definition	Unit	Source
Dependent Variable	$RSCA_t$	Revealed Symmetric Comparative Advantage (RSCA) Indonesia's downstream coffee industry at period *t*	Index	Author calculation
Factor Condition	$LAND_t$	Harvested area of coffee in period *t*	Hectare	FAO Statistics
Demand Condition	$CONS_t$	Domestic consumption of green coffee at period *t*	Bags (60 kg)	Indexmundi
	GDP_t	Gross domestic product at period *t*	US$	Worldbank
Related & Supporting Industries	$MANV_t$	Value added of the manufacturing sector at period *t*	US$	Worldbank
Strategy, Structure, and Rivalry	FDI_t	Foreign direct investment (FDI Inflows) at period *t*	US$	Worldbank
Government & Chance	$PRICE_t$	Average price of coffee in the international market at period *t*	US$	Worldbank

Source: Authors

Table 1: Variable description.

comparative disadvantage. The RCA formula and its transformation into RSCA are explained as follows:

$$\text{RCA}_{ij} = \frac{X_{ij}/X_{it}}{X_{wj}/X_{wt}} \quad (1)$$

$$\text{RSCA}_{ij} = \frac{RCA_{ij}-1}{RCA_{ij}+1} \quad (2)$$

Where X_{ij} is the value of exports of commodity *j* by Indonesia, X_{it} is the total export of all commodities by Indonesia, X_{wj} is the total world exports for commodity j, and X_{wt} is the total world exports for all commodities.

Furthermore, this study will also compare the competitiveness of Indonesia's downstream coffee industry with that of Brazil and Vietnam to enrich the findings and provide a global context for Indonesia's position in the processed coffee value chain. Brazil and Vietnam were chosen because they are both major global coffee producers and have significantly expanded downstream product exports. This comparison provides a strategic basis for assessing the potential and direction for strengthening the competitiveness of Indonesia's downstream coffee industry.

This study employs ARDL to analyse the factors that influence this competitiveness based on the Porter Diamond Model in the short-run and long-run. Furthermore, several steps are employed, namely the unit root test, cointegration test, diagnostic models, and stability test. The linear equation of this study is as follows:

$$RSCA_t = \beta_0 + \beta_1 LnLAND_t + \beta_2 LnCONS_t + \\ + \beta_3 LnGDP_t + \beta_4 LnMANV_t + \beta_5 LnFDI_t + \\ + \beta_6 LnPRICE_t + \mu_t \quad (3)$$

Where $RSCA_t$ = denotes the revealed symmetric comparative advantage of Indonesia's downstream coffee industry at period t. The independent variable includes $LAND_t$ represents the harvested area of coffee in hectares; $CONS_t$ Denotes the domestic consumption of green coffee in thousands of 60-kg bags; GDP_t refers to the gross domestic product, measured in US dollars; $MANV_t$ represents the value added of the manufacturing sector; FDI_t is the foreign direct investment inflows; *PRICE* denotes the average international market price of Robusta coffee; *Ln* is the natural logarithm, β_0 is the intercept, $\beta_1, \beta_2 \ldots \beta_6$ are the regression, and μ_t is the residual term.

A series of preliminary tests is required before ARDL model estimation to verify the data's appropriateness and the underlying assumptions to ensure model robustness. First step is unit root test, as non-stationary variables can produce unreliable results (Engle and Granger, 2012). The Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests are used in testing for the presence of a unit root (Dickey and Fuller, 1981; Phillips and Perron, 1988). The second stage is lag selection for the ARDL model criteria, carried out using LR, AIC, FPE, SC, and HQ criterion. Third, the Bound test stages to overcome the limitations of previous cointegration, which require variables to be at the same order of integration (I(1)) (Engle and Granger, 2012). Fourth, the bounds test to assess the cointegration. Values below the lower bound indicate no cointegration, above the upper bound confirm it, and values in between are inconclusive. Diagnostic checks were also run to validate the model and residuals. These included checks for residual autocorrelation, homoskedasticity, and normality (Wooldridge, 2004). Furthermore,

stability tests were conducted using CUSUM and CUSUMQ to ensure model consistency over time. To ensure the validity of an econometric model requires it to be free from violations of classical assumptions (Wooldridge, 2013). The normality, heterokedasticity, muticolonearity, and autocorrelation was used to evaluation of this model. There is a linear ARDL model can be written as follows:

$$RSCA_t = \beta_0 + \beta_1 \sum_{i=0}^{n} LnLAND_{t-i} + \beta_2 \sum_{i=0}^{n} LnCONS_{t-i} + \beta_3 \sum_{i=0}^{n} LnGDP_{t-i} + \beta_4 \sum_{i=0}^{n} LnMANV_{t-i} + \beta_5 \sum_{i=0}^{n} LnFDI_{t-i} + \beta_6 \sum_{i=0}^{n} LnPRICE_{t-i} + \mu_t \quad (4)$$

The decision to reject or accept the null hypothesis (H_0) is based on the following conditions. If the calculated F-statistic exceeds the upper critical limit, H_0 is rejected, indicating cointegration between the variables. Conversely, if the F-statistic is below the lower limit, H_0 is accepted, indicating no cointegration.. In short-run form, the framework of ARDL could be expanded by adding an error correction term (ECT_{t-1}). Hence, the short run of ARDL is specified as:

$$RSCA_t = \beta_0 + \beta_1 \sum_{i=0}^{n} \Delta LnLAND_{t-i} + \beta_2 \sum_{i=0}^{n} \Delta LnCONS_{t-i} + \beta_3 \sum_{i=0}^{n} \Delta LnGDP_{t-i} + \beta_4 \sum_{i=0}^{n} \Delta LnMANV_{t-i} + \Delta\beta_5 \sum_{i=0}^{n} LnFDI_{t-i} + \beta_6 \sum_{i=0}^{n} \Delta LnPRICE_{t-i} + \delta ECT_{t-1} + \mu_t \quad (5)$$

Where Δ is the difference organiser, ECT could be utilised to measure the cointegration. A negative and significant of ECT_{t-1} (δ) indicates short-run disequilibrium between the variables is gradually corrected, leading the system to converge toward its long-run equilibrium.

The third objective of this study is to forecast the competitive position of the downstream industry. This study uses three time series forecasting approaches: HP-filter, ARDL forecasting, and ARIMA model to ensure comprehensive forecasting results. First, this study conducts a decomposition before regression analysis, using the Hodrick–Prescott (HP) filter. Second, this study employs the ARDL forecasting to capture forecasting value in the short-term and long-term dynamics based on its initial model in Equations (4) and (5). Third, this study also uses the ARIMA model popularised by Box and Jenkins (1970). This model is predicated on the construction of forecasts of future values as a linear combination of past values and lags of forecast errors. It does not involve independent variables in predicting future values; rather, it utilises trends, patterns, seasonal characteristics, and information within the data series itself to generate forecast values. The general ARIMA model is presented as follows:

$$Y_t = \mu + \alpha_1 Y_{t-1} + \ldots + \alpha_p Y_{t-p} - \theta_1 et\text{-}1 - \theta_q e_{t-q} \quad (6)$$

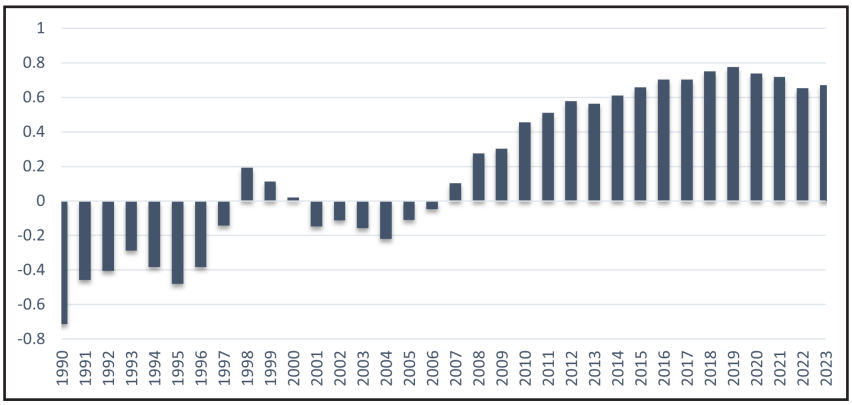
where Y_t is the differenced time series value, α and θ are unknown parameters, and e are independent, identically distributed error terms with zero mean. The lagged autoregressive (AR) processes are symbolised by p, and that of a moving average (MA) process are symbolised by q.

To provide a more comprehensive evaluation of model stability and to reduce potential over-optimism from trend-based forecasting, this study incorporates a simulation approach adopted from study by (Suroso et al., 2023). The analysis examines two key external risk channels, namely price shocks and consumption shocks, which are considered major pathways through which changes in global market conditions may influence the competitiveness of Indonesia's downstream coffee industry. Each type of shock is modeled through three alternative scenarios representing 5, 10, and 15 percent changes in the respective variables, while other factors are kept constant to isolate the effects. This scenario framework allows the model to simulate realistic global market disturbances and assess their potential impact on the Revealed Symmetric Comparative Advantage (RSCA) index, using 2023 as the baseline year for comparison.

Result and discussion

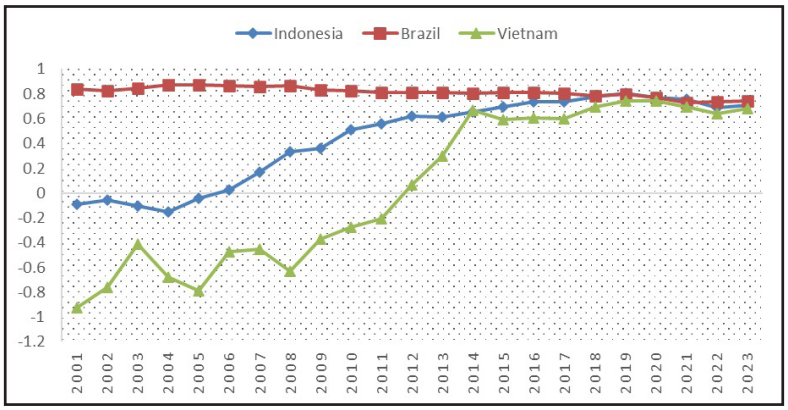
The Indonesia's downstream coffee industry competitiveness

Based on the RSCA calculation results for the period 1990 to 2023 in Figure 2, the competitiveness of Indonesia's downstream coffee industry shows a significant structural transformation in export performance. In the early 1990s, the RSCA value was in the negative range, as reflected in 1990 at -0.724, reflecting a weak comparative position due to a lack of product processing. Since the early 2000s, the RSCA value has shown a consistent upward trend and entered positive territory, with the highest value recorded in 2019 at 0.804. This finding indicates that the downstream coffee industry in Indonesia has a bright prospect and has the potential to become a country for global market expansion in the downstream coffee industry.



Source: Author analysis, 2025

Figure 2: Indonesia's downstream coffee industry competitiveness.



Source: Author analysis, 2025

Figure 3: Comparative trends of downstream coffee industry competitiveness in Indonesia, Brazil, and Vietnam.

Furthermore, to provide a broader perspective on Indonesia's downstream coffee competitiveness, a comparative analysis was conducted with two major global coffee producers, Brazil and Vietnam. Due to data availability, the Revealed Symmetric Comparative Advantage (RSCA) index was calculated for the period 2001-2023 using the corresponding HS codes for processed coffee products. The results, presented in Figure 3 (above), reveal that Brazil consistently maintained a high and stable RSCA value (around 0.8), indicating a strong and sustained comparative advantage in downstream coffee exports throughout the period. In contrast, Indonesia and Vietnam exhibited dynamic improvement trends. Indonesia's RSCA moved from a negative value in the early 2000s to a strong positive advantage after 2010, peaking around 2019, which reflects a significant structural transformation in its value-added coffee industry. Vietnam showed a similar upward trajectory, transitioning from a deep negative RSCA in the early 2000s to a positive level after 2012, suggesting progressive industrial upgrading in downstream coffee exports. Collectively, the comparative trend highlights Indonesia's successful convergence toward the competitiveness level of traditional leaders such as Brazil and Vietnam, although sustaining this momentum will require continued investment in downstream capacity, innovation, and export sophistication. Accordingly, it is recommended that Indonesia prioritise continuous investment in processing capacity, quality enhancement, and market diversification to consolidate its competitive position in the global value chain.

The Determinants of Indonesia's downstream coffee industry competitiveness

This study also examines the determinants influencing the downstream coffee industry competitiveness, as proxied by the revealed symmetric comparative advantage value. This study uses only factors included in the Porter Diamond model as determinants of the competitive position of the downstream coffee industry in Indonesia. Table 2 shows descriptive statistics, including median, mean, max, min, and standard deviation. These tables are presented to determine

the range and scope of the data used in the study. No variables in this study deviate significantly from a balanced and normal variability (standard deviation, mean). The Mean and Std. Dev. are used to assess the variability of the data.

Table 3 shows the correlation matrix, indicating that all variables have correlation values below 0.8. This suggests that the variables are related but not excessively correlated, confirming the absence of multicollinearity problems in the model. These results further imply that the model specification is well constructed and robust, providing a reliable foundation for the ARDL model.

To examine the potential endogeneity among competitiveness, foreign direct investment (FDI), and economic growth (GDP), this study applied the Toda and Yamamoto, (1995) Granger causality test. The three variables are theoretically interrelated, as higher GDP growth may attract FDI inflows, while increased competitiveness can both result from and stimulate economic expansion and investment. The test results presented in Table 4 indicate no significant causal relationship among the variables at the 5 percent level. This absence of causality suggests that variations in competitiveness, FDI, and GDP move together in the long run through cointegration, but do not dynamically influence each other within the sample period. Consequently, the ARDL estimations are unlikely to suffer from endogeneity bias, supporting the robustness and consistency of the long- and short-run coefficients.

Variables	Mean	Median	Maximum	Minimum	Std. Dev.
$RSCA_t$	0.246	0.242	0.803	-0.467	0.434
$LnLAND_t$	13.922	14.034	14.138	13.523	0.211
Ln $CONS_t$	7.687	7.544	8.496	7.166	0.414
$LnGDP_t$	26.67	26.621	27.907	25.281	0.866
$LnMANV_t$	25.218	25.332	26.211	23.773	0.798
$LnFDI_t$	1.287	1.787	2.916	-2.757	1.338
$LnPRICE_t$	0.516	0.607	1.140	-0.232	0.329

Source: Author analysis, 2025

Table 2: Descriptive statistics.

	RSCA	LnLAND	LnCONS	LnGDP	LnMANV	LnFDI	LnPRICE
RSCA	1.0000						
LnLAND	0.6347	1.0000					
LnCONS	0.7589	0.3348	1.0000				
LnGDP	0.7165	0.7412	0.7746	1.0000			
LnMANV	0.3358	-0.2150	0.3764	0.3141	1.0000		
LnFDI	0.3838	-0.0110	0.4986	0.5043	0.4959	1.0000	
LnPRICE	0.7807	0.5472	0.7316	0.7701	0.2695	0.3848	1.0000

Source: Author analysis, 2025

Table 3: Correlation matrix.

Pairwise Granger Causality Tests			
Lags: 2			
Null Hypothesis:	**Obs**	**F-Statistic**	**Prob.**
LnFDI does not Granger Cause LnGDP	32	0.39693	0.6762
LnGDP does not Granger Cause LnFDI		0.86891	0.4308
RSCA does not Granger Cause LnGDP	32	0.93351	0.4055
LnGDP does not Granger Cause RSCA		2.88479	0.0732
RSCA does not Granger Cause LnFDI	32	1.12773	0.3385
LnFDI does not Granger Cause RSCA		0.86504	0.4324

Source: Author analysis, 2025

Table 4: Granger causality test.

The first assumption that must be met to avoid spurious regression is that all variables must be stationary at the first difference (Granger, Hyung and Jeon, 2001). Table 5 shows the results of the unit root test which shows that t the variable is stationary in the first difference and non-stationary at the level.

Table 6 shows the lag selection criteria determined using a sequentially modified LR test, FPE, AIC, SC, and HQ Criterion. The results indicate that lag 2 is the optimal lag for the ARDL model, as indicated by the atrerisk (*) value for each criterion. This criterion value indicates a higher level of robustness compared to other selection criteria.

Table 7 present the Bound test, which was used to confirm the long-run cointegration in the ARDL model. The bound test results indicate an F-Stat value of 5.205, significant at the 1%, 2.5%, 5%, and 10% levels. Therefore, this model exhibits a long-run cointegration.

Table 8 presented the long-run and short-run estimation. In the long-term estimates, GDP ($LnGDP_t$), manufacturing sector value added (LnMANVt), and foreign direct investment ($LnFDI_t$) show a significant positive effect on the competitiveness of the downstream coffee industry in Indonesia. This result indicates that improved macroeconomic performance, a strengthening of the manufacturing industrial base, and the influx of foreign investment significantly strengthen the comparative advantage of the processed coffee sector. Meanwhile, the variables for land area ($LnLAND_t$) and domestic consumption ($LnCONS_t$) show a negative but insignificant effect, indicating that they do not yet play a dominant role in influencing long-term competitiveness. The export price variable ($LnPRICE_t$) also shows a significant negative effect, reflecting that rising product prices can negatively impact of the downstream competitiveness of the coffee industry.

In the short-term estimation, the $LnGDP_t$ and LnMANVt variables continue to show a significant positive effect, reinforcing the role of economic growth and strengthening the manufacturing sector as key drivers of downstream industry competitiveness.

Variables	Augmented Dickey Fuller		Philip-Perron	
	Level I(0)	First Difference I(1)	Level I(0)	First Difference I(1)
$RSCA_t$	-1.926	-4.261***	-1.954	-4.549***
$LnLAND_t$	-1.910	-4.397***	-1.909	-4.397***
Ln $CONS_t$	-0.289	-5.598***	-0.378	-5.597***
$LnGDP_t$	-0.733	-5.829***	-0.720	-5.829***
$LnMANV_t$	-1.202	-3.923***	-1.392	-6.379***
$LnFDI_t$	-2.256	-5.447***	-2.396	-5.447***
$LnPRICE_t$	-1.959	-4.628***	-2.077	-4.522***

Source: Author analysis, 2025

Table 5: Unit root test.

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-850.292	NA	2.47e+15	55.309	55.633	55.415
1	-667.103	271.829	4.67e+11	46.652	49.242	47.496
2	-571.458	98.730*	3.93e+10*	43.642*	48.500*	45.226*

Source: Author analysis, 2025

Table 6: Lag selection criteria.

K	F-Statistics	Significant	Lower bound I(0)	Upper bound I(1)
5	5.205	10%	2.12	3.23
		5%	2.45	3.61
		2.5%	2.75	3.99
		1%	3.15	4.43

Source: Author analysis, 2025

Table 7: Bound test.

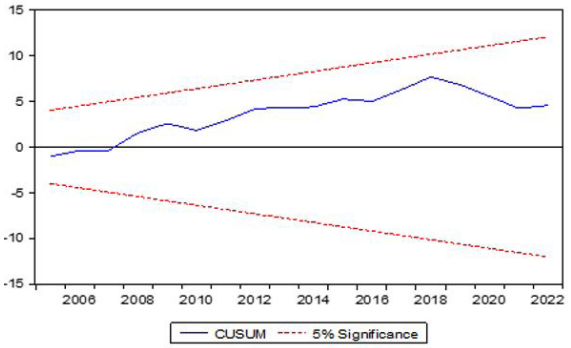
The export price variable (LnPRICEt) shows a significantly negative effect, which means that excessive price pressure can reduce the industry's competitiveness. In addition, the lag domestic consumption variable (D(LnCONS$_t$(-1))) has a significant negative effect, while FDI (D(LnFDIt(-1))) also shows positive significant effect. The value of (CointEq(-1)) is −0.341 and significant at the 1% level, indicating that approximately 34.1% of the short-term imbalance will be corrected towards long-term equilibrium each period. The adjusted R-squared value of 0.977 means that the model can explain 97.7% of the variability in industry competitiveness, and the Durbin-Watson value of 1.997 indicates the absence of autocorrelation. Therefore, our model is fit and robust for the estimation.

Variables	Coefficient	Std. error	Probability
Longrun Estimation			
LnLANDt	-1.131	0.816	0.184
LnCONSt	-0.247	0.195	0.222
LnGDPt	0.830	0.398	0.053*
LnMANVt	1.737	0.600	0.010**
LnFDIt	0.151	0.056	0.015**
LnPRICEt	-0.407	0.203	0.061*
CointEq(-1)	-0.341	0.071	0.000***
Constant	-3.629	5.795	0.539
Shortrun Estimation			
RSCA (-1)	0.659	0.071	0.000***
LnLAND	-0.385	0.260	0.157
LnCONS	-0.166	0.129	0.214
LnCONS(-1)	-0.113	0.112	0.328
LnCONS(-2)	0.195	0.095	0.056*
LnGDP	0.416	0.096	0.001***
LnGDP(-1)	0.133	0.053	0.022**
LnMANV	0.592	0.155	0.001***
LnFDI	0.010	0.014	0.506
LnFDI(-1)	0.014	0.015	0.355
LnFDI(-2)	0.028	0.014	0.070*
LnPRICE	-0.296	0.059	0.000***
LnPRICE(-1)	0.158	0.049	0.005***
Constant	-1.236	2.072	0.559
R-squared	0.987		
Adjusted R-squared	0.977		
Durbin-Watson stat	1.9974		

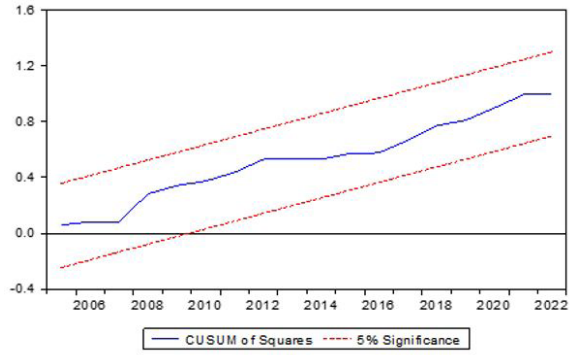
Notes: *, **, and *** are significant at 10%, 5%, and 1%, respectively.
Source: Author analysis, 2025

Table 8: Long-run and short-run estimations.

Furthermore, we also conducted stability tests to verify the model consistency over time, to ensure the validity of the estimates and the consistency of the economic inferences. Figure 4 shows the stability tests, indicating that the model is stable through the CUSUM and CUSUMQ tests. The graph plot shows that the blue line does not cross the red line at the upper and lower limits, which are the critical value line indicating the estimation technique's stability. Furthermore, the CUSUM and CUSUMSQ plots do not support parameter instability. These results indicate that the downstream competitive positioning model used in this study has been correctly determined, confirming its stability over the sample period.



CUSUM



CUSUM of Squares

Source: Author analysis, 2025

Figure 4: CUSUM and CUSUM of squares.

Table 9 presents various diagnostic test results for the classical model assumptions. The probability value of the Breusch–Godfrey is 0.798, as well as the heteroscedasticity test value with several tests, including Breusch–Godfrey, Glesjer, and Harvey, showing probability values of 0.995, 0.851, and 0.310 > α (0.05) respectively, so there are no heteroscedasticity and autocorrelation problems in this model. We also ran a data normality test to ensure the data used in this research model was normally distributed. The probability value was found to be 0.626 > α (0.05), so it can be stated that all data in this model was normally distributed.

	Obs*R-square	F-Statistics	Probability
Serial correlation: Breusch-Godfrey Serial Correlation LM Test	0.449	0.11	0.798
Heteroskedasticity Test: Breusch-Pagan-Godfrey	12.585	0.894	0.995
Heteroskedasticity Test: Glesjer	13.597	1.021	0.851
Heteroskedasticity Test: Harvey	19.181	2.122	0.31
Jarque-Bera and Probability			
	Jarque-bera		Probability
Normality: Jarque-Bera (Probability)	0.935		0.626

Source: Author analysis, 2025

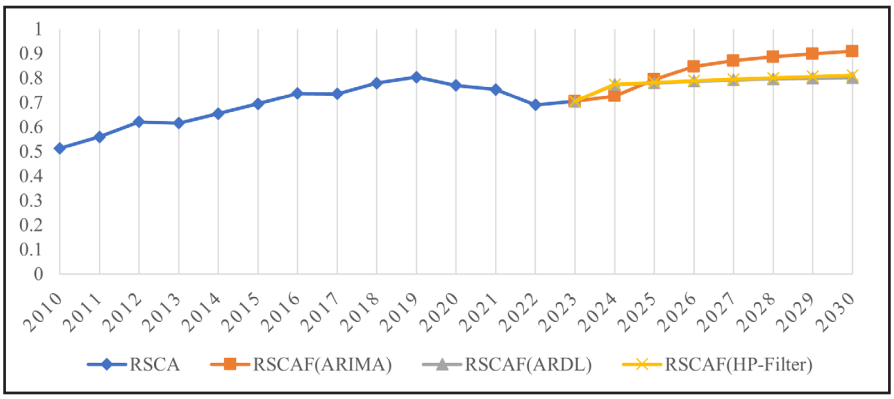
Table 9. Diagnostic test.

Forecasting of Indonesia's downstream coffee industry competitiveness

Figure 5 and Table 10 presents the forecasted results of the RSCA value, representing Indonesia's downstream coffee industry's competitiveness for 2024–2030, based on three forecasting approaches: ARIMA, ARDL, and HP-Filter. The HP-Filter model produces a conservative and stable projection, with the RSCA value gradually increasing from 0.774 in 2024 to 0.811 in 2030. This projection reflects a linear trend based on historical patterns, assuming minimal structural changes in processed coffee export dynamics. In contrast, the ARIMA approach produces the most optimistic projection, with the RSCA value estimated to increase from 0.727 to 0.909 over the same period. This sharp increase indicates the potential for significant acceleration in competitiveness, which aligns with expectations of industrial reforms and improvements in downstream capabilities. The ARDL model, on the other hand, produces more moderate but realistic results, with the RSCA value increasing from 0.773 to 0.800. This projection reflects a balance between short and long-term dynamics, without exhibiting the extremes of ARIMA. Collectively, these three models reveal a consistent upward direction, suggesting that Indonesia's downstream coffee industry is beginning to show encouraging signs of improvement in its competitive performance.

The forecast results show early indications of improvement and underlying growth potential within Indonesia's downstream coffee industry. Rather than signalling immediate expansion, the projections point to gradual structural strengthening supported by improvements in processing capability, product innovation, and export diversification. These patterns suggest that Indonesia is progressively moving toward a more competitive and resilient value-added coffee sector. However, the realisation of this potential will depend on consistent policy implementation and responsiveness to global market dynamics. From a policy perspective, the findings emphasise the importance of maintaining strategic support for industrial upgrading, technological advancement, and market development to translate this potential into tangible competitiveness gains. Encouraging greater participation from both domestic and international investors in processing, branding, and quality improvement will also be essential for consolidating Indonesia's position within the global processed coffee value chain. Overall, the forecasting results provide meaningful signals of emerging competitiveness, reflecting a gradual transition toward higher value creation and sustainable downstream development.

Furthermore, this study incorporates the potential impact of global demand shocks to capture how external market dynamics may shape the future performance of Indonesia's downstream coffee industry. The simulation framework focuses on two key scenarios that represent the primary channels of global demand fluctuation. The first is the consumption-shock scenario, which captures the impact of declining global coffee consumption on export performance. The second is the price-shock scenario, which reflects the effects of rising international coffee prices on competitiveness. Figure 6 presents the results of the simulation analysis, showing a consistent decline in competitiveness under both consumption and price shock scenarios as the magnitude of the shocks increases. Under the consumption-shock scenario, the baseline value of 0.7403 decreases slightly to 0.7306 when consumption falls by 5 percent, and continues to decline to 0.6963 and 0.6624 at 10 and 15 percent reductions, respectively. This pattern indicates that a contraction in global coffee consumption moderately weakens Indonesia's



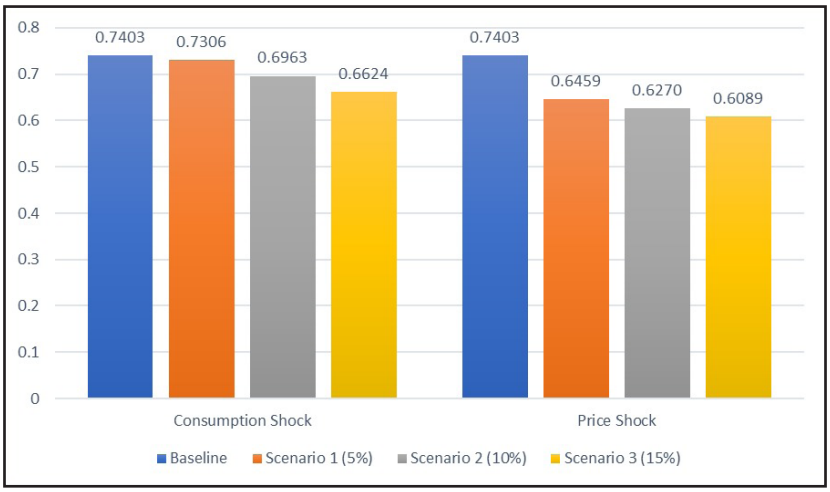
Source: Author analysis, 2025

Figure 5: Forecasting of Indonesian downstream coffee industry competitiveness.

Year	HP-Filter	ARDL	ARIMA
2024	0.774322018	0.773399179	0.726954439
2025	0.782046522	0.78048254	0.793637138
2026	0.788792255	0.786782517	0.846184877
2027	0.794817133	0.792100257	0.870719061
2028	0.800358973	0.796220719	0.886370239
2029	0.805628422	0.799014356	0.898496871
2030	0.810794746	0.800482256	0.908817676

Source: Author analysis, 2025

Table 10: Forecasting of Indonesian downstream coffee industry competitiveness.



Source: Author analysis, 2025

Figure 6: The Simulation of RSCA under shock scenario, value from actual data 2023.

downstream industry performance. Under the price-shock scenario, the impact is more substantial, with competitiveness declining from 0.7403 to 0.6459, 0.6270, and 0.6089 under 5, 10, and 15 percent price increases. The sharper decrease under the price-shock simulation demonstrates that fluctuations in export prices have a more substantial and more immediate effect on Indonesia's downstream coffee competitiveness compared to consumption shocks. The observed pattern suggests that the global demand shift driven by price dynamics poses a greater challenge to Indonesia's downstream coffee industry than changes in aggregate consumption. Price instability directly affects export margins, production costs, and value-added returns, which in turn influence the competitive structure of the industry. The results imply that the resilience of Indonesia's

downstream coffee sector is closely tied to the stability of international coffee prices, reflecting its dependence on global market valuation and cost transmission mechanisms within the value chain.

The competitive position of the downstream coffee industry in Indonesia has exhibited significant potential, as evidenced by a consistent growth trend and an enhancement in competitiveness over the past two decades. This growth in industrial competitiveness is inseparable from the government's strategic role in encouraging downstream processing through fiscal incentives, strengthening logistics infrastructure, and expanding access to foreign markets through bilateral and regional trade agreements. Furthermore, industrial transformation is also driven by improved product quality and connectivity within a more complex and digital global value chain system, including the integration of technology into production and distribution processes (Suzianti et al., 2024). Nevertheless, challenges in adopting global quality standards and sustainability issues remain crucial factors that must be considered in maintaining competitiveness (Wang et al., 2024). The success of commodity-based industries depends on adapting to evolving market expectations, including supply chain sustainability and transparency (Gardner et al., 2019). However, in reality, for emerging markets like Indonesia, adopting sustainable certification strengthens the legitimacy of Indonesian downstream coffee products in premium export markets. However, this certification process is often more accessible to large-scale players than to small businesses (Donovan, Blare and Poole, 2017). The main obstacles to certification adoption by smallholder farmers in Indonesia include high costs, low direct economic incentives, and weak local institutional support, reflecting a disconnect between compliance with standards and the tangible benefits experienced by upstream actors (Glasbergen, 2018).

The results of the ARDL estimation based on the Porter Diamond model indicate that land area has no significant effect on industry competitiveness. This finding differs from Yadav and Chattopadhyay (2024), who found that yield positively contributes to the export competitiveness of agricultural products, and Long (2021) emphasised the importance of land availability in supporting large-scale production in the upstream sector. However, because this study focuses on the downstream industry, the role of land becomes less dominant, as competitiveness is determined more by processing efficiency, post-harvest technology utilisation, supply chain integration, product quality standards, and the ability to create differentiation and added value that aligns with market preferences. In the demand condition component, GDP has a positive effect in both the short and long term. Exporting countries with high GDP are linked to greater export competition, especially among regions with similar economic profiles (Li et al., 2022). Higher GDP can intensify competition for export markets, particularly in regions with many similar exporters. Furthermore, GDP can also significantly enhance the competitiveness and growth of a country's manufacturing sector, thereby creating greater added value (Hotsawadi and Gea, 2024).

Interestingly, this study reveals that in the short term, domestic consumption can reduce the competitiveness of downstream industries. Domestic consumption and competitiveness are closely linked, particularly in the context of global disruption and supply chain changes (Willer and Aldridge, 2023). Increasing domestic consumption can strengthen food security and resilience and drive stable demand for industries, including downstream sectors such as coffee processing. However, excessive reliance on the domestic market or high domestic market concentration can reduce international competitiveness and limit productivity gains from participation in global trade (Fambeu and Yomi, 2025). Therefore, encouraging domestic consumption needs to be balanced with active involvement in international trade and avoiding excessive domestic market concentration to maintain sustainable competitiveness and productivity growth. A country's industrialisation capacity represents related and Supporting Industries. This study shows that manufacturing value-added has a positive and significant impact on short- and long-term competitiveness. Investing in advanced technology and innovation can increase product added value, directly strengthening competitiveness (Huo, 2014; Chikán et al., 2022). Downstream industries with dynamic production capabilities and strong innovation management tend to outperform those that rely solely on basic production capabilities.

Furthermore, FDI, as a proxy for Firm Strategy and Rivalry, has a significant positive effect in both the short and long term, as it enables technology transfer, the adoption of international quality standards, and the expansion of export market networks (Skare and Cvek, 2020). Simionescu

et al. (2021) stated that FDI is a driver for integration in global value chains, especially when directed to the downstream sector and supported by facilitative policies. This study also revealed that price, as a component of government and change in the Porter Diamond model, has a negative effect on competitiveness. These results indicate that increasing commodity prices do not automatically contribute to improved competitiveness, especially if downstream products do not yet have a strong brand position or cannot meet premium market preferences (Yu et al., 2024). The increase in commodity prices does not necessarily strengthen the competitiveness of downstream industries, considering that Indonesian exports are still dominated by raw material-based products that produce low added value, and the export structure is not yet optimally diversified, limiting the industry's capacity to respond to demands for innovation and quality in the global market. Therefore, policies to increase competitiveness are insufficient to rely solely on production expansion or macroeconomic growth, but must also be directed at creating an innovative, vertically integrated downstream ecosystem capable of producing high-value processed coffee products.

Conclusion

This study reveals that the competitiveness of the downstream coffee industry in Indonesia has exhibited significant potential, as evidenced by a consistent growth trend and an enhancement in competitiveness over the past two decades. The Porter Diamond model developed in this study reveals that GDP, value-added in the manufacturing sector, and foreign direct investment play significant roles in driving competitiveness, both in the short and long term. Conversely, variables such as land area and domestic consumption have not significantly contributed to the downstream industry's competitiveness. The forecasting results developed in this study using ARIMA, HP Filter, and ARDL forecasting also indicate that the competitiveness of the downstream coffee industry in Indonesia is projected to continue growing between 2024 and 2030.

These findings carry important implications for both policymakers and industry stakeholders, indicating that strategies to enhance the downstream coffee industry competitiveness should prioritise strengthening manufacturing capabilities, improving product quality, and optimising the flow of foreign investment. Furthermore, government policy must be directed to developing pricing strategies oriented toward premium markets and product differentiation, rather than simply focusing on raw commodity volume or price. This study is limited in the scope of variables analysed, as it does not explicitly include institutional factors, regulations, technology, and the dynamics of the global crisis. The omission of these dimensions may reduce the model's ability to capture structural transformations and external disruptions, such as technological adoption, climate-related risks, or policy and market shocks that could influence long-term competitiveness. Future studies are recommended to incorporate these factors through more complex and comprehensive scenario-based or simulation analyses, enabling the assessment of alternative policy, technological, and environmental pathways. In addition, future research may employ a longer dataset in forecasting analysis to improve the robustness and accuracy of the results, and replication of this study in other major coffee-producing countries is encouraged to strengthen the empirical findings and enhance generalizability.

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References

[1] Ashardiono, F. and Trihartono, A. (2024) "Optimizing the potential of Indonesian coffee: a dual market approach", *Cogent Social Sciences*, Vol. 10, No. 1. E-ISSN 2331-1886. DOI 10.1080/23311886.2024.2340206.

[2] Balassa, B. (1965) "Trade Liberalisation and "Revealed" Comparative Advantage", *The Manchester School of Economic and Social Studies*, Vol. 33, No. 2, pp. 99-123. ISSN 0025-2034. DOI 10.1111/j.1467-9957.1965.tb00050.x.

[3] Box, G. E. P. and Jenkins, G. M. (1970) "*Time Series Analysis: Forecasting and Control*", San Francisco: Holden Day.

[4] Chikán, A., Czakó, E., Kiss-Dobronyi, B and Losonci, D. (2022) "Firm competitiveness: A general model and a manufacturing application", *International Journal of Production Economics*, Vol. 243. E-ISSN 1873-7579, ISSN 0925-5273. DOI 10.1016/j.ijpe.2021.108316.

[5] Dickey, D. A. and Fuller, W. A. (1981) "Time Series With a Unit Root", *Econometrica*, Vol. 49, No. 4, p. 1059. E-ISSN 1468-0262, ISSN 0012-9682.

[6] Donovan, J., Blare, T. and Poole, N. (2017) "Stuck in a rut: emerging cocoa cooperatives in Peru and the factors that influence their performance", *International Journal of Agricultural Sustainability*, Vol. 15, No. 2, pp. 169-184. ISSN 1473-5903. DOI 10.1080/14735903.2017.1286831.

[7] Engle, R. F. and Granger, C. W. J. (2012) "Co-Integration and Error Correction: Representation, Estimation", *Econometrica,* Vol. 55, No. 2, pp. 251-276. E-ISSN 1468-0262, ISSN 0012-9682. DOI 10.2307/1913236.

[8] Fambeu, A. H. and Yomi, P. T. (2025) "Does Domestic Concentration Cancel the Potentially Beneficial Effect of International Competition on Firm Productivity? Evidence from Manufacturing Firms in Cameroon", *Journal of the Knowledge Economy*, Vol. 16, pp. 14818-14841. E-ISSN 1868-7873. DOI 10.1007/s13132-024-02388-9.

[9] Gardner, T. A., Benzie, M., Börner, J., Dawkins, E., Fick, S., Garrett, R., Godar, J., Grimard, A., Lake, S., Larsen, R. K., Mardas, N., McFermott, C. L., Meyfroidt, P., Osbeck, M., Persson, M., Sembres, T., Suavet, C., Strassburg, B., Trevisan, A., West, C., Wolvekamp, P. (2019) "Transparency and sustainability in global commodity supply chains", *World Development*, Vol. 121, pp. 163-177. E-ISSN 1873-5991. DOI 10.1016/j.worlddev.2018.05.025.

[10] Glasbergen, P. (2018) "Smallholders do not Eat Certificates", *Ecological Economics*, Vol. 147 (Feb.), pp. 243-252. E-ISSN 1873-6106, ISSN 0921-8009. DOI 10.1016/j.ecolecon.2018.01.023.

[11] Hoffman, J. (2014) "*The world atlas of coffee: from beans to brewing--coffees explored, explained and enjoyed*", Buffalo, New York: Firefly Books. ISBN 978-1770854703.

[12] Hotsawadi, H. and Gea, I.V. (2024) "Measuring the Competitiveness and Efficiency of Indonesian Non-Oil and Gas Exports to Non-Traditional Markets", *Jurnal Hubungan Luar Negeri*, Vol. 9, No. 2. E-ISSN 3047-9770. DOI 10.70836/jh.v9i2.58.

[13] Huo, D. (2014) "Impact of country-level factors on export competitiveness of agriculture industry from emerging markets", *Competitiveness Review*, Vol. 24, No. 5, pp. 393-413. E-ISSN 2051-3143, ISSN 1059-5422. DOI 10.1108/CR-01-2012-0002.

[14] ICO (2022) "*World Coffee Statistics Report 2022*", International Coffee Organization. [Online]. Available: https://ico.org/what-we-do/world-coffee-statistics-database/ [Accessed: Nov. 3, 2024].

[15] Innayatuhibbah, G. A., Rahayu, E. S. and Ferichani, M. (2024) "Export competitiveness of Indonesian coffee in the United States market", *Scientific Horizons*, Vol. 27, No. 2, pp. 125-135. E-ISSN 2709-8877, ISSN 2663-2144. DOI 10.48077/scihor2.2024.125.

[16] Jalata, D. H. (2021) "Competitiveness and Determinants of Coffee Export in Ethiopia: An Analysis of Revealed Comparative Advantage and Autoregressive Distributed Lag Model", *Journal of Economics and Sustainable Development*, Vol. 12, No. 5, pp. 43-62. E-ISSN 2222-2855. DOI 10.7176/jesd/12-5-05.

[17] Kementerian Pertanian (2023) "*Statistik Perkembunan Unggulan Nasional 2021-2023*". [Online]. Available: https://repository.pertanian.go.id/handle/123456789/20225 [Accessed: Nov. 3, 2024]. (In Indonesian).

[18] Li, E., Chen, Y., Hu, G. and Lu, M.(2022) "Competition between Export Cities in China: Evolution and Influencing Factors", *Land*, Vol. 11, No. 2. ISSN 2073-445X. DOI 10.3390/land11020201.

[19] Long, Y. (2021) "Export competitiveness of agricultural products and agricultural sustainability in China", *Regional Sustainability*, Vol. 2, No. 3, pp. 203-210. ISSN 2666-660X. DOI 10.1016/j.regsus.2021.09.001.

[20] Manalu, D. S. T. , Harianto, Suhamo and Hartoyo, S. (2019) "Comparative Analysis of Indonesian and Vietnamese Coffees Competitiveness in the World Market", *International Journal of Progressive Sciences and Technologies (IJPSAT)*, Vol. 13, No. 2, pp. 141-146. ISSN 2509-0119.

[21] Nasution, S. P., Wibowo, R. P., Supriana, T. and Iskandarini (2024a) "Analysis Competition Coffee Exports from Producing Countries in the United States Market with Use Almost Ideal Demand System (AIDS) Model", *Journal of Ecohumanism*, Vol. 3, No. 8, pp. 2096-2101. E-ISSN 2752-6801, ISSN 2752-6798. DOI 10.62754/joe.v3i8.4890.

[22] Nasution, S. P., Wibowo, R. P., Supriana, T. and Iskandarini (2024b) "Analysis of Indonesia coffee exports competitiveness in the United States and Japan to promote sustainable market", *IOP Conference Series: Earth and Environmental Science*, Vol. 1302, No. 1. ISSN 1755-1315. DOI 10.1088/1755-1315/1302/1/012137.

[23] Pascucci, F. (2018) "The export competitiveness of Italian coffee roasting industry", *British Food Journal*, Vol. 120, No. 7, pp. 1529-1546. E-ISSN 1758-4108. ISSN 0007-070X. DOI 10.1108/BFJ-05-2017-0306.

[24] Porter, M. E. (1991) "Toward a Dynamic Theory of Strategy", *Strategic Management Journal*, Vol. 12, pp. 95-117. E-ISSN 1097-0266. ISSN 0143-2095.

[25] Purwawangsa, H., Irfany, M. I. and Haq, D. A. (2024) "Indonesian Coffee Exports´ Competitiveness and Determinants", *Jurnal Manajemen dan Agribisnis*, Vol. 21, No. 1, pp. 59-71. E-ISSN 2407-2524. DOI 10.17358/jma.21.1.59.

[26] Rahardjo, B., Akbar, B. M. B., Iskandar, Y. and Shalehah, A. (2020) "Analysis and strategy for improving Indonesian coffee competitiveness in the international market", *BISMA (Bisnis dan Manajemen),* Vol. 12, No. 2, p. 154. ISSN 2549-7790. DOI 10.26740/bisma.v12n2.p154-167.

[27] Rosiana, N., Nurmalina, R., Winandi, R. and Rifin, A. (2018) "Dynamics of Indonesian Robusta Coffee Competition Among Major Competitor Countries Dinamika Persaingan Kopi Robusta Indonesia Dengan Negara-Negara Pesaing Utama", *Jurnal Tanaman Industri dan Penyegar*, Vol. 5, No. 1, pp. 1-10. ISSN 2356-1297. (In Indonesian).

[28] Sachs, J. D., Cordes, K., Rising, J., Toledano, P. and Maennling, N. (2019) "Ensuring Economic Viability and Sustainability of Coffee Production", Columbia Center on Sustainable Investment. DOI 10.2139/ssrn.3660936.

[29] Simionescu, M., Pelinescu, E., Khouri, S. and Bilan, S. (2021) "The main drivers of competitiveness in the EU-28 countries", *Journal of Competitiveness,* Vol. 13, No. 1, pp. 129-145. ISSN 1804-1728. DOI 10.7441/joc.2021.01.08.

[30] Skare, M. and Cvek, D. (2020) "A vector autoregression analysis of foreign direct investment and its link to competitiveness", *Journal of Competitiveness*, Vol. 12, No. 4, pp. 127-142. ISSN 1804-1728. DOI 10.7441/joc.2020.04.08.

[31] Sunarharum, W.B., Ali, D. Y., Nugroho, P. I., Asih, N. E., Mahardika, A. P. and Geofani, I. (2021) "The Indonesian coffee consumers perception on coffee quality and the effect on consumption behavior", *IOP Conference Series: Earth and Environmental Science*, Vol. 733, No. 1. DOI 10.1088/1755-1315/733/1/012093.

[32] Suroso, A.I., Fahmi, I., Tandra, H. and Haryono, A. (2023) "Assessing the Effect of Internet Indicators on Agri-Food", *Economies*, Vol. 11, No. 10, pp. 1-17. E-ISSN 2227-7099. DOI 10.3390/economies11100246.

[33] Suryana, A.T., Saleh, Y., Dewi, T. G. and Rahayu, H. S. P. (2024) "Global competitiveness of coffee Products: A comparative study of Indonesia and Vietnam", *Coffee Science*, p. e192237, pp. 1-11. E-ISSN 1984-3909. DOI 10.25186/.v19i.2237.

[34] Suzianti, A., Kaniaswari, R., Fathia, S. N., Amaradhanny, R. D., Muslim, E. and Alfian, E. T. (2024) "Towards a sustainable coffee supply chain: the role of digital platform capability in increasing organisational agility", *International Journal of Sustainable Engineering*, Vol. 17, No. 1, pp. 80-97. DOI 10.1080/19397038.2024.2400987.

[35] Tampubolon, J., Ginting, A., Nainggolan, H. L. and Tarigan, J. R. (2023) "Indonesian Coffee Development Path: Production and International Trade", *Asian Journal of Agricultural Extension, Economics & Sociology*, Vol. 41, No. 12, pp. 316-328. ISSN 2320-7027. DOI 10.9734/ajaees/2023/v41i122335.

[36] Tandra, H., Suroso, A. I., Syaukat, Y. and Najib, M. (2022) "The Determinants of Competitiveness in Global Palm Oil Trade", *Economies*, Vol. 10, No. 6, pp. 1-20. ISSN 2227-7099. DOI 10.3390/economies10060132.

[37] Toda, H. Y. and Yamamoto, T. (1995) "Statistical inference in vector autoregressions with possibly integrated processes", *Journal of Econometrics*, Vol. 66, pp. 225-250. E-ISSN 1872-6895, ISSN 0304-4076. DOI 10.1016/0304-4076(94)01616-8.

[38] Tsai, P. H., Chen, C. J. and Yang, H. C. (2021) "Using Porter"s Diamond Model to Assess the Competitiveness of Taiwan"s Solar Photovoltaic Industry", *SAGE Open*, Vol. 11, No. 1. E-ISSN 2158-2440, ISSN 2158-2440. DOI 10.1177/2158244020988286.

[39] Wang, G., Wang, Y., Li, S., Yi, Y., Li, C. and Shin, C. (2024) "Sustainability in Global Agri-Food Supply Chains: Insights from a Comprehensive Literature Review and the ABCDE Framework", *Foods*, Vol. 13, No. 18. E-ISSN 2304-8158. DOI 10.3390/foods13182914.

[40] Wang, L., Sun, T.-L. and Cai, Z.-Q. (2022) "Dynamics of Chinese Export Comparative Advantage: Analysis Based on RSCA Index", *Journal of Mathematics*. E-ISSN 2314-4785, ISSN 314-4629. DOI 10.1155/2022/2566259.

[41] Widyantini, R. (2019) "Analysis of The Competitiveness of Indonesian Coffee in The Export Market", *Cendekia Niaga*, Vol. 3, No. 1, pp. 14-23. E-ISSN 2548-3145. DOI 10.52391/jcn.v3i1.458.

[42] Willer, D. F. and Aldridge, D. C. (2023) "Enhancing domestic consumption to deliver food security in a volatile world", *Global Sustainability*, Vol. 6, pp. 2022-2024. E-ISSN 2059-4798. DOI 10.1017/sus.2023.17.

[43] Wooldridge, J. M. (2004) "*Introductory Econometrics - A Modern Approach*", 2nd ed., OH, USA: South-western College Pub: Cincinnati. ISBN 13 978-0-324-66054-8.

[44] Wooldridge, J. M. (2013) "Introductory Econometrics: A Modern Approach", 5th ed., Tolerance Analysis of Electronic Circuits Using MATHCAD. South Western Cengage Learning. ISBN 13 978-1-111-53104-1.

[45] Yadav, A. K. and Chattopadhyay, U. (2024) "Identifying the Factors of Export Competitiveness for Agricultural Products", *Asian Journal of Agricultural Extension, Economics & Sociology*, Vol. 42, No. 6, pp. 241-253. DOI 10.9734/ajaees/2024/v42i62485.

[46] Yu, Z., Feng, G., Liu, H., Peng, H. and Dong, X. (2024) "Sustainable market? The impact of downstream market concentration on high-quality agricultural development: evidence from China"s dairy industry", *Frontiers in Sustainable Food Systems*, 8 Sept. ISSN 2571581X. DOI 10.3389/fsufs.2024.1453115.

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