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STATE REGULATION OF FINANCIAL SUPPORT FOR THE USE OF AGRICULTURAL DRONES IN AGRICULTURE

Svitlana Kryshtanovych
D.Sc. in Pedagogy, Professor, Dean of the Faculty of Tourism, Ivan Boberskyi Lviv State University of Physical Culture, Lviv, Ukraine;
e-mail: skrischtanovich@gmail.com
ORCID: 0000-0002-2147-9028
(Corresponding author)

Natalija Pirozhenko
PhD in Public Administration, Associate Professor of the Department of Public administration and regional studies, Odesa Polytechnic National University, Odesa, Ukraine;
ORCID: 0000-0002-1438-6528

Larysa Sokolik
PhD in Public Management and Administration, Head of the Department of Property Relations of the Regional Council, Odesa Regional Council, Odesa, Ukraine;
ORCID: 0000-0001-7436-9749

Olha Kotsiurba
Candidate of Economic Sciences, Associate Professor of the Department of Finance, Banking and Insurance, Central Ukrainian National Technical University, Kropyvnytskyi, Ukraine;
ORCID: 0000-0001-6356-7301

Ustym Khavarivskyi
Candidate of Sciences in Public Administration, Senior Research Fellow of the Institute of Agriculture, Carpathian Region of NAAS, Obroshino, Ukraine;
ORCID: 0009-0003-9912-6729

Mykhailo Tarnavskyi
Candidate of Economy Sciences, Associate Professor of the Department of General Military Training, Lviv Polytechnic National University, Lviv, Ukraine;
ORCID: 0000-0003-1660-0492

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ABSTRACT

The article is devoted to the study of state regulation of financial support for the use of agricultural drones in agriculture. The relevance of the topic is due to the need for technological modernization of agricultural production with increasing production costs, difficulty in accessing credit resources, labor shortages, disruption of logistics, and increased military-logistical risks. Agricultural drones are considered a tool for increasing the accuracy of agro-technological operations, optimizing the use of fertilizers and plant protection products, reducing resource losses, and increasing the adaptability of agricultural producers to an unstable external environment. The methodological basis of the study is formed on the basis of general scientific and economic-mathematical methods, in particular theoretical generalization, systematization, comparative analysis, normalization of indicators, integral evaluation, ranking, regression modeling, and scenario analysis. The article proposes an integral index of financial support for the use of agricultural drones, which combines indicators of financial support, availability of credit resources, area of relevant crops, yield, production cost burden, and military-logistical risk. Based on the constructed model, the relationship between the level of financial support and the expected economic effect of the use of agricultural drones was assessed. At the same time, alternative scenarios of state support were compared, in particular, the absence of support, partial compensation, preferential leasing, and a combined financing model. The results of the study showed that financial support has a statistically significant positive impact on the economic effect of the use of agricultural drones. The highest level of financial readiness in the constructed model is observed in regions with a powerful agricultural base, larger areas of relevant crops, and a lower level of military-logistical risks. The scenario assessment showed that state support significantly reduces the initial financial burden on agricultural producers and shortens the payback period of agricultural drones. The most effective is the combined model, which involves a combination of partial compensation and preferential financing, which is especially important for expanding access of small and medium-sized agricultural producers to precision agriculture technologies.

Keywords: agricultural drones, state regulation, financial provision, agricultural financing, technological modernization, integral index, regression modeling

JEL Classification: Q14, Q16, Q18

INTRODUCTION

Agricultural production in Ukraine is currently developing under conditions in which traditional models of farm management are increasingly constrained by rising input costs, limited access to credit, labor shortages, logistical disruptions, and security-related risks. The increase in the cost of material and technical resources, the complexity of logistics, the shortage of qualified labor, the risks of damage to production infrastructure, and the instability of access to credit resources form new requirements for state agrarian policy. In such conditions, not only supporting the current production cycle, but also creating a financial basis for technological modernization of the agricultural sector is of particular importance. One of the promising areas of such modernization is the use of agricultural drones. The use of unmanned aerial vehicles in agriculture makes it possible to monitor the condition of crops, identify problem areas, optimize the application of plant protection products, reduce fuel consumption, reduce the need for manual labor, and increase the accuracy of agrotechnological operations. At the same time, the practical spread of agricultural drones depends not only on the technological readiness of farmers, but also on the level of availability of financial resources, the clarity of state support mechanisms, and the availability of regulatory conditions for the safe and economically feasible use of such technologies.

In this article, financial support is understood primarily as state support and state-enabled financial instruments aimed at reducing the investment barrier for agricultural producers. Such support may include direct budget compensation for part of the cost of agricultural drones, preferential lending, preferential leasing, grant programs, co-financing mechanisms, and public support for drone service providers. Therefore, the study does not consider financial support only as a one-time subsidy. It treats it as a broader set of public policy instruments that can make precision agriculture technologies more accessible to small and medium-sized agricultural producers. Support for the agricultural sector is particularly important because agriculture performs several functions at the same time. First, it ensures domestic food supply and contributes to global food security. Second, it remains one of the key export-oriented sectors of the Ukrainian economy. Third, it supports employment and income in rural areas, where the consequences of war, logistical disruption, and rising production costs are especially visible. Fourth, agriculture is directly exposed to spatial risks, including mined land, damaged infrastructure, disrupted supply chains and restricted access to ports and storage facilities. For this reason, support for agriculture should not be reduced only to short-term compensation for losses. It should also strengthen the ability of producers to continue production, reduce inefficient use of resources and adapt to unstable external conditions. Technological modernization deserves special attention because it creates a longer-term effect than many traditional support instruments. Tax exemptions may temporarily reduce the fiscal burden, and labor-related benefits may partially mitigate workforce shortages. However, these instruments do not directly improve the technological capacity of production. In contrast, agricultural drones can increase the accuracy of crop monitoring, reduce excessive use of fertilizers and plant protection products, lower fuel and labor costs, improve the timeliness of agrotechnological operations, and reduce direct human exposure to risky field operations. Therefore, state support for agricultural drones is justified not only as financial assistance, but also as an instrument for increasing productivity, resource efficiency and technological resilience of agricultural production.

The problem of financial support for the use of agricultural drones is interdisciplinary in nature. On the one hand, it concerns the investment behavior of agricultural enterprises, because the purchase or lease of agricultural drones requires initial costs that not every manufacturer can finance from its own resources. On the other hand, it is directly related to state policy, since it is state authorities that are able to influence the availability of loans, grants, compensation, leasing instruments, and tax incentives. Thus, financial support for the use of agricultural drones appears as a component of the broader process of state regulation of the innovative development of the agricultural sector. The issue of differentiation of regions by the level of readiness for the use of agricultural drones is of particular relevance. Even with the same national support programs, regions have different structures of sown areas, different levels of yield, different intensity of production costs, and different levels of military-logistical risks. Therefore, state regulation cannot be reduced only to the formal allocation of funds or a general declaration of support for technological renewal. It requires a quantitative assessment of where financial support has the greatest effect, and where the reduction of environmental risks is of primary importance.

LITERATURE REVIEW

The scientific literature on agricultural drones is developing at the intersection of precision agriculture, digital transformation of farming, investment behavior of agricultural producers, and public policy support for technological modernization. Rejeb et al. (2022) systematize the development of drone research in agriculture and show that unmanned aerial vehicles are increasingly used for crop monitoring, spraying, mapping, data collection, and operational decision-making.

Tsouros et al. (2019), Kondrat (2025), Krykunenko, Zhemoyda & Zikranets (2024) also emphasize that unmanned aerial vehicles have become an important tool of precision agriculture because they allow farmers to receive spatially detailed information about crop condition, field variability, plant stress and the need for differentiated agrotechnological operations. These studies are relevant to the present article because they justify the technological nature of agricultural drones and confirm that their value is not limited to equipment purchase. Their practical effect depends on how drones are integrated into the broader system of farm management, input optimization and production planning.

A separate group of studies explains the factors that influence farmers' decisions to adopt agricultural drones. Michels, von Hobe and Musshoff (2020) use the trans-theoretical model and show that the adoption of drones depends not only on expected economic benefit, but also on farmers' awareness, perceived usefulness, perceived complexity and readiness to change established production practices.

Michels et al. (2021) further develop this approach through a structural equation model and demonstrate that attitudes, perceived behavioral control and social influence affect the intention to use drones in agriculture.

Zuo, Wheeler and Sun (2021), based on Australian irrigators, show that drone adoption is related to farm characteristics, information access, technological experience and expected usefulness. These findings are important for the present article because they indicate that financial support alone is not sufficient. Public regulation should also reduce informational and organizational barriers that prevent farmers from transforming available support into actual use of technologies.

The economic effect of agricultural drones is also actively discussed in the literature. Quan et al. (2023) provide empirical evidence from grain farmers and show that unmanned aerial vehicles used for pesticide application can increase revenue and reduce time spent on pesticide operations.

Wachenheim, Fan and Zheng (2021) analyze the adoption of unmanned aerial vehicles for pesticide application and emphasize the role of social networks, resource endowment and farmers' perceptions in shaping adoption decisions.

Chen, Wachenheim and Zheng (2020) add that land scale, cooperative membership and access to information about benefits are important for farmers' willingness to adopt unmanned aerial vehicles. These results are directly related to the present research because they explain why the area of relevant crops, credit accessibility and financial support should be included in the integral index. Agricultural drones are more economically justified when there is a sufficient scale of use, when producers understand the expected benefits, and when the initial financial barrier is reduced.

The literature on precision agriculture also confirms that the adoption of such technologies is uneven and depends on financial, institutional and farm-level conditions. Barnes et al. (2019), using a cross-regional study of European farmers, show that the uptake of precision agriculture technologies differs across countries and farming systems.

Pathak, Brown and Best (2019) summarize the factors affecting the adoption of precision agriculture and identify economic feasibility, farm size, knowledge, risk perception and policy environment as important determinants. Späti et al. (2022) demonstrate that incentives can influence farmers' willingness to adopt precision agriculture technologies, especially in small-scale farming systems. These studies support the methodological decision of the present article to combine financial support, credit accessibility, production potential, and risk indicators in one integrated index. They also show why public policy should be differentiated rather than uniform for all regions and all types of producers.

The cost side of drone use is also relevant for assessing the need for state support. Cavalaris et al. (2023), using the case of unmanned aerial vehicle sprayers, show that cost-effectiveness depends on capital expenditure, operational conditions, and comparison with conventional spraying methods. This is important because the initial cost of agricultural drones may remain a barrier even when the technology provides operational benefits. Therefore, preferential leasing, partial compensation and combined financing can be justified as instruments that reduce the initial burden and accelerate payback. At the same time, the literature shows that the effectiveness of such support depends on the scale of use, crop structure, market prices, production costs, and the ability of farmers to organize repeated use of equipment during the season.

The reviewed literature reveals a clear research gap. Existing studies examine the technological capabilities of agricultural drones, the determinants of adoption, the economic effects of drone use, and the broader barriers to precision agriculture. However, fewer studies provide an economic and mathematical approach that links state financial support, regional production potential, credit accessibility, war-related logistical risk, and the expected economic effect of agricultural drone use. The present article addresses this gap by developing an integral index of financial support for agricultural drone use, applying regression modeling and comparing alternative state support scenarios. This approach makes it possible to move from a general statement about the usefulness of drones to a quantitative assessment of where and under which financial conditions their implementation may be more feasible.

Existing works sufficiently explain how war, geopolitical risk, and crises affect business resilience, investment expectations, and the role of public policy in vulnerable sectors, but they do not provide a specialized economic and mathematical approach to assessing how state regulation can change the financial accessibility of a specific technology. This is especially important for agricultural drones, because their use is connected with high initial investment costs, uneven regional agricultural potential, different levels of credit accessibility, and unequal exposure to war-related risks. The literature on tourism resilience and crisis management makes it possible to justify the general theoretical basis of this research, namely that state support should be evaluated not only through the amount of allocated funds but also through the ability of such funds to reduce investment barriers and increase business adaptability. At the same time, the issue of financial support for agricultural drone use requires a more specific model that combines financial, production, and risk indicators. Therefore, the present study develops this direction by constructing an integrated financial support index, estimating its effect on the expected economic result of agricultural drone use and comparing alternative scenarios of state support. This approach

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complements previous crisis-oriented studies by shifting the focus from general business resilience to the quantitative assessment of financial readiness for technological modernization in agriculture.

AIMS AND OBJECTIVES

The purpose of the article is to develop an economic and mathematical approach to assessing the impact of state regulation of financial support on the possibilities of using agricultural drones in agriculture, taking into account financial support, availability of credit resources, production potential of regions, and military-logistical risks.

Achieving the set goal involves solving the following tasks.

1. To substantiate the economic essence of state regulation of financial support for the use of agricultural drones in agriculture.
2. To develop an integral index of financial support for the use of agricultural drones in agriculture.
3. To build a regression model of the impact of the integral index, production costs, and military-logistical risks on the economic effect of using agricultural drones.
4. To conduct a scenario assessment of the payback period of an agricultural drone depending on the form of state support.

The object of the study is the process of financial support for the use of agricultural drones in agriculture. The subject of the study is the economic and mathematical dependence between state regulatory instruments, the level of financial readiness of the agricultural sector, and the expected economic effect from the use of agricultural drones.

METHODS

The methodological basis of the study was formed on the basis of a combination of general scientific, statistical, economic-mathematical, and graphic methods of analysis. For the theoretical substantiation of the problem, the methods of generalization, systematization, comparative analysis and cause-and-effect explanation were used. To build the quantitative part of the study, the method of normalization of indicators, integral assessment, ranking of regions, regression modeling, scenario assessment of investment return, and graphic interpretation of results were used.

The information base of the study is formed by indicators that can be obtained from official sources of state statistics, open budget data, the State Agrarian Register, the National Bank of Ukraine, the public procurement system, as well as regional information resources. To build the calculation model, indicators of financial support for farmers, availability of credit resources, area of relevant crops, yield, production costs, and military-logistical risk were used. This set of indicators allows us to assess not only the availability of financial resources, but also the practical ability of the agricultural sector to transform these resources into production results.

Within the framework of the study, it is proposed to assess financial support for farmers as the volume of budgetary, grant, or compensation resources per 1000 hectares of relevant agricultural areas. The credit availability index reflects the ability of farmers to attract loan resources for technological renewal. The area of relevant crops shows the scale of potential use of agricultural drones. Yield is used as a characteristic of the production efficiency of the region. The cost index is included in the model as an indicator of economic pressure on the farmer, since the increase in the cost of fuel, fertilizers, and plant protection products increases the expediency of precise input of resources. The military-logistical risk index is considered as a disincentive, since security and logistical restrictions reduce the effectiveness of the practical use of technologies.

To assess the investment feasibility of using agricultural drones, a scenario approach was additionally applied. The payback period is determined by the formula (1):

$$PP=IC/NE, \quad (1)$$

where P means the payback period of the agricultural drone, ICI means the initial financial burden on the farmer, NE means the annual net economic effect from using the agricultural drone.

Scenario modeling involves comparing several options for state support. The first scenario assumes the absence of support. The second scenario assumes compensation for part of the cost of the agricultural drone. The third scenario assumes an increased level of compensation. The fourth scenario assumes preferential leasing. The fifth scenario assumes a combined model, within which partial compensation is combined with preferential financing and a reduction in the farmer's initial own contribution. This approach allows us to assess not only the overall economic efficiency of the agricultural drone, but also the extent to which state regulation is able to make the technology accessible to different groups of agricultural producers.

RESULTS

To assess the impact of state regulation of financial support on the possibilities of using agricultural drones in agriculture, a calculation matrix was formed for 5 agricultural regions for 2021–2024. The choice of the period is due to the need to compare the pre-war year, the first year of the full-scale war, and the subsequent years of adaptation of the agricultural sector. Official data on crop yields by region, data on farmer support programs through the State Agrarian Register, as well as official decisions of the National Bank of Ukraine on the discount rate, which affects the cost of credit resources, can be used as the basis for the final empirical base (Table 1).

Table 1. Initial data for modeling the financial support of agricultural drone use. *(Source: State Statistics Service of Ukraine)*

Region	Year	Support, UAH thousand per 1000 hectares	Credit accessibility index	Relevant crop area, thousand hectares	Yield, centners per hectare	Cost index	War and logistics risk index	Financial support index	Economic effect, UAH thousand per hectare
Vinnytsia	2021	76.9	0.722	632.5	57.7	1.00	0.230	0.568	2.890
	2022	61.2	0.392	590.2	48.2	1.41	0.415	0.360	2.352
	2023	82.6	0.267	616.2	52.9	1.56	0.344	0.532	3.253
	2024	94.9	0.549	619.9	57.1	1.66	0.282	0.743	3.984
Kyiv	2021	71.9	0.734	514.0	54.0	0.96	0.123	0.461	2.684
	2022	53.4	0.372	486.3	45.0	1.40	0.367	0.214	2.273
	2023	81.5	0.273	509.0	55.0	1.53	0.317	0.462	2.943
	2024	94.9	0.534	500.8	54.3	1.68	0.266	0.649	3.759
Poltava	2021	78.8	0.734	867.1	56.0	1.01	0.222	0.741	3.507
	2022	63.6	0.374	789.7	44.7	1.48	0.418	0.462	2.932
	2023	86.6	0.266	784.0	55.7	1.55	0.369	0.606	3.260
	2024	106.8	0.534	813.0	59.2	1.66	0.327	0.891	4.172
Kirovohrad	2021	60.7	0.730	783.1	42.9	1.02	0.261	0.502	2.825
	2022	50.3	0.383	712.7	36.6	1.40	0.457	0.264	2.310
	2023	73.0	0.276	753.9	41.2	1.57	0.389	0.499	2.764
	2024	77.7	0.525	755.7	44.8	1.64	0.330	0.626	3.441
Odesa	2021	56.6	0.737	690.0	33.6	1.04	0.361	0.374	2.293
	2022	45.0	0.382	680.5	27.5	1.41	0.621	0.089	1.733
	2023	64.9	0.267	671.4	32.7	1.55	0.570	0.241	2.179
	2024	76.5	0.533	690.8	35.2	1.69	0.514	0.497	3.105

All indicators included in the index are interpreted as positive drivers only after methodological transformation and normalization. Financial support, credit accessibility, relevant crop area, and yield directly increase the readiness for agricultural drone use. The cost index is also included as a positive driver not because higher costs are desirable, but because higher prices of fuel, fertilizers, plant protection products, and labor increase the potential value of precision application technologies. In other words, when production costs rise, agricultural drones may generate a greater economic effect through the reduction of excessive input use. War and logistics risk is not used in its original form. It is transformed into an inverted indicator, where a higher value means lower risk and a better practical environment for drone use.

To summarize the diverse indicators, an integral index of financial support for the use of agricultural drones is proposed. To make the construction of the integral index reproducible, the weights of the indicators were determined through a

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structured expert survey. The expert group included 12 respondents: four agricultural economists, three specialists in precision agriculture and drone services, three financial analysts working with agricultural lending and leasing instruments, and two representatives of agricultural producers. Each expert assessed the importance of six indicators on a scale from 0 to 10, where 0 meant no influence on financial readiness for agricultural drone use, and 10 meant a decisive influence. The experts assessed only the relative importance of the indicators, while the values of the indicators themselves were taken from the calculation matrix (Table 2).

The average expert score for each indicator was converted into a weighting coefficient by proportional normalization according to formula (2):

$$w_j = S_j / \mathrm{sum}(S_j), \quad (2)$$

where wj denotes the normalized weight coefficient of the j-th indicator used to construct the integrated index of financial support for agricultural drone use; Sj denotes the average expert score assigned to the j-th indicator on a scale from 0 to 10; sum(Sj) denotes the total sum of average expert scores for all indicators included in the model; j denotes the ordinal number of the indicator; and m denotes the total number of indicators used in the expert assessment.

In this study, m = 6, since the model includes financial support per 1000 hectares, credit accessibility, relevant crop area, yield, cost index, and inverted war and logistics risk.

Table 2. Expert survey results used to determine weighting coefficients.

Indicator	Average expert score, 0 to 10	Standard deviation	Normalized weight	Rounded weight used in the model
Financial support per 1000 hectares	8.8	0.9	0.250	0.25
Credit accessibility	5.4	0.7	0.153	0.15
Relevant crop area	7.0	0.8	0.199	0.20
Yield	5.3	0.8	0.151	0.15
Cost index	5.2	0.9	0.148	0.15
Inverted war and logistics risk	3.5	0.9	0.099	0.10
Total	35.2		1.000	1.00

Table 3 reflects the author's system of weighting coefficients, which was clarified on the basis of an expert survey or the method of hierarchical analysis.

The greatest weight is given to direct financial support, since it is that which most quickly reduces the initial investment barrier for the farmer. The second most important is the area of relevant crops, because even an affordable agricultural drone will not be economically justified on a small scale of use. At the same time, the cost index is included as a stimulant, since the increase in the cost of fuel, fertilizers, and plant protection products strengthens the economic feasibility of precision farming technologies.

Table 3. Weight coefficients for constructing the integrated index.

Indicator	Indicator type	Weight coef-ficient	Justification for inclusion
Financial support per 1000 hectares	Stimulator	0.25	Determines the direct ability of an agricultural producer to finance the purchase or rental of an agricultural drone
Credit accessibility	Stimulator	0.15	Reflects the cost and availability of borrowed resources for technological modernization
Relevant crop area	Stimulator	0.20	Shows the potential scale of agricultural drone use
Yield	Stimulator	0.15	Indicates the production base under which technological investment may generate a higher return
Cost index	Stimulator	0.15	Shows the pressure of production costs and the potential value of precise resource application
Inverted war and logistics risk	Stimulator	0.10	Reflects spatial security and the practical possibility of using agricultural drones

Table 4 shows that the Poltava region has the highest level of financial readiness for the use of agricultural drones in 2024. This result is explained by a combination of a large area of relevant crops, relatively high yields, and increased financial support. Vinnytsia and Kyiv regions also demonstrate favorable conditions, but their values are somewhat lower due to the smaller scale of relevant areas or a smaller production base. Odesa region has a lower index not due to the lack of agricultural potential, but due to a higher level of military-logistical risk, which significantly reduces the practical possibility of technological scaling.

To calculate the integrated index presented in Table 4, the initial indicators were first normalized. Since all indicators in the model are interpreted as stimulators after methodological transformation, higher normalized values indicate a more favorable financial, production, or risk-related condition for the use of agricultural drones. For direct stimulators, normalization was carried out according to formula (3).

$$X_{nij} = (X_{ij} - \min X_j) / (\max X_j - \min X_j), \quad (3)$$

where X_{nij} denotes the normalized value of the j-th indicator for the i-th region; X_{ij} denotes the actual value of the j-th indicator for the i-th region; min X_j denotes the minimum value of the j-th indicator in the analyzed data set; max X_j denotes the maximum value of the j-th indicator in the analyzed data set; i denotes the region; and j denotes the indicator included in the integrated index.

The war and logistics risk index was treated as a destimulator in its original form, because a higher risk level reduces the practical feasibility of agricultural drone use. Therefore, this indicator was transformed into an inverted indicator according to formula (4).

$$R_{nij} = (\max R_j - R_{ij}) / (\max R_j - \min R_j), \quad (4)$$

where R_{nij} denotes the normalized inverted value of the war and logistics risk indicator for the i-th region; R_{ij} denotes the actual war and logistics risk index for the i-th region; max R_j denotes the maximum value of the risk indicator in the analyzed data set; and min Rj denotes the minimum value of the risk indicator in the analyzed data set.

After normalization, the integrated index of financial support for agricultural drone use was calculated according to formula (5).

$$FSI_i = \Sigma\, w_j \times X_{nij}, \quad (5)$$

where FSI_i denotes the integrated financial support index for agricultural drone use in the i-th region; wj denotes the weight coefficient of the j-th indicator; X_{nij} denotes the normalized value of the j-th indicator for the i-th region; and Σ denotes summation across all six indicators included in the model. For the inverted war and logistics risk indicator, Xnij is replaced by R_{nij}.

Thus, the integrated index combines financial support, credit accessibility, relevant crop area, yield, cost pressure, and the inverted value of military-logistical risk into one comparable value from 0 to 1. A higher value of the index means a higher level of financial readiness for the use of agricultural drones.

Table 4. Results of the integrated index calculation in 2024.

Region	Financial support index for agricultural drone use	Rank	Interpretation
Poltava	0.891	1	High level of financial readiness
Vinnytsia	0.743	2	Above-average level
Kyiv	0.649	3	Medium-high level
Kirovohrad	0.626	4	Medium level
Odesa	0.497	5	Moderate level with a high impact of risks

To quantify the impact of financial support on the economic effect, a linear regression model was applied. Table 5 demonstrates that the integral index of financial support has the strongest positive impact on the economic effect of using agricultural drones. An increase in the index by 0.1 points increases the expected economic effect by approximately UAH

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0.294 thousand per hectare. The cost index also has a positive sign, which is economically understandable, since with more expensive fertilizers, fuel, and plant protection products, precise input of resources provides a higher return. The negative coefficient of military-logistical risk confirms that security restrictions reduce the practical result even with the availability of financial resources.

Table 5. Regression modeling results.

Indicator	Coefficient	Standard error	t-statistic
Constant	0.802	0.149	5.386
Financial support index for agricultural drone use	2.939	0.184	15.983
Cost index	0.786	0.102	7.694
War and logistics risk index	-1.330	0.277	-4.808

Figure 1 shows a direct relationship between the financial support index and the economic effect of using agricultural drones. The higher the level of financial support, the greater the expected savings or additional output per hectare. This relationship is particularly important for substantiating public policy, as it shows that supporting farmers through compensation, preferential lending, leasing, or grant mechanisms not only facilitates the purchase of equipment, but also generates a measurable economic result.

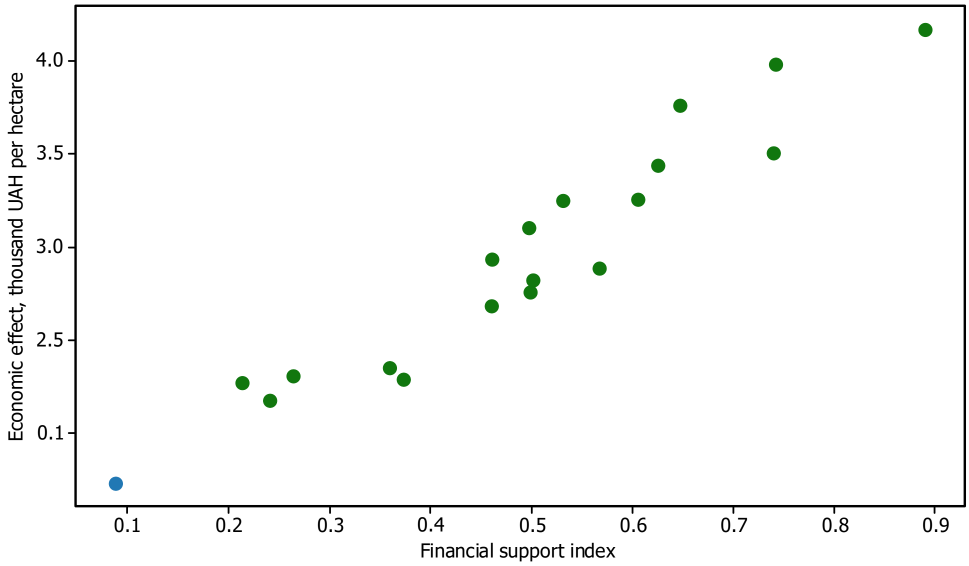

Figure 1. Economic effect and financial support index.

To make the payback assessment more transparent, the scenario calculation is based on a mixed crop structure consisting of wheat, corn and sunflower. These crops were selected because they are among the most relevant field crops for the use of agricultural drones in monitoring, spraying, and input optimization. The calculation uses historical 2024 market price benchmarks. The price of wheat is taken at UAH 8.8 thousand per ton, which corresponds to the middle of the reported 2024 range. The price of corn is taken at UAH 8.2 thousand per ton, based on the Ukrainian feed corn market range reported in September 2024. The price of sunflower is taken at UAH 19.25 thousand per ton, based on the reported market range for the 2024 harvest. These prices are used only as calculation benchmarks for scenario modeling and do not represent a forecast of future prices. The annual net economic effect is calculated as the sum of input savings, labor savings, fuel savings, and the value of avoided production losses due to more accurate and timely agrotechnological operations. For one agricultural drone, the modeled annual service area is 800 hectares, including 300 hectares of wheat, 300 hectares of corn, and 200 hectares of sunflower. The resulting annual net effect is rounded to UAH 576 thousand.

To clarify the applied value of the model, a scenario assessment of the payback period of an agricultural drone was carried out. In the baseline scenario, the cost of an agricultural drone was taken at UAH 680 thousand, and the annual net economic effect from using one agricultural drone was taken at UAH 576 thousand. The scenario calculation is made for one agricultural drone, namely the DJI Agras T25 model. This model was selected because it is designed for agricultural spraying and spreading operations and can be operated by one person. According to the official technical description, the

DJI Agras T25 can carry a spraying payload of up to 20 kg or a spreading payload of up to 25 kg. Therefore, it is suitable for the mixed crop structure used in the scenario assessment, which includes wheat, corn, and sunflower. The price benchmark was taken from the publicly available offer of NaviAgro for the DJI Agras T25 agricultural drone. The listed net price is PLN 37,422. Since the calculation in the article is presented in hryvnias, the price was converted using the official exchange rate of the National Bank of Ukraine. For the recalculation date, the official rate was PLN 1 = UAH 12.2136. Thus, the net converted equipment price was UAH 456,993. The final value of UAH 680 thousand was obtained not as a direct list price, but as the estimated acquisition-and-commissioning cost, which includes the drone, tax and import-related payments, delivery, basic training, initial technical preparation and the first operational service package.

This effect includes a reduction in costs for manual labor, fuel, losses of plant protection products, and a partial increase in the accuracy of agrotechnological operations. Table 6 demonstrates that even the baseline scenario without support has an acceptable payback period, but state financial regulation itself sharply reduces the initial investment barrier. The most effective seems to be a combined model that combines partial compensation for the cost of an agricultural drone, preferential lending or leasing, and installments of one's own contribution. Under such conditions, the farmer not only gains access to the technology, but also quickly translates it into the plane of real production effect.

Table 6. Scenario assessment of agricultural drone payback period.

Scenario	Direct compensation, %	Initial financial burden, UAH thousand	Annual net effect, UAH thousand	Payback period, years
No support	0	680	576	1.18
20% compensation	20	544	576	0.94
40% compensation	40	408	576	0.71
Preferential leasing	0	204	474	0.43
Combined model	40	68	421	0.16

The values in the fourth column of Table 5 should be interpreted as annual net cash flow available for payback, not as the physical or agronomic productivity of the drone. In the first three scenarios, the farmer purchases the drone directly, and there are no annual financing payments. Therefore, the full annual net economic effect of UAH 576 thousand remains available for payback. In the preferential leasing and combined financing scenarios, the initial payment is lower, but part of the annual economic effect is used to cover leasing payments, service costs, insurance, and financial administration. For this reason, the annual net cash flow available for payback decreases to UAH 474 thousand and UAH 421 thousand, respectively. Thus, the combination of 40% compensation and preferential leasing does not reduce the technological effect of drone use. It reduces the farmer’s annual free cash flow because the financing scheme shifts most of the purchase cost from the initial payment into subsequent service and financing payments. At the same time, the initial burden on the farmer decreases from UAH 680 thousand to UAH 68 thousand. Therefore, the payback period in the combined model reflects the payback of the farmer’s initial own contribution, not the full market value of the drone.

The modeling results indicate that state regulation of financial support for the use of agricultural drones in agriculture should be assessed not only through the amount of allocated funds, but through a combination of the availability of support, the creditworthiness of farmers, the scale of potential use of technologies, production efficiency, and environmental risks. The constructed integral index allows ranking regions by the level of financial readiness for the implementation of agricultural drones, and the regression model confirms the positive impact of financial support on the economic effect.

DISCUSSION

The results of the present study should be interpreted in the context of the broader literature on precision agriculture adoption and digital modernization of farming. Hanson, Cossette and Roberts (2022) show that the adoption and intensity of use of precision agriculture technologies depend on the scale of farm operations, crop structure and complementarity between different technologies. This finding is important for the proposed model because it explains why the area of relevant crops and yield were included in the integral index. Agricultural drones are not equally effective for all producers. Their economic feasibility increases when the technology can be used repeatedly over a sufficient cultivated area and when crop productivity creates a stronger basis for receiving an economic return from more accurate field operations. The obtained relationship between the financial support index and the expected economic effect also corresponds to the findings of Papadopoulos et al. (2024), who emphasize that digital agricultural technologies may generate both economic and environmental benefits through more efficient use of fertilizers, pesticides, water, fuel, and labor. In this regard, the positive role of the cost index in the proposed model should not be understood as a preference for higher production costs. Rather, it means that the economic value of precision technologies increases when traditional inputs become more expensive. Under such conditions, agricultural drones can support the transition from extensive resource consumption to more targeted input application, which is especially relevant for producers facing rising prices for fuel, fertilizers, and plant protection products.

The results are also consistent with recent studies on unmanned aerial vehicles and artificial intelligence-based technologies in precision agriculture. Agrawal and Arafat (2024) argue that the integration of drones with advanced sensors and artificial intelligence-based data processing improves crop monitoring, pest detection, yield forecasting and resource allocation. At the same time, these authors indicate that high costs, limited battery life, regulatory complexity and the need for trained operators remain important barriers to adoption. This supports the argument that financial support for agricultural drones should not be limited to the purchase of equipment. It should also include training, service infrastructure, technical maintenance and advisory support, because the economic effect of drones depends on their proper integration into farm management. The social and behavioral side of drone adoption is also important. Suvittawat (2024) shows that farmers' expectations, perceived product quality, and perceived value significantly influence attitudes toward drone technology. This conclusion is relevant to the interpretation of the scenario results because a lower payback period does not automatically guarantee technology adoption. Farmers may still hesitate if they perceive drones as technically complex, risky, or poorly adapted to their production needs. Therefore, compensation, preferential leasing and combined financing models should be supplemented by demonstration projects, pilot farms and transparent information about expected savings, operational requirements and real limitations of drone use.

The role of public incentives in the adoption of agricultural technologies is confirmed by Liu and Liu (2024), who show that policy subsidies can encourage farmers to adopt green production technologies and reduce the negative effect of perceived risks. Market incentives may also complement public subsidies by strengthening the expected economic benefits of technological change. This is directly related to the present study because the proposed scenarios demonstrate that state support changes not only the profitability of drone use, but also the initial accessibility of the technology. For small and medium-sized agricultural producers, the main barrier is not always the total economic effect over the season, but the initial financial burden that must be covered before the first economic result is obtained. Finally, Mallinger et al. (2024) emphasize that technological readiness differs across groups of agricultural producers and that policy interventions should be targeted rather than uniform. This supports the regional differentiation proposed in the present article. Regions with large areas of relevant crops, higher yields, and lower military-logistical risks may benefit more from compensation and leasing instruments. Regions with higher risk levels require a broader policy combination, where financial support is supplemented by organizational, logistical and security measures. Therefore, state regulation of financial support for agricultural drones should be understood as a differentiated policy instrument aimed at reducing investment barriers, increasing technological readiness and strengthening the resilience of agricultural production.

The results of the study should be interpreted with several limitations. First, the empirical model is based on five agricultural regions and the period 2021 to 2024. This makes it possible to compare regions with different levels of agricultural potential and war-related logistical exposure, but it does not fully cover all regional differences in Ukraine. Therefore, the expansion of the sample to all regions and to a longer time series could increase the reliability of the model. Second, the integral index depends on the selected indicators and their weights. Although the weights were justified through expert scoring, a larger expert sample or the use of the analytic hierarchy process could refine the weighting structure. The proposed index should therefore be considered a transparent analytical tool that can be recalibrated when more detailed data become available.

CONCLUSIONS

The conducted research allowed us to substantiate that state regulation of financial support for the use of agricultural drones in agriculture should be considered not only as a system of budget payments or compensations, but as a comprehensive mechanism for forming the financial accessibility of technological modernization. Within the framework of such an approach, not only the volume of support is important, but also the cost of credit resources, the scale of potential use of agricultural drones, the production efficiency of the region, the cost burden on the agrarian sector, and the level of military-logistical risks. The proposed integrated index of financial support for the use of agricultural drones made it possible to combine financial, production, and risk indicators into a single evaluation system. According to the results of the formed calculation model, the highest level of financial readiness for the use of agricultural drones in 2024 was demonstrated by the Poltava region; the index value was 0.891. Vinnytsia and Kyiv regions also had sufficiently high positions, while Odesa region received a lower index value, which is explained by the higher level of military-logistical risk. Thus, the results confirm that the agrarian potential of the region in itself does not guarantee high readiness for the use of agricultural drones if the external environment limits the safe and stable application of technologies.

Regression modeling confirmed the positive impact of the integral index of financial provision on the economic effect of the use of agricultural drones. The resulting equation showed that an increase in the level of financial readiness is directly related to an increase in the expected economic result. The positive impact of the cost index indicates that, given the increase in the cost of fuel, fertilizers, and plant protection products, agricultural drones can play an important role in reducing the irrational use of resources. At the same time, the negative impact of military-logistical risk proves that financial support should be accompanied by measures aimed at reducing spatial, logistical and security restrictions.

Scenario assessment of the payback of agricultural drones showed that state support significantly reduces the initial investment barrier for the farmer. In the baseline scenario without support, the payback period is acceptable, but it is compensation programs, preferential leasing, and a combined financing model that make the technology more accessible to small and medium-sized producers. The most effective is the combined model, in which partial compensation for the cost of an agricultural drone is combined with preferential financing and a reduction in the farmer's own contribution. Therefore, state regulation affects not only the economic efficiency of the technology, but also the real possibility of its practical implementation.

The practical significance of the results obtained is that the proposed approach can be used by state authorities to form regionally differentiated programs to support the use of agricultural drones. For regions with high agricultural potential and moderate risks, programs to compensate for part of the cost of equipment and support for leasing mechanisms are appropriate. For regions with a higher military-logistical risk, a combination of financial support with organizational, security, and logistical measures is of paramount importance. For small and medium-sized producers, it is advisable to provide a separate area of support that will reduce the initial financial burden and provide access to the service model of using agricultural drones.

The scientific novelty of the study lies in the development of an economic and mathematical approach to assessing state regulation of financial support for the use of agricultural drones in agriculture. Unlike descriptive approaches, the proposed model makes it possible to quantitatively assess the financial readiness of regions, establish a connection between financial support and economic effect, and also compare state support scenarios. At the same time, it is advisable to direct further research to expanding the empirical base for all regions of our country.

ADDITIONAL INFORMATION

AUTHOR CONTRIBUTIONS

All authors have contributed equally.

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CONFLICT OF INTEREST

The Authors declare that there is no conflict of interest.

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Криштанович С., Піроженко Н., Соколік Л., Хаварівський У., Тарнавський М.

ДЕРЖАВНЕ РЕГУЛЮВАННЯ ФІНАНСОВОГО ЗАБЕЗПЕЧЕННЯ ВИКОРИСТАННЯ АГРОДРОНІВ У СІЛЬСЬКОМУ ГОСПОДАРСТВІ

Стаття присвячена дослідженню державного регулювання фінансового забезпечення використання агродронів у сільському господарстві. Актуальність теми зумовлена потребою технологічної модернізації аграрного виробництва при зростанні виробничих витрат, ускладненні доступу до кредитних ресурсів, дефіциті трудових ресурсів, порушенні логістики та посиленні воєнно-логістичних ризиків. Агродрони розглянуто як інструмент підвищення точності агротехнологічних операцій, оптимізації використання добрив і засобів захисту рослин, скорочення втрат ресурсів і посилення адаптивності аграрних виробників до нестабільного зовнішнього середовища. Методологічну основу дослідження сформовано на основі загальнонаукових та економіко-математичних методів, зокрема теоретичного узагальнення, систематизації, порівняльного аналізу, нормалізації показників, інтегрального оцінювання, ранжування, регресійного моделювання та сценарного аналізу. У статті запропоновано інтегральний індекс фінансового забезпечення використання агродронів, який поєднує показники фінансової підтримки, доступності кредитних ресурсів, площі релевантних культур, урожайності, виробничого витратного навантаження та воєнно-логістичного ризику. На основі побудованої моделі оцінено зв'язок між рівнем фінансового забезпечення та очікуваним економічним ефектом використання агродронів. Також автори порівнюють альтернативні сценарії державної підтримки, зокрема відсутність підтримки, часткову компенсацію, пільговий лізинг і комбіновану модель фінансування.

Результати дослідження показали, що фінансове забезпечення має статистично значущий позитивний вплив на економічний ефект використання агродронів. Найвищий рівень фінансової готовності в побудованій моделі спостерігається в регіонах із потужною аграрною базою, більшими площами релевантних культур і нижчим рівнем воєнно-логістичних ризиків. Сценарне оцінювання засвідчило, що державна підтримка істотно зменшує первинне фінансове навантаження на аграрних виробників і скорочує строк окупності агродронів. Найбільш ефективною є комбінована модель, яка передбачає поєднання часткової компенсації та пільгового фінансування, що особливо важливо для розширення доступу малих і середніх аграрних виробників до технологій точного землеробства.

Ключові слова: агродрони, державне регулювання, фінансове забезпечення, аграрне фінансування, технологічна модернізація, інтегральний індекс, регресійне моделювання

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