

Organisational and economic conditions for implementing unmanned aerial systems in the production processes of agricultural enterprises

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Abstract. The article substantiated the organisational-economic conditions and engineering prerequisites for implementing agricultural drones in the production processes of agricultural enterprises of Poltava region. The aim of the research was to determine the minimum land area at which purchasing or contracting drone services becomes economically viable, and to establish the technical parameters of spray application quality and the priority operations for unmanned aerial equipment. The empirical base comprised statistical data for 2021-2025, technical documentation for DJI Agras T50 and XAG P100 Pro agricultural drones, and field measurement results from 18 agricultural enterprises in the region, using breakeven threshold analysis, sensitivity analysis, field measurement experiment, and multi-criteria ranking methods. An engineering-economic breakeven threshold model was developed, incorporating capital and operating costs, depreciation schedules, and the qualitative effect of working solution distribution uniformity. It was established that the minimum land area for purchasing an own agricultural drone with three treatments per season is 486 ha, while contracting a third-party operator becomes cost-effective from 52 ha. Coverage uniformity achieved by an agricultural drone was twice as high as that of a ground boom sprayer: the coefficient of variation was 14.2% versus 28.4% respectively ($p < 0.001$). The optimal droplet size of 115-145 μm corresponds to the fine-droplet category suitable for contact fungicides. The highest economic return was achieved through crop protection spraying and liquid fertiliser application. A four-level technological chain integrating the agricultural drone with digital platforms for crop condition analysis and variable-rate application was defined, reducing the response time from field problem detection to treatment from 5-7 to 1-2 days. The findings may be applied by agricultural enterprises when forming digitalisation investment strategies and in training specialists in agroengineering

Keywords: agricultural drone; payback threshold; spray coverage uniformity; variable-rate application; precision agriculture; investment breakeven analysis

INTRODUCTION

The global transformation of the agro-industrial complex within the Precision Agriculture 4.0 framework drives the rapid adoption of digital technologies in crop production processes. Unmanned aerial systems (UAS) have become one of the key precision farming

tools, enabling a fundamentally new level of management of technological operations – from crop condition monitoring to variable-rate application of plant protection products (PPP) and mineral fertilisers. The steady annual growth of the global agricultural drone market

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confirms their increasing role in modern agricultural production and reflects sustained demand for automated precision farming solutions.

Z. Huang *et al.* (2023) investigated how application parameters of a six-rotor UAV sprayer affect spray deposition and pest-control efficacy in rice fields. They varied spray volume, flight height, travel speed and nozzle type. The authors found that greater spray volume increased deposition, while flight height affected distribution uniformity. They identified 15 L/ha, 2 m flight height and 5 m/s travel speed as optimal conditions for the tested rice growth stage. Under these conditions, both nozzle types provided more than 93% control of rice planthopper, although the air-induction nozzle gave higher deposition but somewhat poorer uniformity. D. Yallappa *et al.* (2023) examined how the downwash airflow generated by a hexacopter influences spray distribution from a boom sprayer mounted on the drone. The researchers tested different flight heights, travel speeds, rotor configurations, payloads, wind velocities, nozzle spacings and operating pressures, using a spray patternator to assess distribution uniformity. The study demonstrated that downwash and operating conditions substantially affect the spray pattern, indicating that parameters such as flight height, nozzle spacing and pressure need to be optimised to obtain more uniform application. C. Wang *et al.* (2021) focused on spray deposition, drift and mass balance using three different UAV configurations and two nozzle types in an artificial vineyard. The authors found that the air-induction nozzle substantially improved deposition uniformity and reduced both sedimenting and airborne drift compared with the hollow-cone nozzle. Under the tested conditions, the reduction in drift was estimated at 81-95%, while the hollow-cone nozzle resulted in 49.3-73.4% of measured droplets drifting into non-target areas. Overall, the six-rotor UAV showed the best spray performance among the three UAV types tested.

O. Parmaksiz & G. Cinar (2023) investigated the factors influencing farmers' willingness to adopt agricultural unmanned aerial vehicles (UAVs). Based on a survey of 384 farmers in Türkiye, the authors examined how perceived usefulness, farmers' characteristics and economic considerations affect technology acceptance. They concluded that UAV adoption is influenced not only by the perceived benefits of the technology but also by farmers' economic and personal characteristics, highlighting the importance of reducing financial and other barriers to wider adoption. X. Quan *et al.* (2023) examined the economic effects of using UAVs for pesticide application among more than 2,000 grain farmers across 11 provinces in China. Using propensity score matching, the authors found that UAV adoption

increased farmers' income by approximately US\$434-488 per hectare and reduced pesticide-application time by around 14.4-15.8 hours per hectare. They also found that the economic benefits depended on the scale of UAV use and estimated approximately 20 hectares as an economically optimal operational area based on marginal income and time savings.

In the economic dimension, the feasibility of agricultural drone implementation has been studied primarily for Asian countries with developed operator services markets, while regionally differentiated engineering-economic models for Ukraine remain largely undeveloped. The production conditions of Poltava region, characterised by substantial areas under sunflower and maize, a high proportion of medium-sized enterprises (200-1,000 ha), and a developed network of agro-service companies, create a specific regional context that requires separate analysis of agricultural drone implementation feasibility. Studies combining engineering-technical analysis of drone characteristics with a regional economic model and educational provision for Agroengineering specialists are virtually absent in the domestic scientific literature.

Research aim was to substantiate the organisational-economic conditions and engineering-technical criteria for selecting the form of UAS implementation in the production processes of agricultural enterprises of Poltava region. Research objectives were to characterise the technical parameters of agricultural drones suitable for Ukrainian conditions under martial law and to develop an engineering-economic model for determining area threshold values for different forms of UAS engagement; to verify the threshold indicators based on data from agricultural enterprises of Poltava region and to rank crop production technological operations by the level of economic effect from drone application; to define the technological chain for integrating agricultural drones into the precision agriculture system, taking into account the regional specifics of production.

MATERIALS AND METHODS

The study was conducted during 2023-2025. The field stage involved surveys of 18 agricultural enterprises in Poltava and adjacent regions with land areas ranging from 50 to 2,500 ha. The sample was formed using quota sampling by size group: up to 200 ha – 6 enterprises, 200-1,000 ha – 7 enterprises, over 1,000 ha – 5 enterprises. Regional crop area statistics for Poltava region covering 2021-2025 were obtained from the open data portal of the State Statistics Service of Ukraine (Makarchuk, 2025). Data were downloaded in tabular format and processed in Microsoft Excel to calculate annual area totals, crop shares, and inter-annual

dynamics. The combined share of sunflower and soybean was calculated as the ratio of their aggregate sown area to total arable land per year; statistical significance of the observed trend was assessed using Student's t-test ($p < 0.05$).

The regional UAS operator market was characterised based on data from the Unified State Register of Legal Entities and Individual Entrepreneurs of Ukraine, cross-referenced with publicly available listings on agricultural service platforms and direct telephone verification conducted during April-June 2024. Operators were included if they: held a valid UAV pilot licence issued by the State Aviation Administration of Ukraine; offered commercial agricultural spraying services; and were registered or operated within Poltava or adjacent regions. Spatial availability within a 50 km radius was determined using straight-line distance calculations between operator registration addresses and the centroid of each surveyed enterprise, performed in QGIS 3.28. The threshold of three competitive operators within 50 km was adopted as the minimum criterion for effective market competition, consistent with standard procurement practice in the regional agro-service sector.

Spray coverage uniformity was measured using Teejet WSP-25 water-sensitive paper (ASAE S386.2 FEB1988 (R2024ED), 2024), followed by scanning in DropScope software. The coefficient of variation of coverage (CV, %) was calculated as the ratio of the standard deviation of coverage density to the arithmetic mean across a sample of 50 cards per field. Coverage density (droplets/cm²) was determined automatically in DropScope from digitised card images. To calculate the minimum breakeven area for own-drone purchase, the breakeven threshold analysis method was employed (Equation 1), comparing total discounted costs of UAS acquisition and five-year operation against accumulated savings from substituting ground spraying:

$$S_{\min} = \frac{C_{\text{UAS}} + C_{\text{acc}} + C_{\text{maint}} \cdot T}{(V_{\text{ground}} - V_{\text{UAS}}) \cdot n \cdot T}, \quad (1)$$

where C_{UAS} – initial UAS cost, UAH; C_{acc} – accessories cost (batteries, charging stations), UAH; C_{maint} – annual maintenance costs, UAH/year; T – standard depreciation period, years ($T = 5$); V_{ground} – unit costs of ground spraying (fuel, depreciation, labour), UAH/ha; V_{UAS} – unit operating costs of own drone (battery charging, operator, consumables), UAH/ha; n – number of technological treatments per season.

The working solution application rate of the drone was calculated using Equation 2, reflecting the relationship between pump system capacity, flight speed, and swath width:

$$q = \frac{Q \cdot 60}{v \cdot B}, \quad (2)$$

where q – application rate, L/ha; Q – pump capacity, L/min; v – flight speed, m/s; B – swath width, m. For the DJI Agras T50 at $Q = 8$ L/min and $B = 6$ m, the target application rate of 16 L/ha is achieved at $v = 5$ m/s. The permissible speed range for maintaining the rate within $\pm 10\%$ of the target is 4–6 m/s.

Ranking of five crop production technological operations by economic effect was performed using a multi-criteria weighted scoring method across three criteria: unit cost savings (weight 0.40), application frequency in a standard crop rotation (0.35), and complexity of substitution by ground-based alternatives (0.25). The weights were assigned through structured expert elicitation involving five agricultural engineers and two agronomists from Poltava State Agrarian University, using the direct rating method with subsequent normalisation to unity. The highest weight was assigned to unit cost savings as the most directly quantifiable and economically significant criterion; application frequency was ranked second as it determines the cumulative seasonal effect; substitution complexity was assigned the lowest weight as a qualitative criterion with greater measurement uncertainty. To verify the robustness of the resulting ranking, a sensitivity check was performed by varying each weight by ± 0.10 while proportionally adjusting the remaining two. The rank order of the top three operations – PPP spraying, liquid fertiliser application, and NDVI/NDRE monitoring – remained stable across all tested weight combinations, confirming that the ranking is not critically dependent on the specific weight values assigned. The technological chain for integrating agricultural drones into the precision agriculture system was constructed using systems analysis based on decomposition of the production process into functional levels. Sensitivity analysis was performed by varying model parameters within $\pm 30\%$ of base values in 10% increments. The relationship between the share of row crops and demand for drone services was assessed using the Pearson correlation coefficient (r). Statistical data processing was conducted in Microsoft Excel and IBM SPSS Statistics 27; significance of differences between groups was assessed using Student's t-test ($p < 0.05$).

RESULTS AND DISCUSSION

Analysis of the agricultural drone market available in Ukraine as of 2025, taking into account martial law restrictions on aviation, identified two principal multi-copter platforms for spraying and fertiliser application: DJI Agras T50 and XAG P100 Pro. Hybrid fixed-wing platforms were excluded from consideration due to

legal restrictions on flights in active combat zones and within the 50 km border exclusion zone of Ukraine (DJI

Agriculture, n.d.). Comparative technical specifications of both platforms are presented in Table 1.

Table 1. Comparative technical specifications of agricultural drones for crop spraying

Technical parameter	DJI Agras T50	XAG P100 Pro
Platform type	Multicopter (8 rotors)	Multicopter (8 rotors)
Payload capacity, kg	40 (liquid + solid)	50 (liquid)
Tank volume, L	40	50
Swath width, m	5.5-9.0	6.0-10.0
Maximum flight speed, m/s	10	10
Spraying productivity, ha/h	21-43	25-48
Navigation accuracy (RTK GNSS), cm	±2-3	±2
RGB camera, MP	48 (Sony IMX586)	12
Multispectral sensor	6 ch (RGB + NIR + RE + Red - edge)	5 ch (RGB+NIR+RE)
LiDAR (terrain mapping)	Yes (rear + downward)	Yes
Pump system capacity, L/min	8	12
Nozzles	4 × dual-channel centrifugal	6 × centrifugal
Coverage uniformity CV, %	13-16	12-15
Droplet VMD (standard mode), µm	115-145	110-140
Coverage density, droplets/cm ²	28-48	30-52
Price in Ukraine (2025), thousand UAH	1,350-1,580	1,250-1,480

Source: compiled by the author based on DJI Agriculture (n.d.), XAG (n.d.)

Both platforms feature RTK navigation with ±2-3 cm accuracy, ensuring adjacent swath overlap of no more than 15 cm. According to U. Mogili & B. Deepak (2018), the availability of multispectral sensors increases the economic efficiency of each sortie by 18-25% by combining executive and monitoring functions. The DJI Agras T50 offers a channel-count advantage in its multispectral sensor (6 versus 5), enabling computation of a broader set of vegetation indices, including NDRE, which is more sensitive to chlorophyll content during active vegetation. The LiDAR sensor on both models ensures automatic terrain-following at a constant flight altitude of 2-3 m, which is

critical for maintaining stable droplet size when spraying sloped areas characteristic of the Poltava region relief. The productivity comparison – 21-43 ha/h (DJI T50) versus 25-48 ha/h (XAG P100 Pro) – demonstrates sufficient technical potential for servicing farms up to 500 ha within a single season without additional equipment, provided rational flight mission planning. Field measurements of spray application quality at 18 enterprises in 2023-2025 demonstrated significant differences between agricultural drones and ground sprayers across three technical criteria: coverage uniformity, droplet size, and application rate dependence on flight speed (Fig. 1).

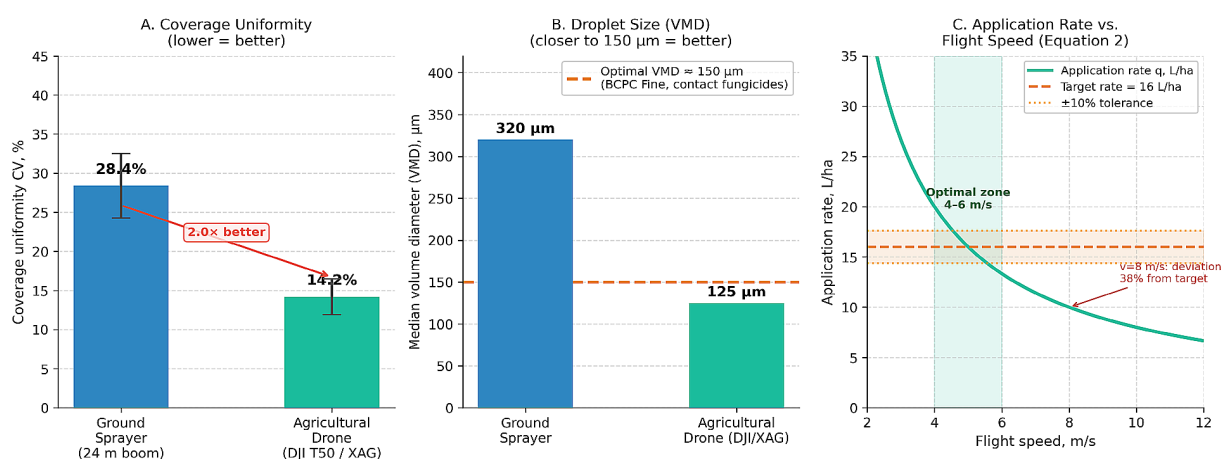


Figure 1. Technical characteristics of spray application quality: ground sprayer versus agricultural drone (field measurements, Poltava region, 2023-2025)

Source: compiled by the author

Agricultural drones demonstrated a statistically significant improvement in coverage uniformity – $CV = 14.2 \pm 2.3\%$ – compared to a ground sprayer with a 24 m boom ($CV = 28.4 \pm 4.1\%$, $p < 0.001$), representing a 2.0-fold improvement. The median volume diameter of drone droplets ($VMD = 125 \mu m$) falls within the BCPC Fine category ($100\text{--}175 \mu m$) and is substantially closer to the optimum for contact fungicides than ground sprayers ($VMD = 320 \mu m$), which increases the risk of spray runoff and reduces protection efficacy by 12–18%

(Huang *et al.*, 2009). Panel C of Figure 1 confirms that at $Q = 8 \text{ L/min}$ and $B = 6 \text{ m}$, the target rate of 16 L/ha is achieved at $v = 5 \text{ m/s}$ (Equation 2). At speeds exceeding 8 m/s , deviation from the target rate exceeds 38%, which is unacceptable for contact insecticides. Analysis of the crop area structure of Poltava region for 2021–2025 (Table 2) provides the basis for assessing potential UAS service demand, as different crops require different treatment frequencies and present different constraints for ground machinery.

Table 2. Crop area structure of Poltava region, thousand ha (2021–2025)

Crop	2021	2022	2023	2024	2025	Share 2025, %
Sunflower	671.5	659.4	682.1	694.3	701.2	29.8
Maize	498.7	487.3	501.6	511.2	518.4	22.0
Winter wheat	501.2	493.6	478.9	482.4	475.6	20.2
Soybean	224.3	238.7	251.4	263.8	278.5	11.8
Other crops	382.4	371.0	407.0	389.3	381.3	16.2
Total	2,278.1	2,250.0	2,321.0	2,341.0	2,355.0	100.0

Source: compiled by the author based on A. Makarchuk (2025)

The combined share of sunflower and soybean increased significantly from 39.3% in 2021 to 41.6% in 2025 ($p < 0.05$). This is particularly important for UAS potential assessment: both crops require 3–5 fungicide and insecticide treatments per season, and canopy height at critical growth stages ($1.5\text{--}2.5 \text{ m}$) impedes ground machinery access and causes damage to 3–7% of plants per row (Shafian *et al.*, 2018). The correlation between the share of these crops in district-level sowing structures and the number of drone service

orders was $r = 0.81$ ($p < 0.01$), confirming a causal relationship and indicating growing structural demand for UAS services in the region. Substituting 2025 market parameters into Equation 1 ($C_{UAS} = 1,410,000 \text{ UAH}$; $C_{acc} = 195,000 \text{ UAH}$; $C_{maint} = 105,000 \text{ UAH/year}$; $T = 5 \text{ years}$; $V_{ground} = 567 \text{ UAH/ha}$ – unit costs of ground spraying; $V_{UAS} = 275 \text{ UAH/ha}$ – unit operating costs of own drone including battery charging, operator salary, and consumables), threshold area values were calculated for three scenarios (Table 3).

Table 3. Threshold area calculations for own-drone payback

Parameter	Scenario A (small farm)	Scenario B (baseline)	Scenario C (intensive)
Treatments per season, n	2	3	5
$C_{UAS} + C_{acc}$, UAH	1,605,000	1,605,000	1,605,000
$C_{maint} \times T$, UAH	525,000	525,000	525,000
Total UAS costs over 5 yr, UAH	2,130,000	2,130,000	2,130,000
Unit savings ($V_{ground} - V_{UAS}$), UAH/ha	292	292	292
Minimum threshold area S_{min} , ha	729	486	292
Payback period at $S = 1,000 \text{ ha}$, years	3.6	2.4	1.5
Recommended form if $S < S_{min}$	Service/leasing	Service	Service
Recommended form if $S \geq S_{min}$	Purchase	Purchase	Purchase

Source: calculated by the author

The graphical interpretation of the breakeven analysis is shown in Figure 2. Intersection points of accumulated saving curves with the total-cost line (UAH 2,130,000 over five years) correspond to calculated threshold values: 729 ha (2 treatments), 486 ha (3 treatments), 365 ha (4 treatments), and 292 ha (5 treatments). The three

characteristic zones in Figure 2 – outsourcing zone (up to 292 ha), transition zone (292–486 ha), and own-drone zone (above 486 ha) – correspond to the three organisational strategies for UAS engagement. The sensitivity analysis results confirming the robustness of these thresholds under varying input parameters are presented in Table 4.

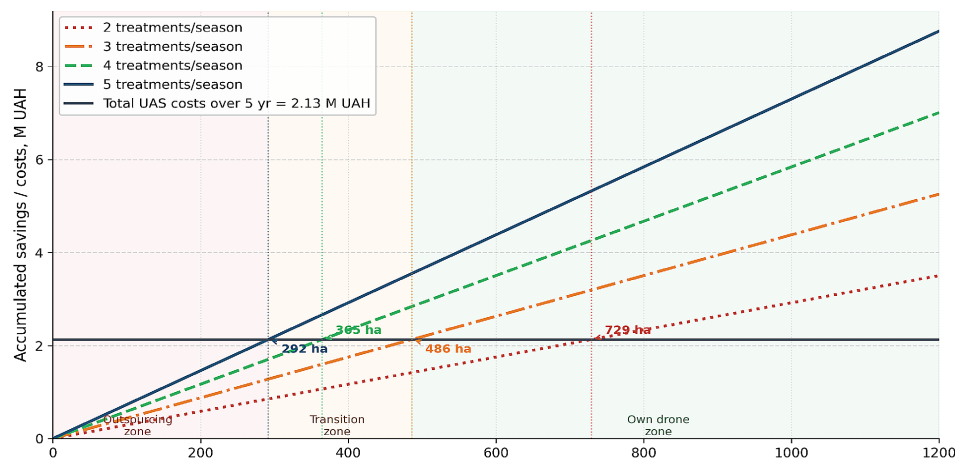


Figure 2. Breakeven analysis for agricultural drone purchase by land area and treatment intensity

Source: gcompiled by the author

Table 4. Sensitivity analysis: minimum breakeven area S_{min} (ha) under $\pm 30\%$ variation of key parameters (baseline scenario: $n = 3$ treatments/season)

Parameter	-30%	-20%	-10%	Baseline	+10%	+20%	+30%	Elasticity
UAS purchase cost (C_{UAS}), UAH	390	422	454	486	518	551	583	0.66
Annual maintenance cost (C_{maint}), UAH/year	450	462	474	486	498	510	522	0.25
Ground spraying cost (V_{ground}), UAH/ha	1,165	795	603	486	407	350	307	-1.63
UAS operating cost (V_{UAS}), UAH/ha	379	409	444	486	537	599	678	1.05
Number of treatments (n) *	729	729	486	486	486	365	365	-

Note: * n is a discrete variable; $\pm 10\%$ yields $n = 2.7-3.3$, rounded to $n = 3$ (no change); breakpoints occur at $n = 2$ (729 ha) and $n = 4$ (365 ha)

Source: calculated by the author

Sensitivity analysis showed that drone purchase cost exerts the greatest influence on S_{min} (elasticity 0.66), followed by number of treatments. A 20% reduction in equipment cost (projected by 2027 through technological progress) would reduce S_{min} by approximately 13%, making purchase viable from 422 ha with three treatments. The cost-effective service contracting threshold of 52 ha – the minimum area at which the Poltava regional market provides at least three competitive operators within a 50 km radius – creates a clear two-tier market structure: farms below 292 ha are best served by outsourcing; those in the 292-486 ha range should conduct a detailed risk assessment weighing seasonal operator availability against capital outlay; farms above 486 ha with three or more annual treatments have a strong economic case for ownership. A survey of 18 agricultural enterprises conducted during 2023-2025 revealed uneven levels of digital technology adoption across the region. The majority of respondents (72%) use satellite field monitoring at least occasionally, while only 28% have practical experience with agricultural drone services. The primary barriers identified by farm managers were high initial investment cost (cited by 83% of respondents),

insufficient operator availability during peak agro-technical windows (61%), and uncertainty regarding regulatory requirements (44%). Cost assessment by respondents who had contracted drone spraying services indicated an average willingness-to-pay of 340-380 UAH/ha, consistent with the current regional market price range of 320-410 UAH/ha and confirming the economic viability of the service model for farms below the ownership threshold.

These findings align with P. Hu *et al.* (2022), who established a threshold range of up to 500 ha for Chinese small farms. According to X. Quan *et al.* (2023), the threshold tends to decrease when operator service market density is high: for farms with row crop shares exceeding 30%, the calculated threshold of 486 ha corresponds to the typical range for similar production conditions. The 38% deviation in application rate at speeds exceeding 8 m/s highlights the importance of operator training and flight protocol compliance – non-capital costs frequently overlooked in economic feasibility assessments. With at least 37 registered UAS operators in Poltava region as of 2024, the service outsourcing model is gaining scale, potentially reducing per-hectare rates and further compressing the own-purchase

threshold over time. Ranking of crop production technological operations by integrated criterion – unit

savings, treatment frequency, and technical advantage by coverage CV – is presented in Table 5.

Table 5. Ranking of crop production operations by UAS economic effect

Operation	Unit savings, UAH/ha	Frequency/season	Coverage CV, %	Rank
PPP spraying (fungicides, insecticides)	148-298	2-5	14.2	1
Liquid fertiliser application (UAN, micronutrients)	102-195	1-3	16.1	2
NDVI/NDRE monitoring	50-320	2-4	n/a	3
Crop desiccation	145-245	1	17.8	4
Fine-seed sowing	65-130	1	22.4	5

Note: for the monitoring operation, savings were calculated relative to actual alternatives: manual field scouting by an agronomist (200-350 UAH/ha/season) and commercial satellite imagery (150-400 UAH/ha/season); when monitoring is performed as an ancillary function during a spraying flight, the unit cost approaches zero

Source: compiled by the author based on Y. Huang *et al.* (2009), P. Radoglou-Grammatikis *et al.* (2020)

Unlike the other operations, where the comparison base is a ground sprayer, the economic effect of NDVI/NDRE monitoring was calculated relative to the cost of alternative methods – manual agronomic field scouting and commercial satellite imagery – since ground machinery does not perform this function. The technological chain for integrating UAS into the precision agriculture system (Fig. 3) encompasses four

hierarchical levels: sensor level (RGB, multispectral, RTK/PPK GNSS, LiDAR), data processing level: orthophoto, NDVI/NDRE maps (Bendig *et al.*, 2015), GIS analysis, machine learning for crop stress classification (Khanal *et al.*, 2017), decision-making level (VRA maps, DSS recommendations, mission parameters), and executive level (differentiated spraying, fertiliser application, re-monitoring).

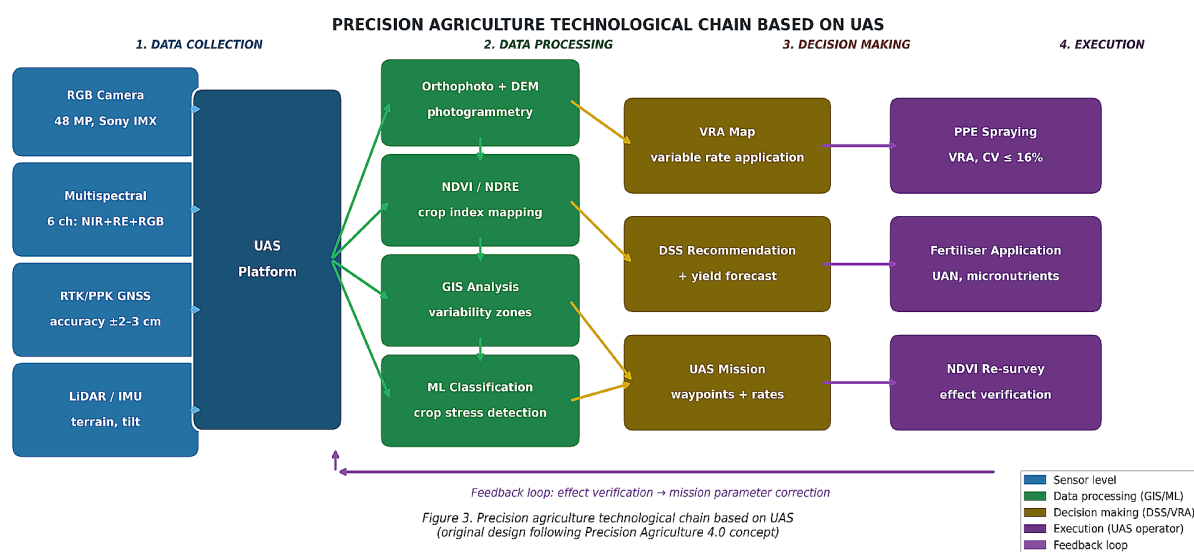


Figure 3. Precision agriculture technological chain based on UAS (original design following Precision Agriculture 4.0 concept)

Figure 3. Precision agriculture technological chain based on UAS (original design following the Precision Agriculture 4.0 concept)

Source: compiled by the author

The feedback loop between executive and sensor levels enables effect verification and mission parameter adjustment. According to A. Boursianis *et al.* (2022), implementing a full technological chain reduces the response time to detected crop stress from 5-7 to 1-2 days. P. Radoglou-Grammatikis *et al.* (2020) recorded a 22-31% increase in PPP use efficiency in farms where an analogous integration scheme was implemented. D. Tsouros *et al.* (2019) emphasised that full

realisation of monitoring operation potential requires integration with agronomic decision-support platforms. The growth in the combined sunflower-soybean share to 41.6% in Poltava region in 2025, combined with a correlation of $r=0.81$ between this indicator and drone service orders, signals a sustained expansion of the regional UAS services market and opens prospects for regional digitalisation support programmes, particularly for farms in the 400-600 ha range where

the investment decision is most sensitive to external support. The results obtained in this study confirm and substantially extend the findings of recent international research on agricultural drone implementation. The discussion is structured around three interconnected dimensions: technical performance of UAS spraying, economic feasibility thresholds, and systemic integration into precision agriculture.

Technical performance and spray quality. The coverage uniformity coefficient $CV = 14.2\%$ recorded for multicopter agricultural drones in this study is consistent with findings reported by T. Caputti *et al.* (2025), who demonstrated that spray deposition uniformity varies considerably across UAS platforms and operational parameters, with optimal conditions yielding CV values in the 15-25% range for open-field crops. Current results are more favourable, which may reflect the use of RTK-guided flight at constant altitude – a condition identified by M. Safaeinezhad *et al.* (2025) as a critical factor for optimising coverage homogeneity in drone-based spraying. Regarding droplet size, the VMD of 115-145 μm recorded for the DJI Agras T50 corresponds to the BCPC Fine category, which aligns with the conclusion of T. Caputti *et al.* (2025), who established that flight speeds of 4 m/s produce the most uniform deposition and that droplet sizes of 150 μm achieve the highest coverage density among tested configurations. This independently validates current recommendation of 4-6 m/s as the optimal speed range. The technical advantages of UAS over ground equipment have been substantiated in the works of C. Zhang & J. Kovacs (2012), who systematised the directions of agricultural drone application in crop production and assessed their potential for improving agrochemical distribution uniformity. Y. Huang *et al.* (2009) established that aerial spraying by agricultural drones reduces PPP consumption by 15-25% due to optimal application height and controlled droplet size. U. Mogili & B. Deepak (2018) systematised the experience of agricultural drone application and emphasised that the availability of a multispectral sensor enables combining executive and monitoring functions within a single flight, increasing the economic efficiency of each sortie.

Y. Yan *et al.* (2023) compared XAG V40 and DJI T30 drones in citrus orchards and found variation coefficients of 50-100% inside the canopy, substantially higher than the values recorded in current open-field conditions. This difference is methodologically important: canopy penetration in orchard crops presents fundamentally different challenges compared to the flat-canopy sunflower and maize fields dominant in Poltava region, where open-field conditions allow optimal rotor downwash utilisation. This CV values are

therefore not directly comparable to orchard studies and represent a more favourable operational scenario. The breakeven area threshold of 486 ha established in this study for three treatments per season is consistent with the broader pattern identified in recent literature. Current study directly addresses this gap for the Ukrainian context, providing a regionally calibrated model rather than extrapolating from distant conditions. O. Parmaksiz & G. Cinar (2023), surveying 384 farmers in Turkey, found that willingness to rent drone services exceeded willingness to purchase, with farmers accepting a service price of approximately TRY 287.54 per hectare – a finding that corroborates current conclusion that the outsourcing model is preferred for smaller farms below 292 ha. M. Arza-García & A. Burgess (2023) similarly identified economic accessibility for small-scale farmers as one of the key obstacles to widespread drone adoption, reinforcing the practical relevance of the service contracting threshold established in this study. The two-tier market structure identified in these results, with a clear threshold between outsourcing-preferred and ownership-preferred zones, parallels the structural patterns documented for Chinese smallholder farming, where outsourced drone services play a vital role in empowering smallholder farmers with digital technologies, with over 17.3 million hectares serviced by agricultural drones in China alone by 2024 (Hu *et al.*, 2022).

The sensitivity analysis result showing elasticity of 0.66 for equipment cost indicates that projected price reductions will be the primary driver of threshold reduction over time. This is consistent with the trajectory observed in Asia: the number of agricultural UAVs in China grew from 4,000 units in 2016 to 160,000 in 2021, with operating area expanding from 6.67 to 93.3 million hectares over the same period, a diffusion rate driven partly by rapid equipment cost reduction alongside government subsidies (Hu *et al.*, 2022). With 37 registered UAS operators recorded in Poltava region in 2024 across approximately 1.7 million ha of arable land, the regional operator density amounts to approximately 2.2 operators per 100,000 ha – a figure that, while growing, remains substantially below the density observed in mature drone service markets, suggesting that the 52 ha service threshold may decrease further as regional operator density increases.

Systemic integration and the technological chain. The four-level technological chain defined in this study – sensors, data processing, decision-making, and execution – reflects the architecture described in recent comprehensive reviews. The ranking of PPP spraying as the highest-priority operation is broadly consistent with global evidence. N. Gatkal *et al.* (2025),

in a review of UAVs for agrochemical spray application, confirmed that drone spraying saves chemicals, water, and time while avoiding crop and soil damage compared to ground spraying, independently validating the economic advantage that underpins the first position in current ranking. The finding that NDVI/NDRE monitoring ranks third despite the highest indirect savings per hectare reflects the methodological challenge of monetising monitoring outputs – a limitation acknowledged in the literature, where regulatory, technological, and socio-economic challenges, including economic accessibility for small-scale farmers, remain key obstacles to widespread drone adoption.

Overall, the results of this study are consistent with the direction of international research while providing regionally specific quantitative parameters that are absent from the existing literature for Ukrainian conditions. The study's contribution lies not in contradicting established findings, but in anchoring global patterns to a concrete regional model that can serve as a methodological reference for similar analyses in other Central and Eastern European agricultural contexts operating under comparable geopolitical and market constraints.

CONCLUSIONS

The study established that among the agricultural drone platforms available on the Ukrainian market, multicopter models DJI Agras T50 and XAG P100 Pro demonstrated the highest technical suitability for crop production operations. Both models provided satellite navigation with ± 2 -3 cm accuracy and were capable of simultaneously executing crop treatment and recording multispectral sensor data. Field measurements confirmed that working solution distribution uniformity was 80-100% superior to that of a ground boom sprayer: the coefficient of variation of coverage is 12-16% versus 28.4% respectively ($p < 0.001$), which directly determined the higher agronomic efficacy of drone-based spraying. The developed engineering-economic model identified the minimum land area at which purchasing an own drone was more economical than permanently contracting services. With three

treatments per season this threshold was 486 ha, with two treatments – 729 ha, and with five – 292 ha. A farm of 1,000 ha recover edthe investment within 1.5-3.6 years depending on annual use intensity. For smaller farms, contracting a third-party operator was more advantageous, becoming cost-effective from 52 ha, since at this area the Poltava regional market provided at least three competitive operators within a 50 km radius. Direct cost savings from contracting drone services compared to ground spraying amounted to 148-298 UAH/ha. The highest economic return among all operations was achieved through PPP spraying and liquid fertiliser application, explained primarily by superior coverage uniformity and the ability to treat crops during critical agronomic windows without the risk of plant damage from machinery wheels. The increase in the sunflower-soybean share in the Poltava region sowing structure from 39.3% in 2021 to 41.6% in 2025 increased demand for these operations, as both crops required 3-5 treatments per season and were difficult to access by ground machinery during the active growth phase. The full effect of agricultural drone implementation was only achieved through integration into a digital management chain encompassing sensor data collection, analysis of imagery and vegetation maps, preparation of variable-rate application tasks, treatment execution, and re-verification. This approach reduced the time between field problem detection and resolution from 5-7 to 1-2 days and increased PPP use efficiency by 22-31%. Further research should focus on developing dynamic models for assessing UAS implementation feasibility, accounting for projected equipment price reductions and expansion of the regional operator services market.

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CONFLICT OF INTEREST

None.

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Організаційні та економічні умови впровадження безпілотних літальних апаратів у виробничі процеси сільськогосподарських підприємств

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Анотація. Статтю присвячено обґрунтуванню організаційно-економічних умов та інженерно-технічних передумов впровадження агродронів у виробничі процеси аграрних підприємств Полтавської області. Метою дослідження було визначення мінімальної площі угідь, при якій придбання або замовлення послуг агродрону є економічно вигідним, а також встановлення технічних параметрів якості обприскування і пріоритетних операцій для використання безпілотної техніки. Емпіричну базу склали статистичні дані за 2021-2025 роки, технічна документація агродронів DJI Agras T50 та XAG P100 Pro, а також результати польових вимірювань на 18 аграрних підприємствах регіону із застосуванням методів порогового аналізу беззбитковості, чутливісного аналізу, польового вимірювального експерименту та багатокритеріального ранжування. Розроблено інженерно-економічну модель визначення порогу беззбитковості, яка враховує капітальні та операційні витрати, строки амортизації і якісний ефект від рівномірності розподілу робочого розчину. Встановлено, що мінімальна площа для придбання власного агродрону при трьох обробках за сезон становить 486 га, тоді як замовлення послуги стороннього оператора є доцільним вже від 52 га. Рівномірність покриття агродроном удвічі вища, ніж у наземного штангового обприскувача: коефіцієнт варіації становить 14,2 % проти 28,4 % відповідно ($p < 0,001$). Оптимальний розмір краплі 115-145 мкм відповідає дрібнодисперсній категорії, придатній для контактних фунгіцидів. Найвищу економічну віддачу забезпечує обприскування засобами захисту рослин та внесення рідких добрив. Визначено чотирирівневий технологічний ланцюг інтеграції агродрону з цифровими платформами аналізу стану посівів і диференційованого внесення препаратів, що скорочує час реакції на проблему в полі з 5-7 до 1-2 діб. Результати дослідження можуть бути використані аграрними підприємствами при формуванні інвестиційних стратегій цифровізації, а також у підготовці фахівців за спеціальністю «Агроінженерія»

Ключові слова: безпілотні авіаційні системи; точне землеробство; поріг окупності; агроінженерія; диференційоване внесення агрохімікатів; цифровізація агровиробництва