agricultural engineering.eu 81(3), 2026, 155–173
DOI:10.15150/ae.2026.3365

agricultural engineering.eu

Economic relevance of autonomous field robots in maize production

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The economic relevance of autonomous field robots in real-world farming systems has not yet been sufficiently quantified. This study analyses the application of the AgBot 2.055W4 in maize production and related logistical processes on two farms in northwestern Germany. The economic assessment is based on a scenario-based simulation of robotic field operations under different supervision levels (SL), complemented by work-time data on logistical processes. The farms are modelled within a hypothetical machinery cooperation to ensure a consistent representation of resource allocation. A cost–benefit modelling framework is applied, focusing on the relative cost burden of robot use and the contribution of automation benefits to maize production revenues. Across the analysed supervision scenarios, net costs correspond to 28–45 % of output excluding direct and work execution costs, indicating that robot-related costs represent a substantial share of the economic margin available from maize production. Automation benefits contribute at most about 3 % to total production revenues. Although the SL = 0 scenario yields the lowest net costs, a low supervision range (SL = 0.10–0.25) is identified as the most economically plausible option under realistic conditions. Overall, this indicates a comparatively high cost burden alongside a limited economic contribution of automation benefits. While the cost–performance analysis provides important insights, it captures only part of the factors shaping adoption decisions. In practice, adoption may also be driven by labour availability and broader organisational conditions that are not fully reflected by cost-based indicators.

Keywords
agricultural robotics, cost–benefit analysis, supervision levels, field structures, operational conditions

Autonomous field robots are widely considered a technological option to address labour shortages and improve operational efficiency in crop production (Lowenberg-DeBoer et al. 2021b, Benos et al. 2023, Bazargani and Deemyad 2024, Fontani et al. 2025). Recent advances in sensing, navigation and control systems have improved the technical capabilities of agricultural robots. As a result, they can be deployed across a growing range of field operations, including seeding, mechanical weed control and crop monitoring (Bechar and Vigneault 2016, Yang et al. 2023). These advances have led to an increasing diversity of robotic applications in agriculture, ranging from task-specific systems to more integrated field operations (Adamides and Edan 2023). Despite these technological developments, the economic viability of autonomous field robots remains insufficiently understood, particularly under heterogeneous real-world farming conditions (Lowenberg-DeBoer et al. 2020, Spykman et al. 2026).

Economic assessments of autonomous field robots are often conducted at the level of individual fields or specific operations. These studies typically analyse operational costs, labour requirements, and technical performance of robotic systems compared with conventional tractor-based machinery

received 31 March 2026 | accepted 20 August 2026| published 28 August 2026

(Al-Amin et al. 2023, Shang et al. 2023, Spykman et al. 2023b, Vahdanjoo et al. 2023). While such analyses are essential for understanding the economic mechanics of robotic field operations, they often focus on individual tasks or isolated operating conditions and therefore provide only limited insight into the broader economic relevance of robotic technologies within agricultural production systems.

However, the economic performance of autonomous field robots is not determined by isolated operations alone but emerges from the interaction of structural and operational conditions. Field characteristics such as size, spatial distribution and accessibility, as well as coordination requirements, affect field operation efficiency and the allocation of machinery and labour (Lowenberg-DeBoer et al. 2021a, Al-Amin et al. 2023, Maritan et al. 2023, Strine et al. 2025). Several existing studies incorporate these factors within farm-level analyses or optimisation frameworks, focusing on resource allocation and cost structures (Lowenberg-DeBoer et al. 2021a, Ørum et al. 2023). These approaches primarily address system configuration and cost efficiency, but provide limited insight into the relative economic significance of robotic field operations within the overall production system.

Recent empirical and modelling studies based on real-world farm data highlight the importance of logistical processes and coordination requirements in shaping the economic performance of autonomous field robots. Drawing on data from multiple fields across commercial farms, these analyses combine experimental evidence on logistics with scenario-based modelling of field operations. They show that inter-field transport and coordination can lead to additional machinery use and handling efforts, resulting in higher operational costs compared with conventional tractor-based systems (Jorissen et al. 2025a, Jorissen et al. 2025b). Building on this, structural cost models demonstrate that parameters such as field size, route distance, and field accessibility are key determinants of cost variability in autonomous field robot operations (Jorissen and Recke 2026). All three studies are based on the same empirical dataset of AgBot deployments on commercial maize farms.

Although these studies provide important insights into the operational economics of autonomous field robots, including analyses of logistical processes, robot-related cost structures, and the influence of field characteristics on cost variability, they focus primarily on cost structures and field-level variability. As a result, the broader economic relevance of robotic field operations within crop production systems remains insufficiently understood. Their magnitude relative to the overall economic scale of crop production remains unclear.

To address this gap, the present study evaluates the economic relevance of autonomous field robots using a cost-benefit modelling framework based on real-world farm data. The analysis draws on two commercial farms in the Osnabrück district of Lower Saxony, Germany, focusing on maize production. It combines scenario-based modelling of robotic field operations with experimentally derived data on logistical processes. The modelling framework is parameterised using data obtained from field applications of an AgBot 2.055W4 autonomous field robot. Unlike previous studies based on the same dataset, which focused on operational costs and their determinants, the present analysis relates robot-related costs and automation benefits to the overall economic scale of maize production. By analysing robot-related costs, automation benefits, and supervision-related labour effects, the study examines how structural field characteristics and operational conditions influence the economic performance of robotic field operations.

Accordingly, the study addresses the following research questions:

1. How large are the economic effects of autonomous field robot deployment under different supervision conditions?
2. How do structural field characteristics and logistical conditions affect the economic performance of autonomous field robot operations?
3. How economically relevant are automation benefits and robot-related costs relative to the overall economic scale of maize production?

Study area, farms and robotic system

The analysis presented in this study was conducted within the publicly funded research project Experimentierfeld Agro-Nordwest (2020–2024), which examined various digital and robotic systems in agricultural practice (Scholz et al. 2022, Reuter et al. 2023, Jorissen et al. 2025a, Jorissen et al. 2025b, Reuter et al. 2025). The empirical results used in the present analysis are partly derived from autonomous field robot experiments carried out in 2024 (Jorissen et al. 2025a). The study draws on data collected from two commercial farms located in the Osnabrück district of Lower Saxony in northwestern Germany. Both farms operate conventional arable production systems and cultivate maize for silage and grain production.

Within the Agro-Nordwest project, different AgBot platforms developed by AgXeed were tested in 2024 across several crops and field applications, including arable and grassland systems. These included the four-wheeled AgBot 2.055W4 and the tracked AgBot 5.115T2 platforms. Field tests in 2024 included three maize production operations: power harrowing, maize planting, and robotic interrow hoeing. In addition, agronomic field experiments were conducted specifically for the interrow hoeing operation to evaluate its agronomic effects (Reuter et al. 2025).

For the present analysis, the four-wheeled AgBot 2.055W4, equipped with a 55 kW diesel engine, serves as the basis for modelling robotic field operations. The dataset combines modelled fieldwork times with empirically observed logistical processes derived from previous field studies with the AgBot system (Jorissen et al. 2025b, Jorissen et al. 2025a). The analysis is based on a hypothetical machinery cooperation between the two farms, allowing the integration of field-level operations across a heterogeneous set of fields. The smaller farm, Langsenkamp Farm (LaFarm), cultivates 36 ha of maize across nine fields, whereas the larger farm, Westrup-Koch Farm (WKFarm), cultivates 242 ha across 52 maize fields. The farms differ in their production systems, with grain maize grown on LaFarm and silage maize on WKFarm, resulting in a diverse range of field structures and operational conditions considered in the analysis (Jorissen et al. 2025a).

Scenario design and system boundaries

The economic analysis considers the complete maize production process from soil preparation to harvest. The maize production chain was defined based on farm management practices observed on the two participating farms and aligned with standardised management systems outlined in the guidelines provided by the Kuratorium für Technik und Bauwesen in der Landwirtschaft (KTBL) (Kuratorium für Technik und Bauwesen in der Landwirtschaft 2026b). This approach ensures that the scenario reflects both practical farming conditions and established reference systems commonly used in agricultural economic analyses.

The exact management operations vary between the two farms depending on site-specific conditions such as soil type, field slope, and other agronomic factors. However, maize cultivation on both farms is predominantly carried out under reduced tillage systems without ploughing, combined with organic base fertilisation and chemical crop protection. For modelling purposes, a standardised management approach was assumed across all fields to ensure consistency and comparability of results (Table 1).

Table 1: Maize production operations considered in the scenario and corresponding machinery systems

Production stage	Field operation	Typical machinery system	Grain maize (LaFarm)	Silage maize (WKFarm)	Robotic operation considered
Primary tillage	Deep cultivation	Tractor (120 kW) + cultivator (3 m)	✓	✓	No
Soil preparation	Power harrowing	AgBot (55 kW) + power harrow (3 m)	✓	✓	Yes (robotic implementation)
Sowing	Maize planting	AgBot (55 kW) + maize planter (3 m)	✓	✓	Yes (robotic implementation)
Fertilisation	Slurry application	Tractor (120 kW) + drag hose (150 m)	✓	✓	No
Fertilisation	Mineral fertilisation	Tractor (83 kW) + fertiliser spreader (24 m)	✓	✓	No
Weed control	Interrow hoeing	AgBot (55 kW) + row-crop hoe (3 m)	✓	✓	Yes (robotic implementation)
Inter-field robot transport	Transport between fields	Tractor (121 kW) + low-loader	✓	✓	Yes (support operation)
Harvest	Grain maize harvesting	Combine harvester (275 kW) + transport (83 kW)	✓	–	No
Harvest	Silage maize harvesting	Self-propelled forage harvester (275 kW) + transport (83 kW)	–	✓	No
Soil preparation	Stubble cultivation	Tractor (120 kW) + cultivator (3 m)	✓	✓	No

Based on operational experience from the Agro-Nordwest project, three maize production operations were selected as representative use cases for robotic field deployment: power harrowing, maize planting, and interrow hoeing. For the hoeing operation, two passes per growing season were assumed, reflecting common agronomic practice and experimental findings (Reuter et al. 2025). All other operations, including primary tillage, fertilisation, and harvesting, were assumed to be carried out using conventional machinery. Mechanical weed control using the robotic interrow hoe therefore represents a deliberate deviation from the otherwise chemically based weed management typically applied on the farms.

Maize fields were organised into logistical routes representing the daily deployment of machinery across neighbouring fields. This routing concept, developed in previous field studies (Jorissen et al. 2025a, Jorissen and Recke 2026), is incorporated into the modelling of both robotic and conventional field operations. The robot was transported between fields using a low-loader pulled by a conventional 121 kW tractor, reflecting the current logistical requirements for autonomous field platforms under practical conditions. During field operations, the low-loader remained at the field edge while the robot performed its tasks autonomously. For the analysed operations, the robotic system was assumed to operate with implements of 3 m working width, corresponding to the equipment used during the experimental field tests (Reuter et al. 2025).

Analytical framework

The objective of the analysis is to assess the economic relevance of robotic field operations within the maize production systems of the analysed farms. To contextualise the magnitude of automation effects, the results are related to the KTBL indicator Direkt- und arbeitserledigungskostenfreie Leistung (DAL) (Kuratorium für Technik und Bauwesen in der Landwirtschaft 2026a), here translated as output excluding direct and work execution costs. According to KTBL guidelines, DAL is defined as the difference between production revenues and the sum of direct input costs and work execution costs:

$$DAL = R - (DC + WEC) \qquad \text{(Eq. 1)}$$

where R denotes production revenues, DC denotes direct input costs, and WEC denotes work execution costs. Production revenues represent the economic value of the harvested crop and are calculated as crop yield multiplied by the corresponding market price. Direct input costs include expenses for inputs such as seed and fertiliser. Work execution costs include expenses associated with field operations, in particular machinery, labour, and fuel.

In the present analysis, DAL does not represent the full cost base of maize production, as it excludes those field operations that are explicitly modelled within the robotic system. Instead, it serves as a consistent partial cost-based reference for the analysed production system. This specification ensures that DAL provides a stable baseline for comparing automation effects across scenarios while avoiding double counting of the modelled operations and keeping the reference independent of the robotic cost components.

The net costs of robotic field operations are calculated as the difference between the costs associated with the deployment of the robotic system and the economic benefit generated by automation:

$$NC(SL) = C_{robot}(SL) - B_{automation}(SL) \qquad \text{(Eq. 2)}$$

where NC denotes the net costs of robotic field operations, C_{robot} denotes the costs associated with the deployment of the robotic system, and $B_{automation}$ denotes the economic benefit generated by automation.

NC does not represent a fully incremental cost comparison with a conventional reference system, as the costs of replaced conventional field operations are not deducted. Accordingly, NC should be interpreted as an indicator of the economic burden associated with robotic field operations under different supervision scenarios rather than as a replacement-cost comparison with conventional field operations.

Both automation benefits and robot-related costs depend on the assumed supervision level (SL), which describes the share of working time during which the operator supervises the robot. A supervision level of SL = 0 represents robot operation without supervision, whereas SL = 1 represents full supervision during the entire robotic field operation.

The supervision level determines the allocation of operator labour between robot supervision and alternative on-farm activities. Increasing supervision levels raise labour costs associated with operator presence during robotic field work, as a larger share of the operation requires direct human supervision. Conversely, lower supervision levels free up operator labour that can be used for productive on-farm activities. The economic value generated by this reallocated labour constitutes the automation benefit ($B_{automation}$).

When the supervision level is below 100 %, the operator is assumed to return to the farm and perform productive farm work during autonomous operation of the robot. In this case, additional transport between the field and the farm may occur. The associated return transport generates additional machinery, fuel, and labour costs and is therefore included in the calculation of robot-related costs. At a supervision level of SL = 1, the operator remains with the robot in the field and no additional return transport occurs.

Given the still limited empirical evidence on supervision requirements and disturbance-related labour demands under commercial farming conditions (Spykman et al. 2026), supervision levels are represented as predefined scenarios (Lowenberg-Deboer et al. 2021a, Ørum et al. 2023, Maritan et al. 2023). The supervision level therefore represents an aggregated measure of operator labour commitment associated with robot operation rather than an explicit representation of individual disturbance events or intervention processes. Automation benefits are assumed to decrease proportionally with increasing supervision levels, reflecting the assumption that the amount of operator labour available for alternative productive farm activities declines proportionally as supervision requirements increase.

To assess the economic relevance of robotic field operations within the maize production system, net costs are related to DAL as a measure of the economic scale of maize production:

$$\text{Relevance} = NC/DAL \qquad \text{(Eq. 3)}$$

Given the partial definition of DAL, this ratio reflects the relative magnitude of net costs relative to a subset of production activities rather than the full cost structure of maize production. Nevertheless, it provides a meaningful indicator for comparing the economic relevance of robotic field operations across supervision scenarios.

In addition to the cost-based relevance indicator, automation effects are also expressed relative to production revenues (B/R) and DAL (B/DAL). The ratio B/R represents the share of automation benefits in total production value and allows comparison with overall economic output. The ratio B/DAL relates automation benefits to the same partial cost-based reference used in the NC/DAL indicator. Given the definition of DAL, this ratio reflects the relative magnitude of benefits within a subset of production activities rather than the full cost structure.

Data basis

The economic assessment is based on a set of standardised economic assumptions and machinery cost parameters relating to labour, fuel, capital costs, depreciation, repair requirements, and machinery utilisation (Table 2). The underlying working time, logistics, and cost parameters are based on previous AgBot deployment studies conducted within the Agro-Nordwest project and documented in earlier publications (Jorissen et al. 2025b, Jorissen et al. 2025a, Jorissen and Recke 2026). Machine costs were calculated according to the KTBL full-cost framework, which determines hourly machinery rates based on investment costs, depreciation, interest, maintenance, repair requirements, and insurance (Kuratorium für Technik und Bauwesen in der Landwirtschaft 2025). Diesel prices, labour rates, and implement-specific fuel consumption values were derived from KTBL Feldarbeitsrechner reference tables (Kuratorium für Technik und Bauwesen in der Landwirtschaft 2026a).

Table 2: Economic and machinery cost parameters applied in the modelling framework

Parameter	Value
Labour rate (€/h)	21.50
Diesel price (€/l)	1.15
Interest rate	3.0 %
Residual value of the field robot, tractor, implements, and low loader	20 % of the purchase price
Repair cost ratio of the field robot, tractor and low-loader	4.0 % of the purchase price
Repair cost ratio of the implements	2.5 % of the purchase price
Service life of the machines (a)	12
Annual machinery costs: AgBot (€/a)	25,293
Annual machinery costs: Power harrow (€/a)	2,682
Annual machinery costs: Maize planter (€/a)	3,197
Annual machinery costs: Inter-row-hoe (€/a)	4,508
Annual machinery costs: Low-loader (€/a)	5,245
Annual machinery costs: 121-kW tractor (€/a)	18,340

For the estimation of baseline work execution costs of conventional field operations, the KTBL Feldarbeitsrechner was applied using structural field parameters derived from the study farms. In particular, the total maize area processed within a route was used as the reference field size parameter, while the average farm-to-field distance was used as the reference for transport distances. This approach reflects the operational organisation observed during AgBot deployments, where several neighbouring fields are processed consecutively within a single working cycle (Jorissen et al. 2025a). Investment costs for the AgBot platform, tractors, implements, and the low-loader were obtained from manufacturers, suppliers, and the KTBL database (Jorissen et al. 2025a, Kuratorium für Technik und Bauwesen in der Landwirtschaft 2025).

Machinery utilisation levels were derived from the maize area cultivated across both farms and the assumed deployment structure of field operations (Table 3). The resulting annual utilisation rates form the basis for the calculation of machinery hourly rates. This ensures a realistic annual utilisation of the robotic system and associated machinery under the given operational conditions. In contrast, the annual utilisation of the 121-kW tractor was based on KTBL reference values, reflecting its use in additional farm operations beyond low-loader transport. Detailed parameterisation follows previous studies (Jorissen et al. 2025a, Jorissen et al. 2025b).

Table 3: Annual utilisation of machinery components within the analysed machinery cooperation

Machinery component	Annual utilisation (h/a)
Field robot (AgBot 2.055W4)	779
Power harrow / maize planter	195
Inter-row hoe	390
Low-loader	78
121-kW tractor	833

Crop yields were derived from official agricultural statistics for the district of Osnabrück for the year 2024 (Landesamt für Statistik Nds. 2025), as systematic yield measurements were not available for all individual maize fields included in the dataset. Using regional average yields ensures a consistent basis for estimating production revenues across all fields (Table 4). This assumption is supported by agronomic field experiments on robotic interrow hoeing conducted within the Agro-Nordwest project, which indicate no statistically significant yield differences compared with conventional mechanical weed control (Reuter et al. 2025).

Table 4: Assumed crop yields and price levels used in the economic analysis

Parameter	Grain maize	Silage maize
Yield (dt/ha)	109.3	514.1
Price (€/dt)	19.31	3.80

Market prices were obtained from the KTBL database, using data for the Weser–Ems region (Kuratorium für Technik und Bauwesen in der Landwirtschaft 2026c). While grain maize prices are well documented, silage maize is predominantly used as on-farm feed and therefore lacks clearly defined market prices. Alternative approaches could derive implicit price equivalents from feed energy or protein content relative to other feed commodities. However, such approaches introduce additional assumptions and were therefore not applied.

Structural characteristics of maize fields and logistical routes

Overall, maize fields on WKFarm are larger on average (5.5 ha) than those on LaFarm (4.0 ha), while the number of fields grouped within each logistical route is comparable between the two farms (4.3–4.5 fields per route) (Table 5). As a result, the average route size is similar across both production systems (18.4–20.1 ha), reflecting the route-based organisation of machinery deployment across neighbouring fields.

Table 5: Structural characteristics of maize fields and logistical routes

Variable	Unit	LaFarm (Mean ± SD)	WKFarm (Mean ± SD)
Field size	ha	4.0 ± 1.0	5.5 ± 2.7
Number of fields per route	–	4.5 ± 0.7	4.3 ± 1.9
Route size	ha	18.4 ± 7.2	20.1 ± 2.3
Route length	km	15.8 ± 1.8	10.3 ± 9.7
Farm–field distance	km	4.6 ± 2.3	7.4 ± 6.2

Differences between the farms become more apparent when considering the spatial distances involved in field operations. Routes on LaFarm are on average longer (15.8 km) than those on WKFarm (10.3 km), while the average farm–field distance is greater for WKFarm (7.4 km) than for LaFarm (4.6 km). These patterns indicate a more spatially clustered organisation of maize fields on WKFarm, whereas fields on LaFarm are more dispersed. At the same time, fields on LaFarm are located closer to the farm on average, resulting in shorter farm–field distances despite longer route lengths.

WKFarm exhibits greater variability in route length and farm–field distance, reflecting greater spatial heterogeneity, mainly due to the spatial structure of WKFarm. Some routes are located directly around the farm, while others are situated considerably farther away. In contrast, routes on LaFarm are located closer to the farm and exhibit a more homogeneous structure. Compared with WKFarm, route sizes on LaFarm show greater variability, mainly due to route planning. While one route on LaFarm approximates the assumed daily operational capacity of about 20 ha, the second route remains smaller because the available maize area falls short of this target capacity.

Economic baseline of maize production

Revenues and direct input costs are constant across all maize fields, because field-specific yield and input data were not available for the 61 fields included in the analysis (Table 6). Consequently, no variation occurs in these indicators across routes. In contrast, work execution costs vary between routes, as they depend on structural characteristics such as field size, route length, and the distance between farms and fields. The reported standard deviations therefore reflect the spatial heterogeneity of field structures and logistical conditions.

Overall, grain maize production on LaFarm exhibits comparatively low and homogeneous work execution costs, resulting in a higher DAL per hectare (1,188 €/ha). In contrast, silage maize production on WKFarm shows substantially higher and more variable work execution costs, leading to a lower average DAL (550 €/ha). The higher direct input costs on WKFarm are mainly related to increased fertilisation costs, while higher work execution costs are largely driven by more cost-intensive harvesting operations associated with silage maize production. In addition, the greater variability in work execution costs reflects the more heterogeneous spatial distribution of maize fields on WKFarm and the associated logistical requirements.

Table 6: Economic baseline indicators of maize production (LaFarm = grain maize and WKFarm = silage maize)

Economic indicator	LaFarm (Mean ± SD)	WKFarm (Mean ± SD)
Revenues (R)	2,111 ± 0	1,954 ± 0
Direct costs (DC)	398 ± 0	574 ± 0
Work execution costs (WEC)	524 ± 15	830 ± 172
DAL	1,188 ± 15	550 ± 172

Cost and benefit components of robotic field operations across supervision levels

Across all supervision scenarios, robotic deployment leads to positive net costs on both farms, indicating that the automation benefits remain insufficient to offset the additional robot-related costs (Table 7). Net costs increase substantially with rising supervision levels. At low supervision levels (SL = 0), the average net costs amount to approximately 174 €/ha on LaFarm and 141 €/ha on WKFarm. As the supervision level increases, net costs rise steadily and reach their highest values at intermediate supervision levels, peaking at around 266 €/ha on LaFarm and 229 €/ha on WKFarm at SL = 75 %. At full supervision (SL = 1), net costs decline again to approximately 208 €/ha on LaFarm and 184 €/ha on WKFarm, as the operator remains on-site and no additional return transport between farm and field is required.

Table 7: Automation effects under different supervision levels at farm level (€/ha)

Supervision level (SL)	Indicator	LaFarm (Mean ± SD)	WKFarm (Mean ± SD)
0 %	C_{robot}	233.88 ± 37.57	197.88 ± 29.34
	$B_{automation}$	60.03 ± 2.13	56.42 ± 4.68
	NC	173.85 ± 35.40	141.46 ± 30.54
10 %	C_{robot}	240.11 ± 37.88	203.86 ± 29.55
	$B_{automation}$	54.03 ± 1.96	50.77 ± 4.22
	NC	186.08 ± 35.92	153.09 ± 30.54
25 %	C_{robot}	249.46 ± 38.33	212.84 ± 29.87
	$B_{automation}$	45.02 ± 1.63	42.31 ± 3.51
	NC	204.44 ± 36.70	170.53 ± 30.59
50 %	C_{robot}	265.05 ± 39.09	227.80 ± 30.43
	$B_{automation}$	30.02 ± 1.09	28.21 ± 2.34
	NC	235.04 ± 38.00	199.59 ± 30.79
75 %	C_{robot}	280.64 ± 39.85	242.76 ± 31.02
	$B_{automation}$	15.01 ± 0.54	14.10 ± 1.17
	NC	265.63 ± 39.31	228.65 ± 31.14
100 %	C_{robot}	207.80 ± 22.15	183.74 ± 16.05
	$B_{automation}$	0.00 ± 0.00	0.00 ± 0.00
	NC	207.80 ± 22.15	183.74 ± 16.05

Notes: C_{robot} = robot-related costs; $B_{automation}$ = automation benefit; NC = net costs.

This pattern results from two opposing effects. Higher supervision levels increase labour costs associated with operator presence during field operations. At the same time, they reduce the amount of labour that can be reallocated to productive on-farm activities, thereby lowering automation benefits. As a result, net costs increase with supervision level as the gap between robot-related costs and automation benefits widens. This pattern reverses at full supervision (SL = 1), where net costs decline again. At this level, the operator remains in the field and no additional transport between farm and field occurs. The absence of these return trips reduces logistical costs, explaining the lower net costs compared with intermediate supervision levels.

Across all supervision scenarios, robot-related costs are consistently higher on LaFarm than on WKFarm, resulting in higher net costs on LaFarm. This difference is mainly related to structural characteristics of the production systems. On LaFarm, smaller field sizes and lower route capacities reduce operational efficiency and increase fieldwork costs per hectare. In contrast, automation benefits differ only slightly between the two farms and are marginally higher on LaFarm. This is primarily due to shorter farm–field distances, which allow the operator to return more quickly to the farm. Consequently, differences in net costs are mainly driven by the cost structure rather than by automation benefits.

Net costs within the machinery cooperation across different supervision levels indicate a clear non-linear relationship between supervision requirements and economic performance (Figure 1). Under the SL = 0 scenario, automation benefits amount to about 57 €/ha, while robot-related costs reach approximately 203 €/ha, resulting in net costs of around 146 €/ha. Although the lowest net costs are observed at SL = 0, increases remain comparatively moderate at low supervision levels (SL = 0.10–0.25), but become substantially stronger at higher supervision levels. Net costs reach their highest levels at intermediate supervision levels, with values of approximately 205–234 €/ha at SL = 0.50–0.75. At full supervision (SL = 1), net costs decline again to about 187 €/ha, as no additional return transport between farm and field occurs. Overall, the results indicate that intermediate supervision levels lead to particularly high net costs, as declining automation benefits are outweighed by increasing robot-related costs.

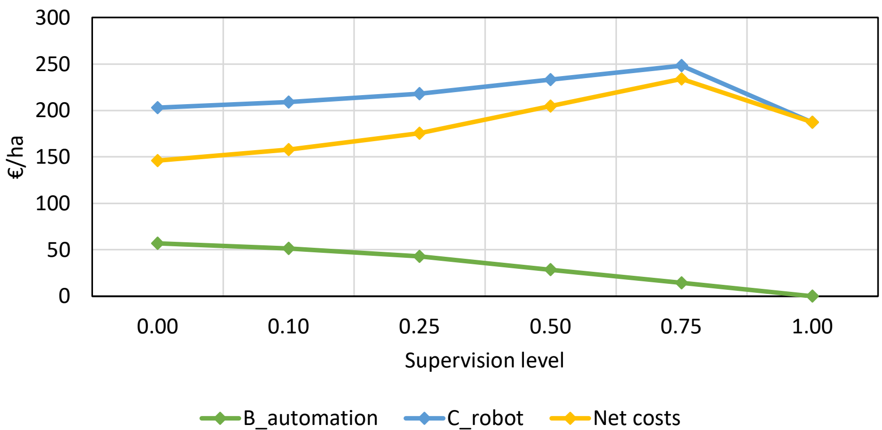

Figure 1: Automation effects under different supervision levels at machinery cooperation level (€/ha)

Relative economic relevance of robotic field operations across supervision levels

The results indicate that the automation benefits represent only a small share of the economic margin of maize production on both farms (Table 8). Under the SL = 0 scenario, the automation benefit corresponds to 5.1 % of DAL on LaFarm and 11.3 % on WKFarm. With increasing supervision level, this share declines steadily as a larger proportion of operator labour must be allocated to supervising the robot rather than performing alternative productive farm activities. At higher supervision levels (SL = 0.75), the relative automation benefit decreases to about 1.3 % of DAL on LaFarm and 2.8 % on WKFarm, before reaching zero under full supervision (SL = 1), where the operator remains on-site and no additional return transport between farm and field is required.

Table 8: Economic relevance indicators under different supervision levels at farm level

Supervision level (SL)	Indicator	LaFarm (Mean ± SD)	WKFarm (Mean ± SD)
0 %	B/DAL	5.1 ± 0.2	11.3 ± 3.7
	NC/DAL	14.7 ± 3.2	30.7 ± 17.7
	B/R	2.8 ± 0.1	2.9 ± 0.2
10 %	B/DAL	4.5 ± 0.2	10.2 ± 3.4
	NC/DAL	15.7 ± 3.2	33.0 ± 18.6
	B/R	2.6 ± 0.1	2.6 ± 0.2
25 %	B/DAL	3.8 ± 0.2	8.5 ± 2.8
	NC/DAL	17.2 ± 3.3	36.6 ± 19.8
	B/R	2.1 ± 0.1	2.2 ± 0.2
50 %	B/DAL	2.5 ± 0.1	5.7 ± 1.9
	NC/DAL	19.8 ± 3.4	42.4 ± 21.9
	B/R	1.4 ± 0.1	1.4 ± 0.1
75 %	B/DAL	1.3 ± 0.1	2.8 ± 0.9
	NC/DAL	22.4 ± 3.6	48.3 ± 24.0
	B/R	0.7 ± < 0.1	0.7 ± 0.1
100 %	B/DAL	0.0 ± 0.0	0.0 ± 0.0
	NC/DAL	17.5 ± 2.1	38.1 ± 16.7
	B/R	0.0 ± 0.0	0.0 ± 0.0

In contrast, net costs represent a substantially larger share of DAL. Depending on the supervision level, net costs amount to 15.7–22.4 % of DAL on LaFarm and 30.7–48.3 % on WKFarm. The highest relative cost burden occurs at higher intermediate supervision levels, roughly between SL = 0.50 and SL = 0.75. This reflects the combination of declining automation benefits and increasing robot-related labour and logistical costs. At full supervision (SL = 1), relative net costs decline again to 17.5 % of DAL on LaFarm and 38.1 % on WKFarm, as the operator remains in the field and no additional return transport between farm and field occurs.

The automation benefit represents only a very small share of total production revenues. Under the SL = 0 scenario, the benefit corresponds to 2.8–2.9 % of revenues on both farms and decreases further as supervision levels increase. This indicates that the economic value generated by automation remains small relative to overall maize production value.

Relative values are consistently higher on WKFarm than on LaFarm. This difference is mainly explained by the lower DAL observed for silage maize production compared with grain maize, which increases the relative magnitude of both automation benefits and net costs. The results for WKFarm also show substantially higher standard deviations across most supervision scenarios, reflecting the more heterogeneous field structure and associated logistical conditions.

For the machinery cooperation, the relative relevance indicators highlight that automation benefits remain small relative to the overall economic scale of maize production. In the SL = 0 scenario, automation benefits correspond to up to 10.4 % of DAL and 2.9 % of production revenues and decline steadily with increasing supervision levels. In contrast, net costs account for 28.4–44.6 % of DAL across the analysed supervision scenarios.

Economic implications of robot-related costs

Across all analysed supervision scenarios, robotic field operations resulted in positive net costs on both farms. This indicates that the additional costs associated with the deployment of the autonomous field robot exceed the automation benefits generated through labour reallocation. Even under the SL = 0 scenario, the automation benefit was insufficient to compensate for the relatively high machinery and logistical costs associated with the robotic system.

These findings are consistent with recent economic assessments of autonomous field robots, which report comparatively high operating costs of robotic systems compared with conventional tractor-based systems, particularly during early phases of technology deployment (Lowenberg-DeBoer et al. 2021a, Lowenberg-DeBoer et al. 2021b, Ørum et al. 2023, Spykman et al. 2023b, Jorissen et al. 2025b, Jorissen et al. 2025a). In these early stages, high investment costs and limited utilisation rates further constrain economic performance (Lowenberg-DeBoer et al. 2020).

Empirical evidence from real-world AgBot deployments shows that additional logistics requirements, such as loading, transport between fields, and coordination with support machinery, lead to measurable increases in time, fuel consumption, and overall costs (Jorissen et al. 2025b, Jorissen et al. 2025a).

Recent empirical and modelling evidence indicates that economic outcomes are highly sensitive to labour substitution assumptions and that robotic systems do not fully replace manual labour under practical conditions (Maritan et al. 2023, Spykman et al. 2023b). This is supported by empirical time-use analyses of commercial field robots, which show that a substantial share of human working time is still required for supervision and intervention, with disturbance-related activities accounting for up to 8–41 % of total labour time (Spykman et al. 2026). Beyond these operational findings, the limited availability of empirical data and the reliance on prototype-based assumptions introduce uncertainty regarding the economic performance of autonomous systems (Lowenberg-DeBoer et al. 2021a, Ørum et al. 2023).

In addition, the comparison between the two farms analysed in this study illustrates how structural field and logistical characteristics jointly shape the resulting cost levels. Robot-related costs were consistently higher on LaFarm than on WKFarm, which is mainly related to the smaller field sizes and lower route capacities observed on LaFarm. Previous research shows that field size, transport distances, and field accessibility are key determinants of cost levels and variability in autonomous operations (Al-Amin et al. 2023, Jorissen and Recke 2026). Smaller and more fragmented field structures reduce operational efficiency and increase per-hectare machinery and logistics costs. The results therefore underline the importance of field structure and logistical organisation as central determinants of the economic performance of autonomous field robots.

The role of supervision levels

The findings of this study highlight that the economic potential of autonomous field robots depends strongly on the degree of operational autonomy achievable under practical conditions. In practice, fully unsupervised robot operation is unlikely to be achievable under real-world conditions. Agricultural environments are highly variable and unstructured, often requiring at least some human involvement to ensure safe and reliable operation (Adamides and Edan 2023). This aligns with findings from the human–robot interaction literature, which highlight the challenges of fully replacing human operators and instead point towards more collaborative interaction modes (Benos et al. 2023).

Against this background, supervision becomes a central determinant of economic performance. While many economic assessments treat supervision only implicitly or in a simplified manner (Lowenberg-DeBoer et al. 2021a, Al-Amin et al. 2023), recent studies identify supervision requirements as a key determinant of economic performance (Shang et al. 2023, Strine et al. 2025). Empirical field studies further show that disturbances during autonomous operation frequently require human intervention, thereby increasing effective supervision levels and limiting the extent of truly autonomous operation under practical conditions (Spykman et al. 2023b).

Given the still limited empirical evidence on supervision requirements and disturbance-related labour demands under commercial farming conditions (Spykman et al. 2026), many economic assessments represent supervision through predefined scenarios rather than modelling individual disturbance events explicitly (Lowenberg-Deboer et al. 2021a, Ørum et al. 2023, Maritan et al. 2023). In this context, supervision should be understood as a broader concept encompassing different forms of labour involvement associated with robot operation, including monitoring, intervention, and disturbance-related activities.

Further studies support this perspective by showing that economically optimal supervision levels are typically found within intermediate ranges rather than at full autonomy, with reported optima varying substantially across operational scenarios, for example between approximately 0.13 and 0.85 of field time (Maritan et al. 2023). This is consistent with other studies that consider multiple supervision scenarios and demonstrate the strong sensitivity of economic outcomes to varying levels of human involvement (Ørum et al. 2023, Strine et al. 2025).

The results of this study partly align with these findings, but also highlight additional complexities. While the lowest net costs are observed under the SL = 0 scenario, this level of operator-free robot operation is unlikely to be achievable under practical conditions. Instead, a low supervision range of approximately SL = 0.10–0.25 appears to be the most economically plausible under realistic operating conditions, as cost increases remain comparatively moderate within this range. This pattern is consistent across both absolute cost measures and relative economic indicators, which show a disproportionate increase in cost burden beyond this range. At higher supervision levels, costs increase disproportionately due to rising labour requirements and additional logistical effort. At full supervision, costs decrease again, reflecting reduced logistical complexity when the operator remains on-site.

Influence of field structure and logistics

The comparison between the two farms highlights the importance of structural and logistical factors in shaping the economic outcomes of robotic field operations. Robot-related costs were higher on LaFarm, mainly due to the smaller field sizes and lower route capacities, which reduced operational efficiency. In contrast, automation benefits were similar across both farms and only slightly higher on LaFarm due to shorter farm–field distances. The higher variability observed for WKFarm reflects its more heterogeneous field structure. Routes are located at varying distances from the farm, leading to greater variation in transport requirements and operational costs. Such heterogeneity is likely to be common in real-world farming systems and should be considered in economic assessments of autonomous agricultural technologies. This is in line with recent studies emphasising that real-world farm structures are often spatially heterogeneous, and that this variability can significantly affect the performance and economic viability of robotic systems (Al-Amin et al. 2023, Ørum et al. 2023).

These findings confirm previous studies showing that field size, route composition, and transport distances are key determinants of the economic performance of autonomous machinery systems (Lowenberg-DeBoer et al. 2021a, Al-Amin et al. 2023, Jorissen et al. 2025a, Jorissen and Recke 2026). More generally, these effects can be explained by established relationships between field structure and operational efficiency in conventional agricultural machinery systems. Field shape and size influence turning time and field efficiency. More complex field conditions require additional manoeuvring, which reduces operational efficiency and ultimately affects machinery performance (Grisso et al. 2004, Griffel et al. 2020).

Field robot deployments often involve additional transport steps and coordination with supporting machinery, such as low-loaders used for transport between fields (Jorissen et al. 2025b, Jorissen et al. 2025a, Jorissen and Recke 2026). This is consistent with studies on conventional agricultural routing and fleet coordination, which show that inefficient path allocation and vehicle routing can substantially increase field completion time (Seyyedhasani and Dvorak 2017, 2018). Studies on agricultural path planning and machine coordination further show that inefficient routing and transport processes can increase idle times of primary machinery (Jensen et al. 2012).

Economic relevance of robotic field operations

Automation benefits correspond to about 11 % of DAL under the SL = 0 scenario and decline to around 8 % at moderate supervision levels (SL ≈ 0.25). Beyond this range, increasing supervision leads to disproportionately higher labour and logistical costs, so that intermittent supervision becomes less efficient and continuous on-site supervision (SL = 1) may be economically preferable. When expressed relative to production revenues, automation benefits amount to around 3 %.

The economic relevance of automation benefits is small when compared to farm-level accounting data for an average German farm. Production revenues amount to approximately 5,410 €/ha, with average profits of around 991 €/ha and a return on sales of about 6.4 % (Bundesministerium für Landwirtschaft, Ernährung und Heimat 2025). A similar pattern emerges when considering public payments for German farms, which amount to approximately 394 €/ha and account for around 8.4 % of production revenues and approximately 35.9 % of farm income on average.

On average, net costs account for approximately 28–45 % of DAL across the analysed scenarios within the assumed machinery cooperation. Relating net costs to DAL positions robot-induced costs within the economic scale of maize production and provides a clear interpretation of their magnitude. In this context, NC/DAL is particularly sensitive to key operational parameters such as supervision level, field structure, and logistical conditions, enabling a differentiated assessment across scenarios. These ratios require careful interpretation, as DAL represents only a partial cost-based reference and excludes field operations covered by the robotic system, such as power harrowing, planting, and hoeing.

From a farm management perspective, the direct economic effects of autonomous field robots remain modest relative to the overall value generated per hectare. Economic studies primarily focus on cost and efficiency aspects of robotic deployment (Lowenberg-DeBoer et al. 2021a, Lowenberg-DeBoer et al. 2021b). However, adoption decisions are unlikely to be driven solely by short-term operating cost considerations. Empirical evidence from early adopters shows that structural, organisational, and operational factors also play a key role (Spykman et al. 2021, Spykman et al. 2023a).

Conclusions

This study shows that the economic relevance of autonomous field robots in maize production is primarily determined by the interaction of supervision level, field structure, and logistical conditions. While robotic field operations generate measurable automation benefits, they remain limited relative to the overall economic scale of maize production. Even under the SL = 0 scenario, automation benefits remain modest, whereas robot-related costs constitute a substantially larger economic burden.

Although the SL = 0 scenario yields the lowest net costs, a low supervision range (SL ≈ 0.10–0.25) represents the most economically plausible operating range under practical conditions. Beyond this range, increasing supervision leads to disproportionately higher labour and logistical costs, while the potential for labour reallocation declines rapidly. This highlights that economic viability depends on the ability to operate within a narrow range of low supervision levels that are both technically feasible and practically achievable under real-world conditions.

These findings suggest that adoption decisions are unlikely to be driven solely by short-term cost considerations. Instead, factors such as labour availability and organisational conditions are likely to play a central role in determining the practical relevance of robotic technologies. In this context, autonomous systems should be understood as part of broader farm management strategies rather than as purely cost-saving technologies.

The analysis is subject to certain limitations related to the modelling approach. Field operations of the robotic system were represented using supervision-level-based scenarios rather than empirical time-use data, which may not fully capture the variability of real-world operating conditions. Future research should therefore incorporate empirical time-use data from real-world deployments and further investigate the interaction between supervision requirements and economic performance.

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Acknowledgements

This research was conducted within the project Experimentierfeld Agro-Nordwest, funded by the Federal Ministry of Food and Agriculture (BMEL), Germany, and administered by the Federal Office for Agriculture and Food (BLE) under grant number 28DE103D22.