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Received: 20 June 2025 | Accepted: 27 October 2025

DOI: 10.1002/agj2.70246

Agronomy Journal

ORIGINAL ARTICLE

Crop Economics, Production, and Management

An economic, environmental, and social analysis of autonomous mechanical weeding in sugar beet farming

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Assigned to Associate Editor Takashi Tanaka.

Funding information
Innovate UK, Grant/Award Number: 10037994; HORIZON EUROPE Food, Bioeconomy, Natural Resources, Agriculture and Environment, Grant/Award Number: 101060759; Bayerisches Staatsministerium für Ernährung, Landwirtschaft und Forsten, Grant/Award Numbers: A/21/17, A/24/07

Abstract

Weeding robots are expected to decrease herbicide use on conventional farms and reduce manual labor on organic farms. A multi-objective linear programming model was used to compare the economic, environmental, and social performance of robotic and non-robotic weed control in conventional and organic sugar beet (*Beta vulgaris* L.) production in Bavaria, Germany. On the conventional farm, the weeding robot generated a mean gross return of €58,612 year^{-1} compared to €57,728 year^{-1} when using herbicide spraying. However, the mean return on total costs for the weeding robot was negative (€−2750 year^{-1}) and substantially lower than the €8663 year^{-1} achieved with herbicide spraying. In organic farming, this technology was more profitable than non-robotic mechanical weeding, generating a mean gross return of €73,098 year^{-1} and a mean return on total costs of €10,373 year^{-1}. The corresponding figures for non-robotic mechanical weeding were € 59,176 and €7,577 year^{-1}. The carbon emission intensity of sugar beet was comparable between weed control strategies on the conventional farm and marginally lower for robotic weeding on the organic farm. On both farms, autonomous mechanical weeding used more skilled labor due to routine supervision, field-to-field transport, and human intervention requirements. Higher skilled labor time with robotics negatively affected farmers' work–life balance. Investment cost, supervision and human intervention requirements, technology specialization, and logistics of field operations were identified as the main barriers to adoption of the tested weeding robot. These barriers should be prioritized when developing future autonomous farm equipment.

Abbreviations: AWU, agricultural work unit; BaySL Digital, Bavarian Special Digital Agriculture Program; CAP, Common Agricultural Policy; CEI, carbon emission intensity; CFT, cool farm tool; EU, European Union; FD20, FarmDroid FD20; HFH-MOLP, Hands-Free Hectare multi-objective linear programming; ROLLMRT, return on operator labor, land, management and risk taking; SO, standard output.

Plain Language Summary

This is the first study simultaneously considering economic, environmental, and social implications of autonomous mechanical weeding. It compares autonomous mechanical weeding with uniform herbicide spraying in conventional farming and non-robotic mechanical weeding in organic farming. The comparison uses farm profitability, carbon emission intensity of sugar beet production, and family labor productivity for typical Bavarian farms. Results show that the tested technology has a higher profitability than non-robotic mechanical weeding in organic sugar beet farming but a lower profitability than herbicide spraying in conventional farming. Robotic weeding has a lower beet carbon emission intensity on the organic farm, but not on the conventional farm. Family labor time increases with robotic mechanical weeding on both farms. The analysis identifies barriers to adopting autonomous mechanical weeding that are relevant to farmers, researchers, technology developers, and policymakers.

1 INTRODUCTION

Weed control practices in agriculture are confronted by challenges such as growing herbicide resistance, a declining availability of herbicide active ingredients, labor shortages, frequent market shocks, environmental impact of herbicide use, and a growing demand for food and ecosystem services (Lytridis & Pachidis, 2024; Marchand, 2023; Shang et al., 2023). These lead to conflicts among different farm-level and societal goals. In conventional farming, weeds are usually managed with herbicide spraying because of its low cost and moderate labor requirements (Griffin & Lowenberg-DeBoer, 2017). However, this practice harms off-target species, contaminates the environment, and poses threats to farm workers and food consumers (Jacquet et al., 2022; Machleb et al., 2020; Pandey et al., 2021). On the other hand, organic farming relies on energy- and labor-intensive methods because conventional herbicides are not allowed. This results in high fuel consumption, soil erosion risk, seasonal labor availability issues, and excessive workloads for farm operators (EUROSTAT, 2024; Fishkis et al., 2024; Uehleke et al., 2024). Innovative weed control technology is expected to enable a transition to sustainable farming while mitigating these challenges (European Commission, 2021; Finger, 2023; Khanna et al., 2022).

Crop robots relying on various weed control strategies have been commercialized in recent years (Future Farming, 2025). Lytridis and Pachidis (2024) divide autonomous weeding technologies into chemical and non-chemical methods, with the former including targeted herbicide spraying and the latter being most frequently represented by mechanical and laser weeding systems. These technologies mainly identify weeding areas through machine vision, though other approaches such as crop geo-referencing also exist (Lytridis & Pachidis, 2024). In Europe, a widely used weeding robot is the FarmDroid FD20 (FD20) manufactured by FarmDroid ApS (Figure 1A) (Future Farming, 2025).

The FD20 is a solar-powered machine able to autonomously sow fine-seed crops such as sugar beet (*Beta vulgaris* L.) and conduct mechanical weeding (FarmDroid, 2025). It relies on real-time kinematic global navigation satellite systems to guide operations throughout the season, including weed detection. It is equipped with six 6-L seed tanks and is capable of placing crop seeds with an accuracy of 8 mm (FarmDroid, 2025) (Figure 1B). In autonomous mechanical weeding mode, it uses weeding hoes for shallow cultivation in the inter-row area (Figure 1C), weeding knives moving in and out of crop rows to control weeds in the intra-row area (Figure 1D), and weed-cutting discs sliding on each side of the row for weeding the close-to-crop area (Figure 1E) (FarmDroid, 2025). The FD20 has also recently been equipped with an optional spot-spraying installation capable of producing spray spots of 7 cm × 7 cm, specifically designed for conventional farmers seeking to reduce herbicide use (FarmDroid, 2025) (Figure 1F). The FD20 was first commercialized as a driverless industrial truck certified under ISO 3691-4:2023 (Lowenberg-DeBoer et al., 2021a). Among other guidelines, this standard imposes a speed limit of 0.3 m s^{-1} (1.08 km h^{-1}) (ISO, 2023). Remote supervision of the FD20 in agricultural fields is now allowed under the European Union (EU) Machinery Regulation (European Commission, 2023). However, operational malfunctions (Maritan et al., 2023), transport among fields (Lowenberg-DeBoer et al., 2021a), and other factors may result in high human supervision and intervention requirements.

FIGURE 1 (A) The FarmDroid FD20 seeding and weeding robot; (B) crop seeding; (C) inter-row weeding hoes; (D) intra-row weeding knives; (E) close-to-crop weed cutting discs; (F) optional spot-spraying. Images are used courtesy of FarmDroid (2025).

The FD20 and its labor implications in German sugar beet production have previously been subject of scientific investigation (e.g., Fishkis et al., 2024; Gerhards et al., 2023; Rossmadl et al., 2023; Spykman, Kopfinger, et al., 2023; Spykman, Rossmadl, et al., 2023). However, available analyses have relied on partial budgeting methods and fixed crop calendars, thus overlooking potential labor management implications that may result from concurrent sugar beet field operations or resource competition with other crops. Additionally, some of the previous FD20 studies assumed a low number of robotic weeding passes (e.g., three and two passes per year in Fishkis et al. [2024] and Shang et al. [2023], respectively, compared to seven passes per year in Talola and Ekman [2025]). This may have underestimated the labor costs associated with this technology. Labor costs and management are of particular importance when considering that labor input reduction is one of the main drivers for adoption of crop robots in agriculture (Spykman et al., 2021; Spykman, Kopfinger, et al., 2023; Tamirat et al., 2023). Therefore, the objective of this study is to estimate the whole-farm labor implications of autonomous mechanical weeding. Besides changing farm labor costs and management, the adoption of technologies such as the FD20 may also affect crop yields. While there is consensus that using the FD20 does not reduce sugar beet yields through mechanical damage (Gerhards et al., 2023; Kopfinger & Vinzent, 2021), the low operational speeds during sowing and weeding may lead to late sugar beet planting and increased weed competition. This is especially relevant in regions where field access during sowing and weeding months is constrained by adverse weather.

From an environmental perspective, adoption of weeding robots is expected to provide benefits such as the mitigation of greenhouse gas (GHG) emissions (Lytridis & Pachidis, 2024). Fishkis et al. (2024) found that FD20 mechanical weed control generated GHG emissions comparable to herbicide broadcast spraying but lower than non-robotic mechanical weeding. Pradel et al. (2022) identified field-to-field transport distance thresholds determining whether robotic weeding in French vineyards reduced GHG emissions. The present study enriches the discussion of GHG emissions of weeding robots by also exploring farmer decisions when simultaneously considering economic and social priorities along with environmental outcomes.

This analysis quantifies farmer preferences for the studied weeding robot or conventional technologies through multi-criteria analysis. The hypotheses are that (i) the FD20 is less profitable than herbicide broadcast spraying on the conventional farm but more profitable than non-robotic mechanical weeding on the organic farm; (ii) treating weeds with the FD20 leads to a lower carbon emission intensity (CEI) of sugar beet production on both farms; and (iii) the FD20 results in a lower family labor productivity regardless of production standard. The critical evaluation of these hypotheses aims to inform farmers, researchers, technology developers, and policymakers about potential trade-offs among economic, environmental, and social goals and analyze farmer decision-making implications when adopting autonomous mechanical weeding.

2 | MATERIALS AND METHODS

2.1 | The Hands-Free Hectare multi-objective linear programming model

Multi-objective analysis integrates incommensurable assessment criteria in a single framework to provide scoring or ranking of alternative farm technologies or practices. Such frameworks are a useful tool to gauge economic, environmental, and social impacts of adopting innovative agricultural technology. Because the acceptance of these impacts may differ depending on the orientation of farmers, multiple scorings or rankings should be produced to represent differing decision-maker profiles. In multi-objective analysis, this is achieved by applying goal weights to define preferences based on the level of importance of each impact type.

This study uses the Hands-Free Hectare multi-objective linear programming (HFH-MOLP) model developed as part of the Digitalisation for Agroecology project (D4AgEcol, 2025). This model is an expansion of the single-objective Hands-Free Hectare linear programming model originally developed by Preckel et al. (2019) and adapted by Lowenberg-DeBoer et al. (2021b). It uses the goal-programming approach described in Hazell and Norton (1986, p. 72) by measuring the deviation from maximization or minimization goals specified for each criterion. The HFH-MOLP model is run in the General Algebraic Modeling System (GAMS Development Corporation, 2023). The HFH-MOLP model code is available in the Supporting Information.

The assessed farm-level goals are maximum farm gross return, minimum sugar beet CEI, and maximum family labor productivity. Three decision-maker typologies are included in this analysis. A profit-oriented farmer is assumed to only prioritize maximum farm gross return. Conversely, the environmentally and socially oriented farmers prioritize noneconomic goals while ensuring farm business viability. The environmentally oriented farmer places a weight of 30% on minimum sugar beet CEI and 70% on maximum farm gross return. The socially oriented farmer aims to optimize family labor productivity besides farm gross return and is assumed to place an importance of 30% and 70% on the social and economic goals, respectively. Farmer typologies simultaneously prioritizing economic, environmental, and social goals are not included in the analysis because they appear to be uncommon in Europe (Bartkowski et al., 2022). The three goals are further described below.

The HFH-MOLP model objective function used in this analysis is as follows:

$$\min G = w_1\left(\frac{G_1^-}{G_1}\right) + w_2\left(1 - \frac{G_2^-}{G_2}\right) + w_3\left(\frac{G_3^-}{G_3}\right) \tag{1}$$

where G is the loss of farmer utility (or satisfaction) minimized by the model by maximizing the achievement of the goals prioritized by each decision-maker typology; w_1, w_2, and w_3 are the weights respectively assigned to the economic, environmental, and social goals; $G^-{}_1$, $G^-{}_2$, and $G^-{}_3$ are variables quantifying the deviation from the goals; and G_1, G_2, and G_3 are the maximum and minimum goal values used to normalize the achievement of each goal.

2.2 | Scenarios

This analysis models a conventional and an organic farm in the German federal state of Bavaria. Farm size corresponds to the Bavarian average of 36.9 ha (StMELF, 2023a), at which a Bavarian farm has a 63% probability of being a part-time business (StMELF, 2023b). The produced crops include sugar beet (*Beta vulgaris* L.), soybean [*Glycine max* (L.) Merr.], winter wheat (*Triticum aestivum* L.), corn (*Zea mays* L.), and spring pea (*Pisum sativum* L.) plus a winter flower mix cover crop succeeding winter wheat and spring pea. These crops are arranged in two rotations typical for the case study region and characterized by different degrees of diversification. The modeled scenarios include two conventional and two organic farming systems relying on different weed control strategies for sugar beet (Table 1). On the conventional farm (Scenarios 1 and 2), the sugar beet crop is assumed to be of the Conviso Smart variety available in Germany since 2023 (LfL, 2022a). This variety is treated with two sprays of the Conviso ONE herbicide commercialized by Bayer (2022). In Scenario 2, this herbicide is applied through spot-spraying at a reduced rate per ha and complimented by eight passes of FD20 weeding. In the non-robotic organic scenario (Scenario 3), sugar beet weed control is conducted with three passes of non-robotic mechanical weeding complemented by two passes of manual weeding. In the organic FD20 scenario (Scenario 4), 13 passes of autonomous mechanical weeding are followed by one pass of low-intensity manual weeding (Kopfinger & Vinzent, 2021; Spykman, Kopfinger, et al., 2023). Crops other than sugar beet are treated with herbicides on the conventional farm and with non-robotic mechanical weeding on the organic farm.

Each scenario is analyzed for a range of field sizes to assess the effects of increased FD20 travel distances between fields.

TABLE 1 Overview of weed control strategies across scenarios.

Production standard	Scenario	Sugar beet (inter-row area)	Sugar beet (intra-row area)	Other crops (both areas)
Conventional	Scenario 1	Herbicide broadcast	Herbicide broadcast	Herbicide broadcast
	Scenario 2	Mechanical weeding (FarmDroid FD20)	Mechanical weeding + spot-spraying (FarmDroid FD20)	
Organic	Scenario 3	Mechanical weeding (tractor implement)	Mechanical weeding (tractor implement) + manual weeding	Mechanical weeding (tractor implement)
	Scenario 4	Mechanical weeding (FarmDroid FD20)	Mechanical weeding (FarmDroid FD20) + manual weeding (low intensity)	

Fields are assumed to be rectangular, of equal size, and with a width to length ratio of 1:4 (Jungwirth & Handler, 2022). The baseline number of fields is estimated from the 1.74-ha mean field size in Bavaria (Zenger & Friebe, 2015). Because average field size in Bavaria is increasing (StMELF, 2023a), the model also tests two larger field sizes. The resulting number of fields in each scenario is 20, 10 or 5. For consistency, field size in the text is referred to as number of fields. Because of the assumed fixed farm size, the number of fields is inversely related to field size, that is, a larger number of fields is to be interpreted as a smaller field size and vice versa.

2.3 | Economic goal

The economic goal is expressed as maximum annual farm gross return. This is calculated as the sum of crop commodity sales and agricultural subsidies received in a year minus variable costs. For each scenario, the whole-farm plan options include 24 rotations differentiated by land allocation pattern and crop sowing and harvest times. Half of the rotations are 4-year rotations of sugar beet, winter wheat, soybean, and winter wheat, with the two winter wheat crops being succeeded by a flower mix cover crop. The second set of rotations are 5-year rotations producing sugar beet, soybean, corn, spring pea, and winter wheat. In the 5-year rotations, winter cover is achieved by planting a flower mix after winter wheat and spring pea and by leaving stubble in the fields after corn. The more diverse 5-year crop rotation is eligible for a wider range of agricultural subsidies but results in higher operational complexity and a lower area allocated to sugar beet. The subsidy eligibility of these two rotations under the EU Common Agricultural Policy (CAP) is described in Table S1. The crop calendars used in the analysis can be requested from the authors.

Selling prices (excluding value added tax) and yields for conventional and organic crops sown and harvested at optimal times are from the "LfL Contribution Margins and Calculation Data" online application (LfL, 2024) (Table 2). Crop yields are adjusted across rotations for suboptimal sowing and harvest times and account for lower yields on field headlands based on experimental data in Ward et al. (2020). These yields may be considered conservative, representing all of Bavaria rather than only regions dominated by sugar beet production, which are usually characterized by high quality soil. Consequently, crops in these regions produce above-average yields and may lead to higher gross margins than estimated in the present study, with possible effects also on crop rotation choices. The optimal sugar beet planting period in Bavaria is the second half of March (Achilles et al., 2020). Sugar beet sown late in the first half of April is assumed to yield 10% less based on expert advice. Sugar beet harvest times occur from the second half of September to the first half of November. Yield losses for early sugar beet harvest range from 3% to 9% depending on harvest time (Association of Franconian Sugar Beet Growers, 2023).

Variable costs include manual weeding labor, fuel consumption, seed, fertilizer, lime, herbicide, fungicide, insecticide, water used in pesticide mixtures, plant growth regulators, hail insurance, and custom-hiring fees for mechanical cover crop termination, manure spreading, and crop harvesting. Annual manual weeding times are assumed to be 144 h ha^{-1} in Scenario 3 (72 h ha^{-1} pass^{-1}) (Kopfinger & Vinzent, 2021) and 21.6 h ha^{-1} in Scenario 4 (i.e., 30% of the time assumed for one pass in Scenario 3) (Spykman, Rossmadl, et al., 2023). The cost of hiring manual weeding labor is €15.74 h^{-1} (Achilles et al., 2020, p. 721). Typical for the region, four seasonal workers are assumed to be available to conduct manual weeding tasks. This assumption is further explored via sensitivity testing to assess the extent to which the FD20 may mitigate the impact of seasonal labor shortages. Fuel consumption is estimated with the online calculator developed by the Agricultural Technology and Construction Board (KTBL, 2024) and adjusted for field efficiency. The latter is estimated based on Al-Amin et al. (2023). Fuel consumption incurred during FD20 transport on public roads is estimated by multiplying the total travel distance by 0.43 L km^{-1} (Achilles et al., 2020). Fuel price is assumed at €1.62 L^{-1} based on the mean price between 2014 and 2024 in Germany (Statista, 2024). The other variable costs included depend on whether the farm is conventional or organic and are available in Table S2.

TABLE 2 Crop selling prices (€ ton^{-1}) and optimal yields (ton ha^{-1}) (LfL, 2024).

Crop	Conventional crop price	Conventional crop yield	Organic crop price	Organic crop yield
Sugar beet	47.96	82.23	90.00	50.31
Soybean	519.63	2.95	1019.17	2.65
Winter wheat	255.78	7.17	478.26	3.97
Corn	247.98	9.77	405.96	5.95
Spring pea	269.08	2.60	562.20	1.99

After optimizing for farm gross return with the HFH-MOLP model, return on total costs (i.e., including both variable and fixed costs) is also estimated to assess the impact of FD20 ownership on farm profitability. This is calculated by deducting fixed costs from farm gross return and expressed as return on operator labor, land, management, and risk taking (ROLLMRT). Fixed costs are provided in Table S3. Annual machinery costs are quantified for owned equipment based on initial investment requirements depreciated over the machinery useful lives provided in Achilles et al. (2020). This is excluding the FD20, whose useful life is assumed to be 10 years (Fishkis et al., 2024; Shang et al., 2023; Spykman, Rossmadl, et al., 2023). Because reliable useful life data for the FD20 and similar robots are not yet available, this assumption is further analyzed via sensitivity testing to explore the economic effect of a shorter useful life as a consequence of rapid technological change or intensive use of the robot. Based on personal communication with the FD20 dealer in southern Germany in August 2024, the purchase price of the FD20 is assumed to be €89,000 for the basic robotic system plus €5,800 for a power bank. The latter is to ensure that the FD20 is able to work for up to 18 h day^{-1} throughout the season. In Scenario 2, the FD20 is equipped with a spot-spraying system requiring an additional investment of €9,000. In the FD20 scenarios, €4,500 are also needed for purchasing a low-bed trailer for public road transport. The assumed FD20 investment costs are further explored in a sensitivity analysis to assess the effects of purchase subsidy schemes such as the Bavarian Special Digital Agriculture Program (BaySL Digital) (StMELF, 2024).

Lastly, sugar beet production costs with allocated opportunity cost of family labor are calculated to assess the economic impact of unpaid family labor time. The farm operator is assumed to be employed off-farm part-time and to work a maximum of 1,150 h $year^{-1}$ (i.e., 144 person-day $year^{-1}$) (LfL, 2022b) (one person-day = 8 h). An additional family member is assumed to be available for the same amount of time for support during peak times. Opportunity cost of family labor is estimated by multiplying the €21 h^{-1} permanent farm employee wage in Germany (Achilles et al., 2020, p. 720) by the number of hours worked in a year plus a 20% additional compensation for marketing and management (Lowenberg-DeBoer et al., 2021b). Acquisition and management of seasonal workers as well as FD20 field setup times are assumed to be remunerated through this additional compensation. Modeling assumptions related to labor and machine times are available in Table S4 for the FD20 and in Table S5 for conventional tractor implements.

2.4 | Environmental goal

The CEI of sugar beet production is estimated via the cool farm tool (CFT) (Cool Farm Alliance, 2024a, 2024b) and expressed in kgCO_2eq per ton of sugar beet produced. The CFT uses Tier 1 and Tier 2 methods developed by the United Nations Intergovernmental Panel on Climate Change for a wide range of agricultural outputs (Cool Farm Alliance, 2024b). The CFT accounts for GHG emissions generated by fertilizer production and use, pesticide use, lime application, machinery fuel and electricity consumption, and crop residue production and management. Unlike methodologies such as life cycle assessments, the CFT does not account for GHGs emitted during manufacturing of farm equipment. Hence, the sugar beet CEI values estimated in this study are to be interpreted as an underestimation in all scenarios because they refer to only a part of the crop life cycle. CFT input values are provided in Table S6. The key differences between FD20 and non-robotic weed control in terms of CEI are a reduced herbicide use in Scenario 2 and electrification of seeding and weeding tasks in sugar beet in Scenarios 2 and 4. In Scenario 1, herbicide weed control is performed with two uniform sprays of Conviso ONE at a rate of 0.5 L ha^{-1} (Bayer, 2022). In Scenario 2, 90% of this rate is assumed to be saved via FD20 spot-spraying (Gerhards et al., 2023). Depending on solar radiation intensity, the FD20 runs on a combination of self-generated solar power and grid electricity stored in its power bank. FD20 electricity consumption is calculated in kWh ha^{-1} by multiplying FD20 machine time per hectare (h ha^{-1}) by its engine power (0.5 kW) (FarmDroid, 2025). The CEI of FD20 electricity consumption is calculated using CFT default values for photovoltaic grid electricity, which include embedded emissions of production.

2.5 | Social goal

The attribution of a social value to innovative agricultural technology as a function of farmers' work–life balance is inspired by the pioneering work of Dalziel et al. (2018) on wellbeing economics. Based on the four definitions of time described in Dalziel and Saunders (2014), farm operator's work–life balance is intended as a desirable proportion between contracted time (i.e., time spent on work activities) and other time. Because this concept is highly subjective, the present analysis relies on an indicator for family labor productivity that, regardless of its absolute value, could be assumed to be a proxy for improved farm operators' work–life balance in the case a weed control strategy generated a relatively higher value. Family labor productivity in sugar beet is measured using the Sustainable Development Goal indicator 2.3.1 expressed as commodity standard outputs (SOs) per agricultural work unit (AWU) (UN Statistics Division, 2024). Commodity SOs and AWUs are respectively expressed in € ha^{-1} and person-day year^{-1} based on 5-year mean reference values provided by EUROSTAT for Bavaria (EUROSTAT, 2020a, 2020b). AWUs only account for family labor input because seasonal worker time does not directly influence the work–life balance of the farm operator. Labor productivity is estimated using the following equation:

$$\text{lp} = \left(\frac{\text{SO}}{\text{SO}_{\text{ref}}}\right) / \left(\frac{\text{AWU}}{\text{AWU}_{\text{ref}}}\right) \tag{2}$$

where lp is the mean family labor productivity per hectare of sugar beet (SO AWU^{-1} ha^{-1}); SO is sugar beet standard output calculated by multiplying yield (ton ha^{-1}) by selling price (€ tonne^{-1}); SO_{ref} is the standard output reference value for sugar beet produced in Bavaria (€2,528.52 ha^{-1}) (EUROSTAT, 2020a); AWU is the family labor time required to cultivate 1 ha of sugar beet (person-day ha^{-1}); and AWU_{ref} is the annual work unit reference value across all economic sectors in Germany (225 person-day year^{-1}) (EUROSTAT, 2020b).

3 | RESULTS

3.1 | Farm profitability

Economic returns by scenario and number of fields are provided in Table 3. Farm gross return is higher in the FD20 scenario on both farm types regardless of number of fields. On the conventional farm, the FD20 spot-spraying scenario generates a 1%–2% higher farm gross return compared to its herbicide broadcast counterpart. The difference gradually grows with the number of fields, indicating that autonomous mechanical weeding gains a higher economic advantage over conventional herbicide spraying despite increased FD20 transport time. This is also regardless of the 20-field case in Scenario 2 undergoing late sugar beet planting on a larger area compared to farms characterized by a lower number of fields (Table 4). This is because the impact of an increased number of fields on sugar beet planting times is even more significant in Scenario 1, resulting in a favorable outcome for Scenario 2. In conjunction with land allocation implications, Scenario 2 is characterized by 90% herbicide savings enabled by spot-spraying and by a reduction of 2%–3% in fuel consumption (Table S7). The latter is the consequence of fuel savings in sugar beet sowing and weeding operations exceeding the additional fuel required for transporting the FD20 between fields.

On the organic farm, reliance on FD20 mechanical weeding (Scenario 4) generates gross returns that are 23%–24% higher compared to Scenario 3. Like on the conventional farm, an increased number of fields leads to a higher economic advantage in the scenario adopting the FD20. This is influenced by fuel savings of 18%–20%, crop rotation allocation, and lower manual weeding time. Additionally, the sensitivity analysis shown in Figure S1 indicates that optimal farm gross return in the FD20 organic scenario is preserved even when only two seasonal workers are available as compared to the four seasonal workers assumed in the baseline analysis. This is not the case in the non-robotic mechanical weeding scenario, where up to 70% of farm gross return is lost.

As shown in Figure 2, Scenario 2 retains the more diverse five-crop rotations regardless of number of fields, prioritizing eligibility for the K32 and OR2 payments described in Table S1. This results in a constant total sugar beet cultivation area on the conventional farm. On the other hand, the organic farm allocates sugar beet to different extents depending on number of fields and weeding strategy. While the five-crop rotations allocate sugar beet to 20% of the land and receive the OR2 payment besides other agricultural subsidies, the three-crop rotations allocate a wider area to sugar beet (25%) but are not eligible for the OR2 payment. Consequently, when the number of fields is higher, the whole-farm plan favors a reduction in sugar beet cultivation to enable more diverse crop rotations eligible for the OR2 payment. Conversely, adopting the FD20 on farms characterized by fewer fields results in more land being allocated to sugar beet and a lower crop diversification overall. The organic farm in the 5-field case benefits from lower manual weeding labor costs, fuel savings, and higher sugar beet sale revenue, which can compensate for a reduced OR2 payment.

Although gross return is always higher in the FD20 scenarios, the cost of this technology negatively affects ROLLMRT in conventional farming (Table 3). Adopting the FD20 to replace herbicide spraying on the conventional farm reduces gross return by 125%–141%, pushing ROLLMRT from a modest profit to negative. The opposite occurs on the organic

TABLE 3 Farm gross return (€ year^{-1}) and return on operator labor, land, management, and risk taking (ROLLMRT) (€ year^{-1}) for a 36.9 ha Bavarian farm.

	Farm gross return (no. of fields)			Return on operator labor, land, management and risk taking (no. of fields)		
Scenario	20	10	5	20	10	5
Scenario 1	56,825	57,881	58,478	7760	8816	9412
Scenario 2	58,189	58,636	59,011	−3172	−2726	−2351
Scenario 3	58,467	59,345	59,715	6869	7746	8117
Scenario 4	72,439	73,157	73,698	9714	10,432	10,973

TABLE 4 Annual sugar beet cultivation area (ha) by sowing time.

	Scenario 1 (no. of fields)			Scenario 2 (no. of fields)			Scenario 3 (no. of fields)			Scenario 4 (no. of fields)		
Sowing time	20	10	5	20	10	5	20	10	5	20	10	5
Optimal sowing	4.8	6.5	7.3	4.7	4.8	5.0	6.5	7.4	7.4	4.7	4.8	5.0
Late sowing	2.6	0.9	0.1	2.7	2.6	2.3	0.9	0.0	0.0	3.3	4.0	4.0
Total area	7.4	7.4	7.4	7.4	7.4	7.4	7.4	7.4	7.4	8.0	8.8	9.0

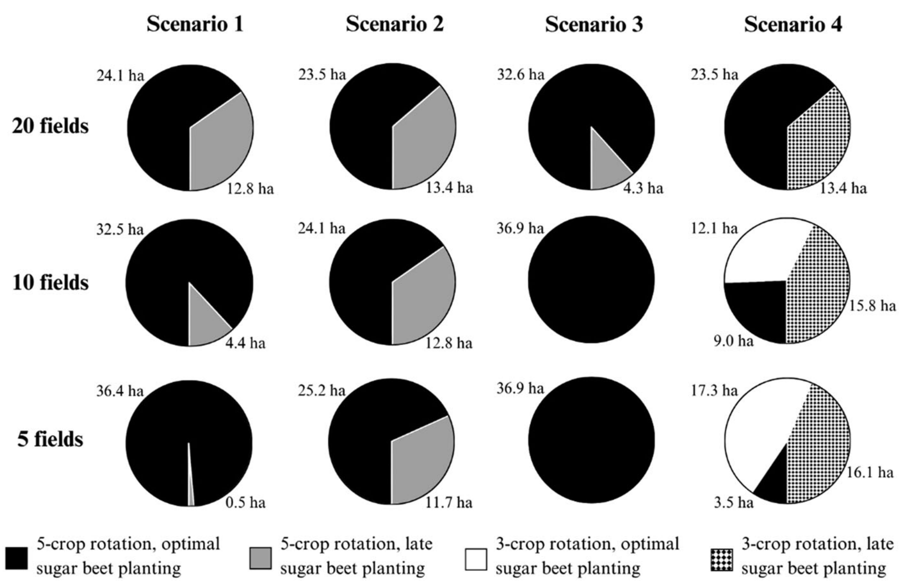

FIGURE 2 Crop rotation allocation by scenario and number of fields. Available land is not allocated to rotations characterized by early sugar beet harvesting in any of the scenarios.

farm, where ROLLMRT in Scenario 4 is 35%–41% higher than in non-robotic mechanical weeding. This indicates that the organic farm can absorb the additional fixed costs resulting from FD20 adoption. Whole-farm budgets by scenario are provided in Tables S7 and S8 for the conventional and organic farms, respectively.

When opportunity cost of family labor is taken into account, adopting the FD20 leads to higher sugar beet production costs on both farms (Table 5). The increases in sugar beet production costs were 4%–7% on the conventional farm and 3%–5% on the organic farm. The higher sugar beet production costs after FD20 adoption are mainly due to the cost of the

TABLE 5 Sugar beet production costs (€ ton^{-1}) with allocated opportunity cost of family labor.

	No. of fields		
Scenario	20	10	5
Scenario 1	34.1	33.1	32.6
Scenario 2	35.6	35.2	34.9
Scenario 3	70.7	69.5	69.1
Scenario 4	72.7	73.0	72.7

TABLE 6 Mean sugar beet carbon emission intensity (kgCO_2 eq ton^{-1}).

Scenario	No. of fields 20	10	5
Scenario 1	36.6	36.1	35.8
Scenario 2	36.3	36.1	35.9
Scenario 3	34.0	33.6	33.4
Scenario 4	33.0	32.9	32.7

TABLE 7 Mean family labor productivity in sugar beet production (SO AWU^{-1} ha^{-1}).

Scenario	No. of fields 20	10	5
Scenario 1	716	743	774
Scenario 2	136	145	152
Scenario 3	466	487	510
Scenario 4	106	112	117

technology and increased opportunity cost of family labor. On the organic farm, the savings in manual labor are higher than the increased opportunity cost of family labor, thus explaining the smaller sugar beet production cost increases.

The effects of an investment subsidy for the FD20 on farm competitiveness compared with Scenarios 1 and 3 are shown in Table S9. These results indicate that, for the conventional farm, a 40% investment subsidy leads to economically competitive sugar beet production costs only in the 20-field case, while a subsidy of 50% is required in the 10- and 5-field cases. On the organic farm, a 30% subsidy is sufficient for the 20-field case, but a 60% subsidy is required in the 10- and 5-field cases. For conventional and organic farms characterized by a lower number of fields, subsidies of 40% are economically competitive only if the FD20 useful life is longer than the 10 years assumed in this study.

3.2 | CEI of sugar beet production

Sugar beet CEI estimates show comparable results on the conventional farm and a minor CEI reduction on the organic farm when using the FD20 (Table 6). The CEI in Scenario 2 is 0.9% lower than in Scenario 1 in the 20-field case, but 0.4% higher in the 5-field case. In the 10-field case, the sugar beet CEI in Scenarios 1 and 2 are equivalent. This is because of the much greater extent of late sugar beet planting in Scenario 2 compared to Scenario 1 when the number of fields is small, leading to sugar beet yield losses and consequently higher GHG emissions per ton of crop produced at constant agricultural inputs. Regardless of the number of fields, herbicide use emissions are close to negligible on the conventional farm. Thus, the 90% herbicide savings in Scenario 2 are not an important factor for reducing the CEI of sugar beet.

On the organic farm, adoption of the FD20 leads to minor sugar beet CEI benefits for all field layouts considered. The 20-field case generates the highest CEI reduction (−2.9%). Like on the conventional farm, the CEI variability across number of fields results from the interactions between average sugar beet yield and fuel consumption. However, in this case, the more substantial fuel savings in the FD20 scenario compensate for the lower sugar beet yields regardless of number of fields. This is because of the higher fuel consumption of non-robotic mechanical weeding compared to herbicide spraying on the conventional farm.

CEIs of sugar beet production by emission component are shown in Table S10. The main contributor to sugar beet CEI is emissions from crop residue due to the high global warming potential of N_2O. The second most important component is fertilizer production and use on the conventional farm and fuel consumption on the organic farm. The CEI contribution associated with photovoltaic electricity used by the FD20 and emissions from plant protection products are close to negligible.

3.3 | Family labor productivity

Family labor productivity per ha of sugar beet is lower when adopting the FD20 regardless of production standard and number of fields (Table 7). In the FD20 spot-spraying scenario, family labor productivity decreases by 80%–81% compared to herbicide broadcast spraying. Using the FD20 in Scenario 2 requires 2.22–2.46 person-day ha^{-1} for sugar beet depending on the number of fields, while Scenario 1 only absorbs 0.45–0.47 person-day ha^{-1}. This increase is mainly due to the additional false sowing pass required to prepare the seedbed before FD20 sowing and the eight weeding passes in Scenario 2 compared to only two passes of herbicide broadcast spraying in Scenario 1. Besides, conventional equipment travels at a substantially higher speed than the FD20 during sowing and weeding.

On the organic farm, labor productivity values drop to a slightly lower extent in the FD20 scenario (−77%). In this case, family labor time in sugar beet is 0.79–0.84 person-day ha^{-1} in the non-robotic mechanical weeding scenario and 3.26–3.63 person-day ha^{-1} in the FD20 organic scenario depending on number of fields. In Scenario 3, the majority of labor input per ha is allocated to hired manual weeding (18 person-day ha^{-1}). In Scenario 4, only 2.7 person-day ha^{-1} are needed for hired manual weeding, but substantially higher family labor time is required for FD20 tasks. These include 13 FD20 weeding passes compared to the three mechanical weeding passes in Scenario 3. Total labor input in sugar beet is lower in Scenario 4 because the time savings in hired manual weeding exceed the additional family labor to manage

TABLE 8 Overview of scenario utility percentages for the production-oriented farmers, environmentally, and socially oriented farmers.

	Production-oriented (no. of fields)			Environmentally oriented (no. of fields)			Socially oriented (no. of fields)		
Scenario	20	10	5	20	10	5	20	10	5
Scenario 1	98%	99%	99%	71%	72%	72%	97%	99%	99%
Scenario 2	100%	100%	100%	73%	73%	73%	76%	76%	76%
Scenario 3	81%	81%	81%	59%	59%	59%	86%	87%	87%
Scenario 4	100%	100%	100%	73%	73%	73%	77%	77%	77%

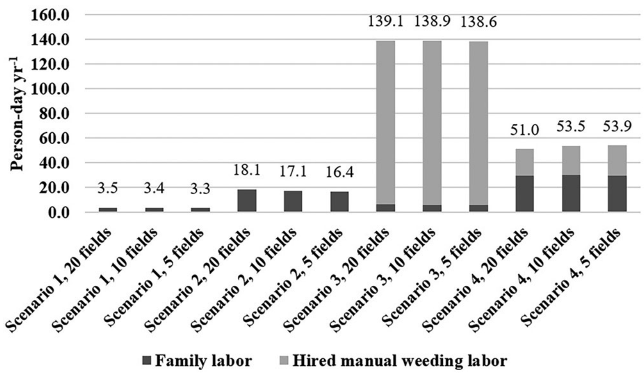

FIGURE 3 Total labor times for sugar beet cultivation.

the FD20. However, hired manual weeding labor time does not affect the family labor productivity indicator; hence, the outcome of the social goal is also negative in Scenario 4. Total labor times for sugar beet cultivation are provided in Figure 3.

3.4 | Utility by farmer typology

Farmer utilities for the tested weed control strategies are provided in Table 8. Preferences between non-robotic and FD20 weed control in sugar beet are comparable for production- and environmentally oriented farmers on the conventional farm, though FD20 scenarios generate slightly higher utilities because of a greater gross return and a lower sugar beet CEI in most cases. Conversely, production- and environmentally oriented farmers obtain substantially greater utility when adopting the FD20 on the organic farm. In this case, the FD20 is strongly preferred because of the improved economic performance enabled by fuel and manual weeding savings in Scenario 4. For the environmentally oriented farmer, the minor sugar beet CEI benefits are not an important factor as indicated by the lower utility achieved compared to the production-oriented farmer. Socially oriented farmers prefer non-robotic weeding on both farms when their objective is measured in terms of family labor productivity. Significant utility differences occur for the socially oriented farmer on the conventional farm because of a much lower labor productivity of sugar beet when relying on the FD20 system. On the other hand, the lower family labor productivity in Scenario 4 is partially compensated by the increased farm gross returns; hence, the utility loss of the socially oriented farmer on the organic farm is approximately half of that on the conventional farm. The number of fields does not affect preferences for any of the farmer typologies considered.

4 | DISCUSSION

This study hypothesized that FD20 use in sugar beet would generate a lower profit on a conventional farm but a higher profit on an organic farm. When fixed costs are excluded, this hypothesis is rejected because FD20 adoption generates a higher gross return on both farm types, especially when the farm is characterized by a high number of fields. This contradicts the finding by Jungwirth and Handler (2022) that farms with larger fields would be more likely to adopt crop robots. Rather, in the present analysis, longer travel distances increased variable costs to a relatively higher degree on the farm using non-robotic weeding, thus favoring adoption of crop robots on farms with smaller fields. However, if technology costs are taken into account, the results support the first study hypothesis because of substantially lower and negative returns on total costs on the conventional farm, but not on the organic farm. This is a barrier to FD20 adoption in conventional farming that will be difficult to mitigate considering the dependency of average-sized Bavarian farms on CAP payments (see Table S7). If autonomous mechanical weeding of sugar beet was incorporated in a more multifunctional technology, it could enable conventional farmers to save on herbicides and fuel without substantially increasing annual machinery costs. Alternatively, the period of active utilization of the FD20 in a year could be expanded by deploying it in suitable winter crops (e.g., Gerhards et al., 2023) or through shared ownership (Jorissen et al., 2025; Spykman et al., 2021).

On the organic farm, FD20 adoption could produce economic benefits even if the technology was only used in sugar beet and assumed to be fully owned. This finding is in line with Shang et al. (2023), who showed that organic farms are able to absorb a higher maximum acquisition value of weeding robots compared to conventional farms. Nevertheless, both conventional and organic farms would be penalized by higher sugar beet production costs, which could be reduced through investment subsidies such as the 40% of FD20 ownership offered through the BaySL Digital program in Bavaria (Spykman & Gabriel, 2023). However, it must be noted that the specific subsidy amount to make the FD20 as competitive as conventional weed control would depends on the FD20 useful life (Table S9). At the assumed useful life of 10 years, subsidies higher than 40% of FD20 ownership costs may be required depending on farm layout. Considering that the useful life of the FD20 may be shorter than what has been assumed in this study due to technical obsolescence and potentially more intensive use, investment subsidies may not be sufficiently effective from an economic perspective. Collecting reliable data on the useful life of the FD20 and other weeding robots is a research gap requiring further attention for appropriate tailoring of such subsidies in the future.

An important factor negatively affecting sugar beet production costs and family labor productivity is the increase in farm operator labor time in the field. These findings identify another important barrier to FD20 adoption, especially for socially oriented farmers and conventional farms. However, it is important to highlight that the adoption of autonomous mechanical weeding not only increases family labor time, but also changes what is being done during that additional time. Depending on farmers' preferences, crop robot supervision may be a more pleasant task than hiring and managing manual weeding labor. This could be an advantage for certain farmer profiles which the family labor productivity indicator used in this study did not capture. Besides, on the organic farm, the assumption that FD20 weeding requires a total of 13 passes is based on recommendations by the FD20 dealer in Germany, but farmers may choose to give up some weeding passes. This may especially be the case for farms characterized by a high number of fields seeking to minimize field-to-field transport. However, reducing FD20 weeding intensity may lead to lower weed control efficacy and consequently higher manual weeding costs or yield losses when manual labor is unavailable. As one of the sensitivity analyses indicated, an intensive use of the FD20 in conditions of seasonal labor scarcity may provide significant gross return benefits. Therefore, socially oriented farmers may prefer to trade-off their time and conduct intensive FD20 weeding to retain higher gross returns when manual labor is scarce.

The second hypothesis of this study was that adopting the FD20 would lead to lower sugar beet CEIs on both farms. Results indicate that the potential for lower GHG emissions per ton of sugar beet produced may depend on the number of fields, and that CEI reductions may be close to negligible even when they are achieved. The degree of late sugar beet planting as a result of machine time bottlenecks during sowing was a more important factor than herbicide and fuel savings in Scenario 2. These findings are in contrast with Fishkis et al. (2024), who estimated that using the FD20 combined with spot-spraying in conventional sugar beet generated 5% lower GHG emissions than uniform herbicide spraying. Besides, neither the present study nor Fishkis et al. (2024) accounted for emissions of GHGs stored in soil resulting from mechanical weeding action. Therefore, the CEI of sugar beet managed with FD20 spot-spraying might be even higher than estimated. On the organic farm, despite a considerable portion of sugar beet being planted late, the FD20 led to sugar beet CEI reductions regardless of the number of fields because it replaced energy-intensive non-robotic mechanical weeding. On both farms, however, a large portion of GHGs emitted from sugar beet farming originated from crop residue and fertilizer use, as also highlighted in Trimpler et al. (2016). Thus, non-herbicide weed control is not a sensible lever for GHG emission and CEI reductions.

CEI is only one of the available indicators to assess the environmental impact of weed control. An example that could be considered in future research is the effect of robotic weeding on crop biodiversity. On the organic farm, sugar beet area allocation was constant in Scenario 3 but increased with a lower number of fields in Scenario 4 (Table 4). This finding aligns with previous claims that technologies developed for a limited range of crops such as the FD20 may have a negative impact on in-field biodiversity by encouraging crop intensification and farm specialization (Lioutas et al., 2021). However, this study adds that this may depend on structural and farm management factors such as the spatial distribution of fields and production standard. The conventional farm modeled in this study, for example, adopted a crop rotation that was equally diverse in Scenarios 1 and 2, thus showing no tendency to reduce crop biodiversity. Additional environmental indicators to be tested may include the effect of FD20 use on soil physical properties (e.g., Bručienė et al., 2022, 2025) or reduced soil compaction as a consequence of lower equipment weight (e.g., Lagnelöv et al., 2023). Given that purchase subsidies with taxpayer money such as the BaySL Digital would require the generation of public goods by the subsidized technology, impact evaluation for the FD20 and other innovations related to a wide range of environmental indicators should be explored.

Crop robots are often expected to provide benefits such as increased profitability, improved environmental outcomes, and reduced labor inputs (Campi et al., 2024; Spykman et al., 2021; Tamirat et al., 2023). In this analysis, the first and second benefits depended on production standard, farm layout, and whether economic performance accounted for fixed costs, while the third benefit was true for hired manual workers in organic farming but not for family labor on any of the farms. On the conventional farm, the main barriers were technology cost, low operational speeds, and technology specialization, which made it difficult to compete with labor- and cost-efficient weed control strategies such as herbicide broadcast spraying. By adopting the FD20, socially oriented farmers managing a conventional farm would face a 393%–426%

increase in family labor time in the field as well as substantial losses of return on total costs. On organic farms, the FD20 provided some economic and environmental benefits, though socially oriented farmers would also be challenged by increased family labor input. An important finding is that the relative economic performance of conventional versus organic farming measured as return on total costs was inverted after FD20 adoption, thus making the latter more attractive to production-oriented farmers. This may encourage the conversion of conventional farmers to organic agriculture, especially considering the mitigation effects that FD20 adoption has on seasonal labor shortages for manual weeding.

These results are tailored to Bavarian farms and may only be representative of other European regions characterized by comparable agricultural practices, farm structures, crop prices, and production costs. Moreover, the FD20 and autonomous mechanical weeding are only one of the potential solutions to improve the profitability and environmental impact of weed control. Further research is needed to conduct multi-criteria comparisons across the range of available weeding technologies. Other approaches such as targeted herbicide spraying via machine vision as well as nonchemical methods including electric, laser, and thermal weeding are also commercially available and require further investigation (Future Farming, 2025; Lytridis & Pachidis, 2024; Vijayakumar et al., 2023; Wei et al., 2010). Nevertheless, some of the implications identified for the FD20 system may also apply to other weeding robots. For example, smaller self-propelled equipment operated in swarms could optimize machine downtime and overcome speed constraints when sufficiently reliable. Alternatively, retrofit kits could be used to convert conventional tractors to autonomous machinery that would utilize common implements without the need to invest in specialized weeding robots.

This analysis has two major limitations. First, the CEI indicator did not consider FD20 manufacturing emissions (e.g., Fishkis et al., 2024; Pradel et al., 2022). While the material composition of modern tractors may not substantially differ from that of specialized weeding robots (e.g., see Pradel et al., 2022), tractor ownership is still required in sugar beet managed with the FD20. Therefore, FD20 manufacturing emissions should be considered in future research, which could possibly negate the CEI benefits encountered in some of the scenarios assessed in this study. Second, the HFH-MOLP model does not currently incorporate weed ecology parameters. Weed species, infestation intensity, and spatial distribution are important variables in determining the efficacy, economic performance, and environmental impact of practices such as mechanical weeding (Slaughter et al., 2008; Yu et al., 2024). For example, because weed infestations tend to be distributed non-uniformly, nonselective FD20 mechanical weed control may become particularly disadvantageous in conditions of low weed infestation or high in-field spatial variability (Slaughter et al., 2008). However, studies assessing robotic weed management via economic-environmental models accounting for weed population dynamics often focus on a single weed species and one herbicide active substance (e.g., Yu et al., 2024). This is because modeling weed population dynamics, herbicide resistance development, and interactions with mechanical weed control requires a vast amount of localized data (Yu et al., 2024). Consequently, focusing on individual weed species and herbicides while relying on highly localized data would make results less representative of wider farm categories.

5 | CONCLUSIONS

This multi-criteria analysis modeled a conventional and an organic general cropping farm located in Bavaria, Germany. Economic, environmental, and social implications of adopting the FD20 weeding robot were investigated by quantifying gross return and return on total costs, sugar beet production costs, sugar beet CEI, and family labor productivity. The use of autonomous mechanical weeding was compared to conventional herbicide broadcast spraying and non-robotic mechanical weeding for a range of farm layouts and for three representative decision-maker typologies.

Results showed that FD20 adoption in conventional farming would be more profitable than conventional herbicide spraying thanks to herbicide and fuel savings, but not if fixed costs were taken into account due to high FD20 investment requirements. Additionally, using the FD20 led to a substantial increase in family labor input and to higher sugar beet production costs.

On the organic farm, the FD20 was more profitable than non-robotic weeding also after accounting for fixed costs because of considerable savings in manual weeding labor and fuel consumption. These cost reductions compensated for the high ownership cost of the FD20 system. However, a substantial increase in family labor input was also encountered on the organic farm, thus leading to higher sugar beet production costs compared to non-robotic mechanical weeding.

On both farms, CEI benefits were relatively slim and lower than what has been estimated in other studies. An increased travel distance during field operation was not an important factor affecting GHG emissions per ton of sugar beet produced while deploying the FD20. Rather, more frequent late sugar beet planting as a result of machine time bottlenecks during sowing in the FD20 scenarios was an important contributor. This research also pointed to the need to explore a wider range of environmental indicators, especially considering that technologies such as the FD20 are being partially subsidized with taxpayer money and should therefore be proven effective in generating public goods.

The variability in economic, environmental, and social performance of the FD20 compared to conventional weed control led to different farmer preferences depending on their personal orientation. At its current development stage, the FD20 is more desirable for production- and environmentally oriented farmers and in organic rather than in conventional agriculture. On the other hand, socially oriented farmers who measure their goal by family labor productivity should consider adopting technologies that can travel faster and require less frequent human intervention or retain current conventional practice.

The main barriers to FD20 adoption identified were the high technology cost when the FD20 was used as a specialized crop robot focused on a single crop and individually owned by the farmer; a lack of consistent and substantial benefits for farmers seeking to reduce GHG emissions per ton of crop produced; and the considerably higher family labor input required to supervise the FD20. With the entry into force of the EU Machinery Regulation, it will be essential to collect empirical data to corroborate these findings and mitigate adoption barriers through schemes favoring multi-purpose equipment, shared ownership, or alternative business models, as well as environmentally friendly, efficient, and reliable technology. Future comparison among multiple innovative weed control technologies will also be important to encourage technology developers to compete in the direction of sustainable farming.

The findings of this multi-criteria analysis are applicable to Bavaria and other European regions characterized by comparable agricultural practices, farm structures, crop prices, and input costs. For other regions of the world where regulation is less stringent or where labor has a lower opportunity cost, other adoption barriers may be more relevant. Likewise, larger and less diverse European farms may achieve economies of scale sufficient to compensate for the high cost of the FD20 and specialized weeding technology in general. However, based on the results of the present analysis, it can be concluded that factors such as multifunctionality, reliability, and logistics of field operation are important aspects to consider for farmers adopting weeding robots and other autonomous equipment.

AUTHOR CONTRIBUTIONS

Elias Maritan: Conceptualization; formal analysis; methodology; writing—original draft. **Olivia Spykman**: Conceptualization; methodology; writing—original draft. **James Lowenberg-DeBoer**: Conceptualization; methodology; supervision; writing—review and editing. **Markus Gandorfer**: Funding acquisition; supervision; writing—review and editing. **Karl Behrendt**: Conceptualization; funding acquisition; methodology; supervision; writing—review and editing.

ACKNOWLEDGMENTS

This work was supported by UK Research and Innovation (UKRI Reference No. 10037994), the EU's Horizon Europe Research and Innovation Programme (Grant Agreement No. 101060759) as part of the Digitalisation for Agroecology project (https://d4agecol.eu/), and by the Bavarian State Ministry for Agriculture, Forestry, Food and Tourism (Grant No. A/21/17 and A/24/07) as part of the project Future Crop Farming (https://future-crop-farming.de/). The authors are grateful to Dr. Xaver Maidl and Dr. Beat Vinzent for insightful discussions.

CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

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SUPPORTING INFORMATION

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How to cite this article: Maritan, E., Spykman, O., Lowenberg-DeBoer, J., Gandorfer, M., & Behrendt, K. (2025). An economic, environmental, and social analysis of autonomous mechanical weeding in sugar beet farming. *Agronomy Journal*, *117*, e70246. https://doi.org/10.1002/agj2.70246