Impact Assessment Tool for Robotic and Extended Reality Applications in Agriculture: Cases from AgRibot Project

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Abstract

This paper presents AgRibot-IAT, a web-based impact assessment tool developed within the European Union AgRibot project to evaluate the socio-economic and environmental implications of robotic and Extended Reality (XR) applications in crop farming. The tool addresses the growing need for transparent and user-customizable decision-support systems capable of assessing the costs and benefits of agricultural robotics under realistic farm conditions. AgRibot-IAT evaluates robotic systems against conventional farming practices using a modular framework based on project use cases located in Belgium, Denmark, Greece, Italy, Spain, and Switzerland.

The assessment framework combines partial budgeting, Net Present Value (NPV) analysis, and scenario analysis to evaluate operational, economic, and environmental indicators associated with agricultural robotics. The platform integrates farm characteristics, machinery specifications, investment data, labor requirements, fuel and agrochemical use, and environmental parameters to support comparative evaluation between robotic and conventional systems.

Default datasets are derived from 6 pilot cases, literature, surveys, and discussions with pilot case leaders about agronomic technical specifications. Given that integration of technology components and field deployment of the use cases is not yet completed, some of the default data is populated to enable the calculations work. So, the focus in this paper is on the functionalities of the tool than on the magnitude of the numbers presented as data and results. Users can customize assumptions and define alternative scenarios to evaluate how changes in operational and economic conditions influence the relative economic performance of robotic systems. The current version focuses on farm-level assessment and supports crop-operation combinations involving maize, potato, tomato, lettuce, apple, and pear production.

AgRibot-IAT is intended to support farmers, advisors and researchers in evaluating the feasibility and sustainability implications of agricultural robotics. The platform provide a scalable and transparent framework for evidence-based investment assessment and technology evaluation.

Keywords: Agricultural robotics, impact assessment, precision agriculture, decision-support systems, sustainability, smart farming, socio-economic analysis.

1. Introduction

Agriculture is increasingly influenced by digitalization, automation, and robotics aimed at improving sustainability, reducing labor dependency, and enhancing operational efficiency. Agricultural robotics is being introduced into a wide range of crop operations, including fertilization, chemical weeding, growth monitoring, thinning, pruning, and selective harvesting. Despite rapid technological development, adoption of robotic systems remains constrained by uncertainty regarding economic feasibility, environmental performance, operational reliability, and long-term investment value.

Appropriate economic assessment methods are essential for informed technology adoption decisions in agriculture (Medici et al., 2021; Pedersen et al., 2019). This is particularly important for field crop robotics because many technologies remain at an early stage of development and are associated with high investment costs and uncertain operational performance (Lowenberg-DeBoer et al., 2020; Shockley et al., 2019; Tamirat et al., 2023).

The literature on robotic applications in field crop farming is growing but remains limited (Lampridi et al., 2019; Lowenberg-DeBoer et al., 2020; Maritan et al., 2023; Pedersen et al., 2006; Vahdanjoo et al., 2023; Ørum et al., 2023). Rose and Bhattacharya (2023), for example, identified several factors influencing adoption of agricultural robots, including investment costs, infrastructure requirements, data ownership, skills, and trust. Gil et al. (2023) analyzed challenges associated with implementation of agricultural robots and highlighted the importance of technological design, economic feasibility, and data integration in local farming contexts. Maritan et al. (2023) investigated economically optimal farmer supervision of robots in field crop production and concluded that supervision requirements vary substantially depending on intervention frequency, supervisor location, and number of robotic units operating simultaneously.

While these studies provide important insights, end-users often find it difficult to determine whether reported results apply to their own farming conditions. Another concern is that many of these technologies primarily benefit large-scale farms (Lowenberg-DeBoer et al., 2022; Pedersen et al., 2019). Small robotic systems may, however, create new opportunities for smaller-scale farms as well.

Several studies have developed tools for evaluating the economic performance of precision agriculture technologies (Medici et al., 2021). Nevertheless, user-customizable tools specifically designed for field crop robotic systems remain limited. There is therefore a need for transparent, flexible, and accessible decision-support tools capable of evaluating robotic technologies under realistic farm conditions (Iakovidis et al., 2025).

In response to this need, AgRibot project developed AgRibot-IAT (https://agribot-iat.onrender.com/), a web-based impact assessment tool designed to evaluate robotic farming systems relative to conventional systems. The platform integrates socio-economic and environmental indicators and supports comparative evaluation using partial budgeting, Net Present Value (NPV) analysis, and scenario analysis. This version of the tool is the first of three planned during the project lifetime.

The current implementation focuses on crop-operation combinations represented in the AgRibot project use cases, including fertilization management, chemical weeding, growth monitoring, thinning, pruning, and selective harvesting. The project use cases are located in Belgium, Denmark, Greece, Italy, Spain, and Switzerland and involve crops such as maize, potato, tomato, lettuce, apple, and pear. AgRibot-IAT provides comparative evaluation of robotic and conventional systems, user customization of operational and economic assumptions, and scenario analysis for alternative farm conditions

The remainder of the paper is organized as follows. Section 2 reviews related literature on agricultural robotics and decision-support systems. Section 3 presents the system architecture of AgRibot-IAT. Section 4 describes the assessment methodology and analytical framework. Section 5 presents the implementation and user workflow. Section 6 discusses the implications and limitations of the framework, while Section 7 concludes the paper.

2. Related Work

Existing literature highlights that adoption of agricultural robots depends not only on technical feasibility, but also on economic viability, operational compatibility, environmental performance, and farmer acceptance. Anastasiou et al. (2025) indicated that robotic and extended reality (XR) technologies can be potential solutions to improve global food security (through tackling agricultural labour shortage) and help with the transition to Agriculture 5.0. However, to unpack the potential of farming technologies, their socio-economic and environmental impacts need be credibly demonstrated under local conditions (Pedersen, Tamirat & Erekalo, 2025; Pedersen, et al., 2026) alongside technical developments.

Lowenberg-DeBoer et al. (2020) reviewed the economics of robots and automation in field crop production and emphasized that many studies evaluate robotics at the level of individual crop operations rather than whole-farm transformation. This observation is particularly relevant for AgRibot-IAT, which focuses on crop-operation combinations represented in the AgRibot use cases. Similarly, Lowenberg-DeBoer (2024) argued that farmers adopt robotic technologies when they generate meaningful operational and economic benefits, including cost savings, workload reduction, increased flexibility, and reduced production risk.

Partial budgeting is widely used in farm management to evaluate the economic implications of changes in production practices. The method is particularly suitable when only selected components of the farming system are modified rather than the entire enterprise. This makes the approach appropriate for evaluating substitution or complementarity between robotic and conventional machinery systems.

Recent studies have also highlighted the importance of integrating operational, economic, and environmental indicators when evaluating agricultural robots. Vahdanjoo et al. (2023), for example, compared robotic and conventional systems across operational and environmental indicators, field dimensions, working widths, and cost components. Such scenario-based comparative approaches are closely aligned with the logic underlying AgRibot-IAT.

Benefits of digital and robotic and XR technologies are highly context-dependent. Environmental and economic outcomes vary across crops, regions, technologies, and management systems. Consequently, flexible and user-customizable assessment tools are required to capture farm-specific conditions and technology configurations.

Decision-support systems are increasingly recognized as important tools for agricultural management because they help farmers, advisors, researchers, and policymakers structure complex decisions. Literature highlights the need for transparent and adaptable decision-support systems, which directly motivates the development of AgRibot-IAT.

Table 1 summarizes how AgRibot-IAT relates to existing literature.

Table 1: Positioning the paper within related literature

Literature Theme	Relevance to AgRibot-IAT
Economics of agricultural robotics	Supports assessment of robotic adoption using farm-level economic indicators
Partial budgeting	Provides the methodological basis for comparing changes from conventional to robotic systems
Precision agriculture sustainability	Supports inclusion of economic and environmental indicators
Decision-support systems	Supports the need for interactive, user-customizable tools
Scenario analyses	Supports comparison of alternative assumptions and technology configurations

3. System Architecture

AgRibot-IAT is a dynamic and user-customizable web-based impact assessment tool to evaluate the socio-economic and environmental implications of robotic applications in agriculture. The platform compares robotic farming systems with conventional agricultural systems at farm level using project use cases as reference scenarios.

The assessment framework combines partial budgeting, Net Present Value (NPV) analysis, and scenario analysis to evaluate the economic and environmental implications of agricultural robotics. The tool integrates operational, technological, investment, and input-use parameters to support comparative evaluation under user-defined assumptions.

AgRibot-IAT evaluates indicators related to operational efficiency, labor use, fuel and agrochemical consumption, CO2e emissions, and investment feasibility.

The platform includes configurable baseline scenarios, customizable parameters, comparative scenario analysis, and a PDF report export functionality. Default datasets are based on AgRibot project use cases located in Belgium, Denmark, Greece, Italy, Spain, and Switzerland.

The system integrates default and user-defined operational, economic, and environmental data associated with robotic and conventional farming systems. The architecture supports comparative evaluation and scenario analysis using discounted cash-flow analysis.

The data management layer stores farm characteristics, operational parameters, machinery specifications, investment data, input-use information, external parameters, and scenario definitions. Users can modify default values to reflect their own farming context and define alternative scenarios to evaluate how changes in selected parameters influence comparative system performance.

User-modified assessment data and temporary scenarios are stored locally during interaction with the platform rather than permanently stored in the database. This design supports rapid experimentation, scenario testing, and privacy-preserving customization.

AgRibot-IAT distinguishes between three analytical layers:

- **AgRibot Default** – Uses default datasets collected from AgRibot project use cases.
- **User-Defined Baseline** – Uses customized data while maintaining baseline comparison

structure.

- **Custom Scenario Analysis** – Allows modification of selected parameters to evaluate alternative operational and economic conditions.

4. Methodology

4.1 Assessment Scope and Use-case Framework

AgRibot-IAT applies a farm-level framework. The analysis is limited to selected crops, operations, and robotic applications represented in the AgRibot project use cases. This scope reflects that performance depends strongly on crop type, field conditions, operation characteristics, machinery configuration, and local production context.

The platform evaluates robotic applications against reference conventional system. For each selected use case, users can compare a baseline conventional system with the corresponding robotic system using a consistent set of assumptions related to farm characteristics, technology specifications, investment costs, input use, and operational parameters.

Default datasets are compiled from project use cases, field experiments, surveys, literature review, expert knowledge, technical specifications, and agronomic information. The use cases represent AgRibot project pilots (https://agribot-project.eu/pilots/) which are summarized in *Table 2*. Each case focuses on a specific crop-operation combination and associated technology package.

Table 2: Overview of use cases

Operation	Crop	Reference location
Fertilizer management	Lettuce	Puglia (Italy). See Milella et al. (2026) for details.
Chemical weeding	Maize, potato	Aliartos (Greece), Mid-Jutland (Denmark), Vaud (Switzerland)
Growth monitoring	Tomato (green house)	Bari (Italy)
Thinning (removing excess fruit)	Apple	Spain and Belgium
Pruning (removing branches)	Apple	Spain and Belgium
Harvesting	Apple	Belgium

The cost-benefit analysis (CBA) model underlying AgRibot-IAT incorporates data on farm characteristics, technology-performance features, investment costs, market prices, real discount rates, and regulatory conditions specific to each use-case area. Because use cases differ substantially in crop type, operation characteristics, and machinery configuration, comparisons across use cases should be interpreted cautiously.

4.2 Assumptions

The assessment framework is based on a set of simplifying assumptions intended to ensure consistent comparison between robotic and conventional systems across the AgRibot use cases.

The main assumptions include:

- One production cycle of the target crop per year
- No management changes occur beyond the target operation represented in each use case.
- Identical transportation requirements between barn and field for robotic and conventional systems
- Full annual utilization of machinery capacity
- Equivalent crop yield and crop quality between robotic and conventional systems

These assumptions simplify the analysis and allow the framework to focus primarily on operational, investment, labor, input-use, and environmental differences between systems.

4.3. Web Technology Stack

AgRibot-IAT was developed using modern full-stack web technologies to ensure scalability, maintainability, and responsive user interaction. The architecture combines a Laravel-based backend with a React-powered frontend integrated through Vite. MySQL (My Structured Query Language) was used for database management, while Axios was used for communication between frontend and backend services. The project code is maintained in a GitLab repository supporting version control and continuous deployment.

The backend was implemented using the Laravel framework, which provides functionality for authentication, database management, API (Application Programming Interface) generation, and application logic. Analytical calculations were implemented as PHP (Hypertext Preprocessor) functions. The frontend interface was developed using React and Bootstrap to provide an interactive and responsive user experience. The interface terminology was designed to be accessible to farmers, advisors, consultants, researchers, and educational users. Global notes and parameter-specific explanations are integrated throughout the interface to support usability. Vite was used as the frontend build tool to improve development efficiency and optimize application performance. Integrating Laravel, React, and Vite, AgRibot-IAT delivers a modern web application architecture capable of supporting scalable agricultural impact assessment.

5. System Implementation and User Workflow

AgRibot-IAT is implemented as a web-based decision-support platform supporting comparative evaluation of robotic and conventional agricultural systems. The platform combines a Laravel-PHP backend with a React-based frontend integrated through Vite and Axios.

The workflow guides users through the assessment process using the following structure:

Home → Cases → Farm → Technology → Investment → Input Use → Parameters → Results

- **Home** – Introduces the scope and objectives of the platform
- **Cases** – Presents AgRibot project use cases and crop-operation combinations
- **Farm** – Allows customization of farm characteristics and operational constraints
- **Technology** – Presents robotic and conventional machinery specifications
- **Investment** – Contains investment data for machinery and technology packages

- **Input Use** – Captures labor, fuel, water, and agrochemical inputs
- **Parameters** – Allows configuration of economic and environmental assumptions
- **Results** – Presents baseline results, scenario analysis, and report export

The interface includes interactive dashboards, comparative visualizations, scenario configuration tools, and real-time result updates.

Forward navigation is only enabled after completion of preceding workflow steps, while users retain the ability to return to previously completed pages. Most parameters can be customized to reflect farm-specific conditions. User-modified cells are highlighted to distinguish customized values from default datasets. Valid ranges are implemented for numerical variables to prevent illogical parameter values.

Project reference datasets are maintained centrally, whereas user-defined scenarios are stored locally during interaction with the platform. This design supports rapid experimentation and privacy-preserving customization.

5.1. Use Case Selection

Users can select one or more use cases for analysis. Multiple cases can be displayed simultaneously; however, comparisons across use cases should be interpreted cautiously because they differ in crop type, production context, and technology configuration.

The paper demonstrates the workflow using the use case of chemical weeding in maize production located in Aliartos, Greece.

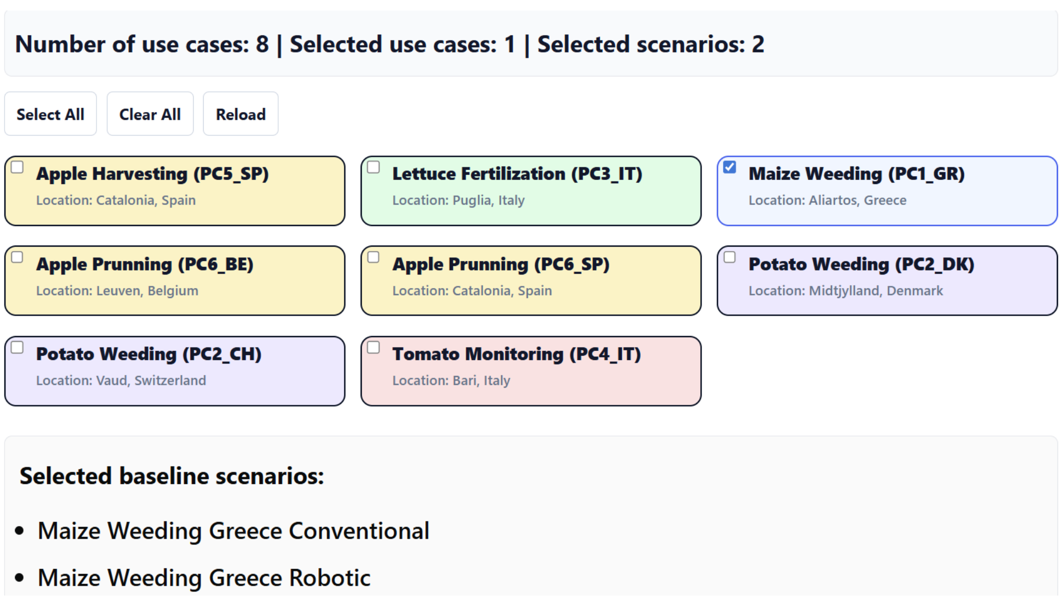


Figure 1: Cases selection page

5.2. Farm Features Customization

Users can review and modify farm size, field dimensions, machinery characteristics, investment costs, machinery life, working parameters, and autonomy levels. Equivalent farm assumptions should be used for robotic and conventional systems to ensure meaningful comparison.

Feature	Description	Unit	Maize Weeding: Conventional (PC1_GR: Aliartos, Greece)	Maize Weeding: Robotic (PC1_GR: Aliartos, Greece)
Farm size	Farm size for case crop	ha	40	40
Field size	Average field size for case crop	ha	10	10
Operation window	Agronomically sensible time window to do an operation pass	days	7	7
Workable hours	Workable hours per day for target operation	h/day	8	8
Workable days	Workable days in a week	days/week	5	5
Operation passes	Number of operations per season	number	2	3

Step 3 of 8 — Farm

⟵ Previous   Next ⟶

Figure 2: Farm characteristics

5.3. Investment Data

Feature	Description	Unit	Maize Weeding: Conventional (PC1_GR: Aliartos, Greece)	Maize Weeding: Robotic (PC1_GR: Aliartos, Greece)
Personnel training	Investment in personnel training to get started	Euro	0	2750
Vehicle investment	Vehicle investment	Euro	170000	200000
Implements investment	Implement investment	Euro	80000	90000
Sensors investment	Sensors investment (for all sensors combined (if any))	Euro	200	900
Navigation investment	Navigation system (RTK, GPS, Lidar,...)	Euro	2	500
Software	Softwares & Digital platforms	Euro	2	200
XR investment	Investment in Augumented Reality (XR, MR, VR) technologies	Euro	0	100

Step 4 of 8 — Investment

Figure 3: Investment data page

5.4. Technology specifications and performance features

Users review technology specifications, working characteristics, investment cost, machinery life, autonomy level etc.

Feature	Description	Unit	Maize Weeding: Conventional (PC1_GR: Aliartos, Greece)	Maize Weeding: Robotic (PC1_GR: Aliartos, Greece)
Fuel for operation	Fuel consumption on operation mode	L/ha/operation	6	4
Working speed	Working speed	km/h	10	6
Working width	Working width of implement	m	18	12
Achievable field efficiency	Maximum achievable field efficiency	%	90	85
Forgone productive time in area equivalent	Lost productive time in area equivalent	ha/field	2	2
Annual capacity of vehicle	Vehicle capacity (maxmimum number of hours vehicle/platform can be used) per year	h/year	1000	800
Daily capacity of vehicle	Number of hours a vehicle/platform can be used for the target operation on a working day	h/day	9	10
Economic life	Economic life (of technology package)	years	15	10
Autonomy	Degree of autonomy (operation without human driver)	% of operation time	0	50
Intervention rate	Degree of human intervention during robotic application	% of operation time	0	20

Figure 4: Technology specifications and performance features

5.5. Input Use

Feature	Description	Unit	Maize Weeding: Conventional (PC1_GR: Aliartos, Greece)	Maize Weeding: Robotic (PC1_GR: Aliartos, Greece)
Labortime: prepare	Labor time to prepare (including tank filling, implement mounting, loading on and from transport medium)	h/operation	1	2
Herbicide	Amount of herbicides	kg/ha/operation	60	45
Fungicide	Amount of fungicides	kg/ha/operation	0	0
Insecticide	Amount of insecticides	kg/ha/operation	0	0
Fertilizer	Amount of fertilizer	kg/ha/operation	0	0
Growth regulator	Amount of growth regulator	kg/ha/operation	0	0
Other pesticides	Amount of other pesticides (e.g., Acaricides, pruning agents, defoliants, biological control)	kg/ha/operation	0	0
Water consumption	Amount of water for target operation	m3/ha/operation	0.4	0.3

Step 6 of 8 — Input use

← Previous   Next →

Figure 5: Input use

5.6. Market-related Parameters

Users review labor, fuel, agrochemical, water, and other operational inputs together with market, accounting, and environmental parameters. In figure 6 a list of prices for different inputs is provided.

Feature	Description	Unit	Maize Weeding: Conventional (PC1_GR: Aliartos, Greece)	Maize Weeding: Robotic (PC1_GR: Aliartos, Greece)
Labor price	Labor price	Euro/h	10	10
Fuel price	Fuel price	Euro/L	1.6	1.6
Herbicide price	Average price of herbicide	Euro/kg	0.8	0.8
Fungicide price	Average price of fungicide	Euro/kg	0.8	0.8
Insecticide price	Average price of insecticide	Euro/kg	0.8	0.8
Fertilizer price	Average price of fertilizer	Euro/kg	0.8	0.8
Growth regulator price	Average price of growth regulator	Euro/kg	0.8	0.8
Other pesticide price	Average price of other pesticides	Euro/kg	0.8	0.8
Water price	Water price	Euro/m3	1	1
Discount rate	Real discount rate	%	4	4
R&M factor	Repair and maintenance factor for vehicle & implement package	Fraction of investment	0.02	0.03
Insurance coefficient	Insurance coefficient for vehicle & implement package	Fraction of investment	0.01	0.025

Figure 6: Market-related parameters

5.7. Results

The **Results** interface provides access to baseline results, scenario analysis, and PDF report export through an integrated workflow.

5.7.1. Baseline results

Users can define custom scenarios by modifying selected parameters and comparing the resulting socio-economic and environmental impacts between robotic and conventional systems.

Baseline results compare AgRibot default with user-defined baseline (see figure 7).

Feature	Description	Unit	Results: AgRibot Default		Results: User-defined Baseline	
			Maize Weeding: Conventional (PC1_GR: Aliartos, Greece)	Maize Weeding: Robotic (PC1_GR: Aliartos, Greece)	Maize Weeding: Conventional (PC1_GR: Aliartos, Greece)	Maize Weeding: Robotic (PC1_GR: Aliartos, Greece)
Area capacity	Area capacity (calculated from working width, working speed and field efficiency).	ha/h	16	17	16	6.1
Operation time	Operation time per hectare per operation	h/ha/operation	0.06	0.06	0.06	0.16
Vehicle units	Number of vehicle units needed to operate the reference farm within operation window	number	0.87	0.82	0.49	1.31
Servable farm size	Farm size that can be served by one machinery during operation window for one pass	ha	258	272	905	342
Labour time: total	Labor time to prepare, operate and intervene	h/ha/season	0.25	0.19	0.25	1.28
Fuel consumption	Fuel consumption for target operation (transport excluded)	L/ha/season	12	4	12	12
Fuel cost	Fuel cost	Euro/ha/season	19	6.4	19	19
Labor cost	Labor cost	Euro/ha/season	2.48	1.88	2.47	13
Water cost	Cost of water	Euro/ha/season	0.8	0.6	0.8	0.9
Agrochemical consumption	Amount of agrochemicals used	kg/ha/season	60	45	60	45
Agrochemical cost	Cost of agro-chemicals	Euro/ha/season	48	36	48	36
R&M cost of one vehicle and implement package	R&M cost of one vehicle and implement package	Euro/year	4,600	5,250	5,000	8,700
Insurance cost of one vehicle	Insurance cost of one vehicle	Euro/year	1,500	2,400	1,700	5,000
Investment for one technology package	Total investment cost for one full package	Euro/package	230,204	213,850	250,204	294,450
Total investment for vehicle units needed for farm	Total investment needed for the farm (scaled by vehicle units needed)	Euro	199,830	175,822	123,833	385,810
Operation and ownership cost	Operation and machinery ownership cost	Euro/season	6,705	7,187	6,135	20,706
Annual Present Value of Cost	Yearly average present value of cost (considering direct financial costs only)	Euro/ha/year	1,234	1,443	432	1,707
Emission	Amount of C02e emission per season (excluding transport)	ton/ha/season	0.03	0.01	0.03	0.03

Figure 7: Baseline results

User-defined baseline scenarios provide the reference point for subsequent scenario analysis. Scenario analysis allows users to evaluate sensitivity to changes in key parameters. In the scenario analysis, parameters are grouped as those applicable for both Conventional and Robotic Systems (such as farm size, field, size), and others applicable only for Robotic System (such as degree of autonomy, human intervention needed). Scenario results are expressed as relative differences between robotic and conventional systems using the user-defined baseline as the reference.

Baseline results are generated for both AgRibot default assumptions and user-defined baseline assumptions. This allows users to understand how project-level default data compare with farm-specific customized inputs. Because AgRibot-IAT is an impact assessment and decision-support tool, the results are not prediction accuracy scores. Instead, the tool produces comparative socio-economic, operational, and environmental impact indicators for robotic and conventional systems.

5.7.2. Scenario Analysis

Scenario analysis (see figure 8 and 9) allows users to evaluate sensitivity to changes in selected input parameters. For example, users may test the effect of changes in labor cost, fuel price, robot purchase price, field size, work rate, repair and maintenance assumptions, discount rate, etc.

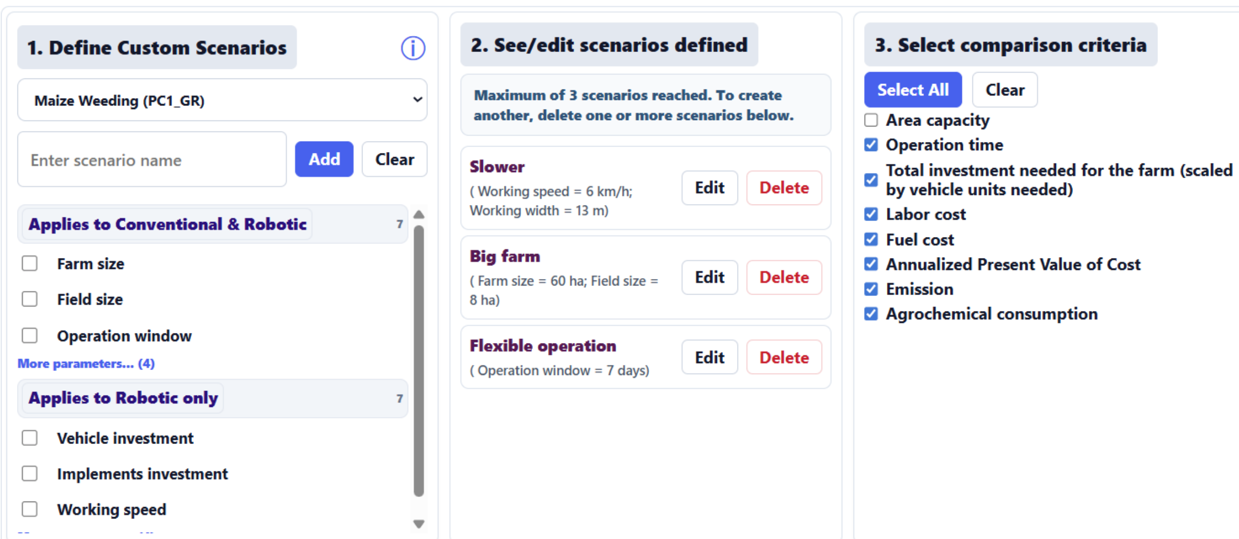
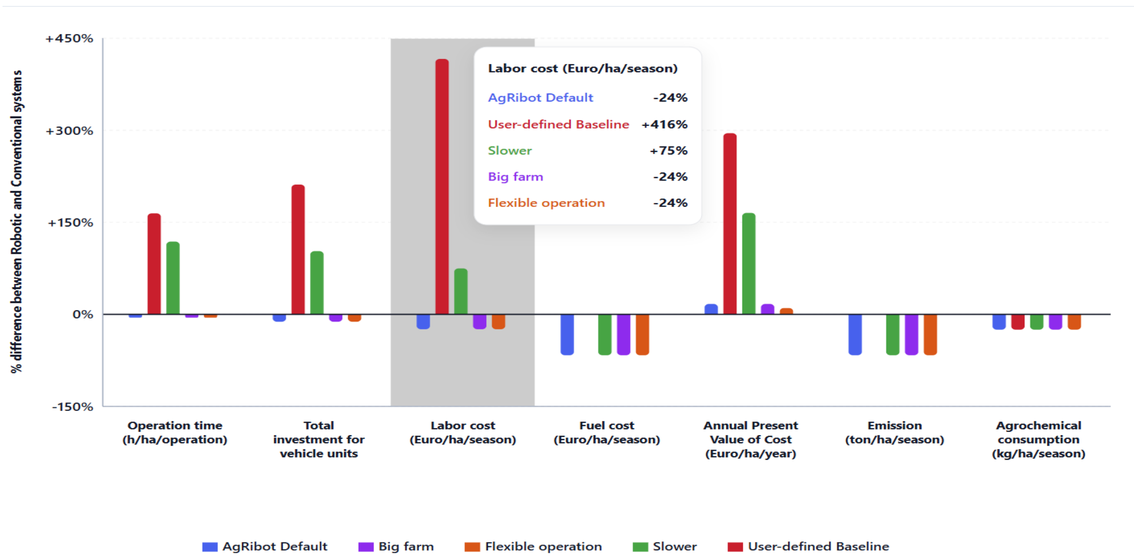


Figure 8: Custom scenario definition dashboard



User-defined Baseline (Farm size = 40 ha; Field size = 10 ha; Working width = 12 m); Slower (Working speed = 6 km/h; Working width = 13 m); Big farm (Farm size = 60 ha; Field size = 8 ha); Flexible operation (Operation window = 7 days).

Figure 9: Scenario Analysis Results

Scenario comparison results are expressed as percentage differences between robotic and conventional systems, using the user-defined baseline as the reference for the respective robotic and conventional systems. This helps users identify whether robotic technology becomes attractive under alternative assumptions. This structure allows users to move from project-defined default assumptions toward farm-specific and scenario-specific assessments.

5.7.3. Report export

The export functionality generates PDF report containing background description, assumptions, list of selected use-cases included for analysis, all data pages and results. Exported reports support documentation, stakeholder communication, teaching activities, and strategic investment planning.

6. Discussion

AgRibot-IAT addresses a practical need in agricultural robotics: the ability to evaluate whether robotic applications provide socio-economic and environmental advantages relative to conventional systems under specific farm-level conditions. The platform is not intended to produce universal conclusions regarding agricultural robotics. Instead, it provides a structured and transparent framework for evaluating selected robotic applications within defined use cases in a user-friendly set-up.

Existing literature indicates that economic performance of agricultural robots is highly context-dependent. Factors such as field size, labor costs, machinery utilization, work rates, repair costs, maintenance requirements, and crop-operation characteristics can strongly influence whether robotic systems become economically attractive. This justifies the design choice of AgRibot-IAT as a user-customizable and scenario-based assessment tool.

The results structure strengthens the decision-support role of the platform. Baseline assessment provides a reference point, scenario analysis supports sensitivity evaluation, and report export facilitates communication among stakeholders.

Interpretation of AgRibot-IAT outputs should remain use-case specific. Because each AgRibot use case represents a unique crop, operation, country context, and technology package, results should not be generalized across all farming systems.

The platform is particularly useful for addressing questions such as:

- Under which assumptions do robotic systems reduce operating costs?
- Which cost categories drive differences between robotic and conventional systems?
- How sensitive are results to labor, fuel, maintenance, and investment assumptions?
- What environmental trade-offs arise from robotic technology adoption?
- How do user-defined assumptions differ from project default datasets?

The web platform demonstrated stable responsiveness, efficient scenario customization, and rapid comparative result generation during testing across AgRibot use cases.

Several limitations should nevertheless be acknowledged. First, the platform is limited to the crops and operations represented in the AgRibot project use cases in Europe. Second, assessment quality depends on the representativeness and reliability of both default and user-provided data. Third, environmental indicators may not capture all life-cycle implications of robotic technologies but a few key indicators

In this regard, future development may include:

- Additional environmental and social indicators
- Improved interoperability with farm data systems
- Expanded scenario-analysis capabilities
- Enhanced report customization
- Support for regional-level assessment

7. Conclusion

This paper presented AgRibot-IAT, a web-based impact assessment platform designed to evaluate the socio-economic and environmental implications of agricultural robotics. The platform integrates partial budgeting, Net Present Value analysis, scenario analysis, and interactive web technologies to support evidence-based evaluation of robotic farming systems.

AgRibot-IAT supports comparative assessment of robotic and conventional agricultural systems through customizable baseline evaluation, sensitivity analysis, and structured report generation. The framework contributes to precision agriculture by providing a scalable and transparent approach for evaluating agricultural robotics under realistic farm conditions.

Although the current implementation focuses on crop-operation combinations represented within the AgRibot project, the framework can be adapted to additional crops, technologies, and management systems. Future work will focus on interoperability with agricultural data systems, refinement of socio-environmental indicators, expanded scenario-analysis capabilities, and support for educational and training activities related to economically viable autonomous agricultural systems.

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The work was also inspired by previous collaboration with the Agricultural University of Athens (AUA) during development of the Agrobot-CBA web tool within the Robs4Crops project, where the University of Copenhagen coordinated development of the cost-benefit analysis framework while AUA supported technical implementation of the platform.

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