EVALUATION OF DIGITAL TWIN ARCHITECTURES FOR PRECISION AGRICULTURE USING MULTI-CRITERIA DECISION ANALYSIS

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ABSTRACT

This paper selected the most suitable digital twin for precision agriculture to enable more precise and rational irrigation on a farm. Six alternatives were evaluated using assessments by seven experts in the field and ten predefined technological, economic and environmental criteria. For this purpose, fuzzy logic in multi-criteria decision-making was applied, specifically the fuzzy Simple Weight Calculation (SiWeC) method to determine criterion weights and the fuzzy Ranking of Alternatives with Weights of Criterion (RAWEC) method for the final ranking of alternatives. The results show that the experts attach the greatest importance to readiness for artificial intelligence integration (AI readiness) and ease of implementation, while the integrated architecture is the most suitable among the alternatives analysed. Its continued application is recommended, subject to a prior assessment of farms' investment capacity and digital readiness.

Introduction

Today, digital transformation can be considered one of the key directions of development in modern agroeconomic systems, particularly given the growing demands for increased productivity, production sustainability and optimisation of existing resources (Wolfert et al., 2017; Klerkx et al., 2019).

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Models involving traditional agriculture face numerous limitations due to climate change, natural resource degradation, input price volatility and the need for more efficient use of water, energy and labour (Gebbers & Adamchuk, 2010). In view of this, precision agriculture is becoming central to the development of the agricultural sector, integrating the Internet of Things (IoT), sensor networks, satellite monitoring, artificial intelligence (AI), machine learning and big data analytics (Liakos et al., 2018; Khanna & Kaur, 2019).

As Tao et al. (2019) state, one of the most advanced concepts in modern digital agriculture is the Digital Twin, defined as a digital replica of a physical system that enables continuous monitoring, simulation, prediction and optimisation of agricultural processes in real time.

Furthermore, Digital Twin architectures enable the effective integration of data from various sources (soil sensors, weather stations, drones, satellites, machinery and farm management information systems), thereby improving the management of production processes, particularly in precision irrigation, input management, yield prediction and resource optimisation (Verdouw et al., 2021). This contributes to a significant increase in productivity, lower costs and improved sustainability, which in turn aligns with the development of the Agriculture 4.0 and Agriculture 5.0 concepts (Saiz-Rubio & Rovira-Más, 2020).

Moreover, selecting the optimal digital twin architecture remains a complex multi-criteria problem. Different architectures, including cloud-based, edge-based, hybrid, AI-driven autonomous, blockchain-integrated and IoT-CPS models, differ according to various criteria (Ferrag et al., 2020). This requires a systematic approach to decision-making that simultaneously encompasses economic, technological, operational, sustainability and other dimensions.

In real-world conditions, the evaluation of DT architectures often relies on expert judgements expressed as linguistic assessments, with subjectivity, imprecision and uncertainty posing significant methodological challenges. Conventional decision-making methods are often insufficient for adequately modelling such conditions, making fuzzy logic one of the most suitable solutions (Zadeh, 1965). Integrating fuzzy approaches with multi-criteria decision-making (MCDM) methods enables more precise modelling of uncertainty and more reliable decision-making in complex systems (Bellman & Zadeh, 1970).

A particularly significant approach in this study is the integration of the fuzzy SIWEC and fuzzy RAWEC methods. Combining these methods provides an integrated framework that enables both the prioritisation of criteria and the ranking of Digital Twin alternatives with a high level of methodological robustness.

Although numerous studies on Digital Twin technologies and individual MCDM methods have been conducted, a research gap remains in the literature regarding the application of an integrated fuzzy multi-criteria approach to evaluating Digital Twin architectures in precision agriculture. Previous research has mainly focused on technical or individual

economic aspects of digitalisation, while an interdisciplinary framework linking technological performance, agroeconomic sustainability, AI readiness and resource efficiency within a single decision-making model is lacking (Verdouw et al., 2021).

Accordingly, the subject of this research would be the evaluation and selection of the optimal Digital Twin architecture for precision agriculture using an integrated fuzzy SIWEC-fuzzy RAWEC model, while the objective would be to identify the architecture that provides the best balance among the existing criteria.

The scientific contribution would be based on the development of an innovative methodological framework for evaluating digital architectures in agriculture, practical support for decision-makers in selecting optimal technological solutions, and a strategic contribution to understanding the digital transition of agriculture. The research thus links agroeconomics, digitalisation, AI and multi-criteria decision-making within a single interdisciplinary model with significant theoretical and practical implications.

In addition, the following research questions arise, which the study should address:

- Which Digital Twin system architecture is the most suitable solution for precision agriculture based on the predefined criteria?
- Which criteria have the greatest influence on selecting the optimal Digital Twin system architecture in modern agricultural systems?
- Does the application of fuzzy MCDM methods enable more reliable evaluation of Digital Twin architectures under conditions of uncertainty and expert subjectivity?

Literature review

Recent research confirms that the Digital Twin system in agriculture is no longer merely a conceptual framework but is becoming a practical technological platform based on IoT sensors, UAV systems, satellite imagery, artificial intelligence, machine learning and cloud/edge infrastructure. Peladarinos et al. (2023) provide a comprehensive review of digital twin applications in smart agriculture and emphasise their importance for more precise decision-making, automation and sustainable resource management. Zhang et al. (2025) also state that Digital Twin technology in agriculture has considerable potential to increase productivity, sustainability and decision-making quality, but that challenges relating to standardisation, interoperability, architectural layers and practical implementation remain unresolved.

Subeesh and Chauhan (2025) view the Agricultural Digital Twin as an advanced form of smart farming system that combines cyber-physical systems, IoT devices, sensors and data on soil, crops, weather conditions and equipment. Their work indicates that data quality, the integration of heterogeneous sources, scalability, costs and the application of systems on real farms remain key problems.

Awais et al. (2025) further emphasise that precision agriculture based on Digital Twin technology requires the integration of IoT, UAV technologies and AI analytics.

Their systematic review covers 167 studies from 2018–2025 and shows that a clearer framework is needed for the design, integration and optimisation of Digital Twin systems in a smart farming environment.

Kim et al. (2024) provide an empirical contribution to the literature by developing an agricultural digital twin for mandarin production. This study shows that it can be used to simulate, monitor and predict actual production processes, confirming that digital twins can have practical value in agronomic and managerial decision-making.

From the perspective of architecture evaluation, it is particularly important that these systems are not uniform. They may differ in their level of data integration, type of sensor infrastructure, data processing approach, degree of AI automation, level of interoperability, costs and sustainability. Therefore, evaluating these architectures naturally falls within multi-criteria decision-making, since selecting the optimal architecture cannot be based on a single indicator alone.

In recent years, multi-criteria methods have increasingly been used in digital and precision agriculture. Kizielewicz et al. (2025), for example, develop an MCDM/MCDA framework for selecting UAV sensors in precision agriculture, using objective weighting methods such as Standard Deviation, Entropy, CRITIC and MEREC. This study is methodologically significant because it demonstrates that selecting digital components in precision agriculture is a multi-criteria problem.

Similarly, Puška et al. (2025) apply an MCDM approach to evaluate mobile applications for small farms. Their study shows that digital solutions in agriculture can be ranked according to functionality, costs, availability, user accessibility and practical value for farmers. In addition to the above, other recent studies and application reviews report the successful use of digital twin systems in agriculture and agribusiness, supporting their increasing adoption (Escribà-Gelonch et al., 2024; Tagarakis et al., 2024; Peladarinos et al., 2024; Gund et al., 2025).

A review of the remaining existing literature reveals a clear research gap: although numerous papers address Digital Twin technology in agriculture and an increasing number address the application of MCDM methods in digital agriculture, few directly integrate these two strands by evaluating alternative DT architectures for precision agriculture. This is precisely why the topic of this study has scientific potential.

Research methodology

The research was conducted in the following five phases:

- Phase 1. Defining the research objective,
- Phase 2. Selecting criteria and alternatives,
- Phase 3. Selecting appropriate experts,
- Phase 4. Processing data using MCDM methods,
- Phase 5. Conducting sensitivity analysis.

The research objective was defined in the preceding introductory section, while the criteria and alternatives were selected through an analysis of scientific and professional literature and additional consultations with the experts selected for this study. The selection was narrowed down to ten technical, economic and environmental criteria, whose names, brief descriptions and types are presented in Table 1 below.

Table 1. Criteria used

Criterion	Criterion name	Criterion description	Type
C1	Cost	Total costs of DT system implementation, infrastructure, maintenance and upgrades	Cost
C2	Interoperability	The system's ability to communicate with IoT devices, sensors, ERP/FMIS platforms and other technologies	Benefit
C3	Scalability	The possibility of expanding the system to include more plots, sensors, users and processes	Benefit
C4	Real-time capability	Speed of data collection, processing and response in real time	Benefit
C5	Cybersecurity	Level of protection of data, infrastructure and communication channels	Benefit
C6	Sustainability	Contribution to sustainable resource use, waste reduction and ecological balance	Benefit
C7	Ease of implementation	Ease of implementation, expertise required and setup time	Benefit
C8	ROI	Expected return on investment through increased productivity and reduced costs	Benefit
C9	AI readiness	System readiness for integrating AI/ML models and advanced analytics	Benefit
C10	Resource efficiency	Efficiency in the use of water, energy, pesticides, fertilisers and labour	Benefit

Source: Authors

The importance of individual criteria has also been described in previous scientific studies, with an overview and their application presented in Table 2 below.

Table 2. Overview of the previous use of the criteria

Criterion	Criterion name	Recommended source	Application in criterion selection
C1	Cost	Klerkx, L., Jakku, E., & Labarthe, P. (2019)	Costs of digital agriculture adoption, investment barriers
C2	Interoperability	Wolfert, S., Ge, L., Verdouw, C., & Bogaardt, M. J. (2017)	Integration of IoT, FMIS and Big Data
C3	Scalability	Tao, F., Zhang, H., Liu, A., & Nee, A. Y. C. (2019)	Scalability of Digital Twin systems
C4	Real-time capability	Khanna, A., & Kaur, S. (2019)	Real-time monitoring and decision-making
C5	Cybersecurity	Ferrag, M. A., Maglaras, L., & Derhab, A. (2020)	Cybersecurity in IoT and smart farming
C6	Sustainability	Kamilaris, A., Kartakoullis, A., & Prenafeta-Boldú, F. X. (2017)	Sustainable digital agriculture

Criterion	Criterion name	Recommended source	Application in criterion selection
C7	Ease of implementation	Rogers, E. M. (2003)	Adoption and implementation of innovations
C8	ROI	Lowenberg-DeBoer, J., & Erickson, B. (2019)	Profitability of precision agriculture technologies
C9	AI readiness	Liakos, K. G., et al. (2018)	AI/ML readiness of the system
C10	Resource efficiency	Gebbers, R., & Adamchuk, V. I. (2010)	Resource optimisation through precision agriculture

Source: Authors

An overview and description of the proposed alternatives are presented in Table 3. These are Digital Twin system architectures currently available on the market and increasingly used for irrigation and the management of production processes on a farm.

Table 3. Alternatives used

Alternative	Architecture name	Brief description
A1	Cloud-based Digital Twin	Centralised DT architecture based on cloud platforms for data storage, processing and analysis
A2	Edge-based Digital Twin	Local data processing through edge devices and gateway systems
A3	Hybrid Digital Twin	A combination of cloud and edge approaches to balance local speed and centralised analytics
A4	AI-driven Autonomous DT	A DT system with integrated AI/ML models for autonomous decision-making
A5	Blockchain-integrated DT	DT architecture with a blockchain layer for security and traceability
A6	IoT-CPS Integrated DT	A fully integrated DT with IoT networks and cyber-physical systems

Source: Authors

Expert selection is an integral part of the research, and the opinions of seven experts were used for this study. The composition of the expert panel took into account their experience in the field, the institutions from which they came, their availability and their ability to provide prompt and reliable opinions (assessments) within the study. Faculty members from the Faculties of Agriculture in Belgrade and Novi Sad and researchers from national scientific institutes whose research activities are partly based on the topic analysed in this study were engaged. They had previously received a questionnaire designed by the authors, in which they provided their expert assessments.

The required calculations were based on the application of multi-criteria methods, specifically their fuzzy variants. The SIWEC (*Simple Weight Calculation*) method was selected to determine the relative importance of the criteria. The choice of this method is justified by the need to incorporate expert knowledge and preferences into criterion weighting through a transparent and cognitively less demanding procedure. Unlike subjective methods based on pairwise comparisons or prior ranking of criteria, SIWEC allows experts to directly assess the importance of each criterion. This procedure

reduces the number of assessments required, facilitates the inclusion of more criteria and simplifies group decision-making. An additional advantage of the method is the possibility of assigning different levels of importance to experts according to their experience, expertise and knowledge of the research problem. Individual assessments are used to form aggregated and normalised weights that express the relative importance of the criteria in the decision-making context under consideration (Puška et al., 2024).

The most important contributions of the SIWEC method are its ease of application, flexibility (through combination with other methods), potential for fuzzy extension, suitability for a large number of criteria, transparency, lower cognitive burden on decision-makers (experts) and previous successful practical application. In this study, we used the fuzzy variant of this method, whose steps are presented below:

Step 1. Assessing the criteria using linguistic values.

Step 2. Transforming linguistic values into fuzzy numbers.

Step 3. Normalising fuzzy numbers.

$$\tilde{n}_{ij} = \frac{x_{ij}^{l}}{max\ x_{ij}^{u}}, \frac{x_{ij}^{m}}{max\ x_{ij}^{u}}, \frac{x_{ij}^{u}}{max\ x_{ij}^{u}}$$

Where $max\ x_{ij}^{u}$ is the maximum value of the fuzzy number.

Step 4. Calculating the standard deviation ($st.dev_j$).

Step 5. Weighting the normalised values.

$$\tilde{v}_{ij} = \tilde{n}_{ij} \times st.dev_j$$

Step 6. Calculating the sum of weights.

$$\tilde{s}_j = \sum_{j=1}^{n} \tilde{v}_j$$

Step 7. Determining criterion weights.

$$\tilde{w}_j = \frac{s_j^{l}}{\sum_{j=1}^{n} s_j^{u}}, \frac{s_j^{m}}{\sum_{j=1}^{n} s_j^{m}}, \frac{s_j^{u}}{\sum_{j=1}^{n} s_j^{l}}$$

For the final ranking of the alternatives analysed, we used the fuzzy *Ranking of Alternatives with Weights of Criterion* (RAWEC) method. The innovative fuzzy Ranking of Alternatives with Weights of Criterion (RAWEC) method was used to rank the predefined cultivars. The RAWEC method was developed by Puška et al. (2024a), and its steps are as follows:

Step 1. Formation of the decision matrix.

Step 2. Normalization of the decision matrix

$$n_{ij} = \frac{x_{ij}^{l}}{\max x_{j}^{u}}, \frac{x_{ij}^{m}}{\max x_{j}^{u}}, \frac{x_{ij}^{u}}{\max x_{j}^{u}}; \; n'_{ij} = \frac{\min x_{j}^{l}}{x_{ij}^{u}}, \frac{\min x_{j}^{l}}{x_{ij}^{m}}, \frac{\min x_{j}^{l}}{x_{ij}^{l}}; \text{ for benefit criteria}$$

$$n_{ij} = \frac{\min x_{j}^{l}}{x_{ij}^{u}}, \frac{\min x_{j}^{l}}{x_{ij}^{m}}, \frac{\min x_{j}^{l}}{x_{ij}^{l}}; \; n'_{ij} = \frac{x_{ij}^{l}}{\max x_{j}^{u}}, \frac{x_{ij}^{m}}{\max x_{j}^{u}}, \frac{x_{ij}^{u}}{\max x_{j}^{u}}; \text{ for cost criteria}$$

Where, $x_{j\,min}$ is the minimum value of individual criterion, and $x_{j\,max}$ is the maximum value of individual criterion.

Step 3. Calculating the deviation from the criterion weight

$$\tilde{v}_{ij} = \sum_{i=1}^{n} \tilde{w}_j \cdot \left(1 - \tilde{n}_{ij}\right); \tilde{v}'_{ij} = \sum_{i=1}^{n} \tilde{w}_j \cdot \left(1 - \tilde{n}'_{ij}\right)$$

Where, $\tilde{w}_j$ is the criterion weight

Step 4. Defuzzification

$$v_{ij\,def} = \frac{v_i^{l} + 4v_i^{m} + v_i^{u}}{6}; v'_{ij\,def} = \frac{v_i^{l} + 4v_i^{m} + v_i^{u}}{6}$$

Step 5. Calculating the value of the RAWEC method

$$Q_i = \frac{v'_{ij} - v_{ij}}{v'_{ij} + v_{ij}}$$

For the application of these methods, that is, for the calculations themselves, the fuzzy scale presented in Table 4 below was used. The scale shows linguistic values converted into numbers.

Table 4. Fuzzy assessment scale

1	Very low	VL	(1,1,2)
2	Low	L	(1,2,4)
3	Medium Low	ML	(2,4,6)
4	Medium	M	(3,5,7)
5	Medium Good	MG	(5,7,9)
6	Good	G	(7,9,10)
7	Very good	VG	(9,10,10)

Source: Puška et al., 2024

Results and discussion

The study analyses the selection of a digital twin architecture to improve precision irrigation and resource management on a medium-sized farm. The subject of the analysis is the architectural option for a Digital Twin system. The user context involves a farm considering the integration of data on soil moisture, weather conditions and irrigation

system operation with a digital model for condition monitoring and decision support. The six alternatives in Table 3 above are compared according to the ten predefined criteria.

The first step is to construct the initial decision matrix using linguistic values obtained from expert assessments for each predefined criterion (Table 5).

Table 5. Initial decision matrix for the criteria

Expert/ Criteria	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
E1	VG	G	G	G	MG	M	G	ML	VG	ML
E2	G	G	VG	MG	M	ML	MG	L	G	M
E3	G	G	M	G	VG	L	G	G	VG	M
E4	MG	MG	G	G	MG	ML	VG	MG	VG	ML
E5	G	G	G	MG	MG	L	VG	M	VG	ML
E6	G	MG	G	G	MG	ML	G	ML	G	ML
E7	MG	G	G	VG	MG	L	VG	ML	VG	ML

Source: Authors, based on the expert survey

Following the subsequent steps of the selected method, the research results show that "AI readiness" (C9; 0.1318) and "Ease of implementation" (C7; 0.1244) have the greatest relative importance in selecting digital twin architectures for precision agriculture. This pattern of weights can be interpreted as an effort by experts to combine advanced analytical capabilities with the practical feasibility of introducing the technology (Table 6). Similar findings are reported by Purcell and Neubaue**r** (2023), who identify these functions as a basis for improving decision support and automation in agriculture. This in itself indicates the importance of future system upgrades, but does not confirm the quality of its predictions or its economic viability.

Table 6. Ranking of criteria

ID	Criterion	Type	$\tilde{w}_j$
C1	Cost	Cost	0.1171
C2	Interoperability	Benefit	0.1151
C3	Scalability	Benefit	0.1164
C4	Real-time capability	Benefit	0.1171
C5	Cybersecurity	Benefit	0.0997
C6	Sustainability	Benefit	0.0482
C7	Ease of implementation	Benefit	0.1244
C8	ROI	Benefit	0.0702
C9	AI readiness	Benefit	0.1318
C10	Resource efficiency	Benefit	0.0602

Source: Authors' calculations

The high assessment of the criterion relating to ease of implementation indicates that technological sophistication represents only one part of the decision to select a digital solution. This can be linked to the study by Klerkx et al. (2019), which considers the adoption of digital technologies in terms of farmers' skills, changes in work, knowledge systems and institutional relationships. All of this points to the need to adapt Digital Twin systems to the competencies available to users and the organisation of production. The practical implication is that the development of advanced functionalities should be accompanied by training, advisory support and clear operating procedures.

In addition, the cost and real-time capability criteria have equal weights (0.1171), while scalability (0.1164) and interoperability (0.1151) are assessed as almost equally important. In line with the above, Verdouw et al. (2021) emphasise that digital twins enable the management of agricultural processes based on data available in near real time and the simulation of the consequences of interventions. The results of this paper complement this understanding by showing that, alongside system functionality, experts attach importance to costs and the possibility of system integration and expansion.

Table 7. Initial decision matrix for the alternatives

Expert I										
	C1	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**	**C8**	**C9**	**C10**
A1	ML	MG	MG	M	MG	G	MG	G	VG	G
A2	ML	G	G	ML	ML	MG	MG	M	MG	MG
A3	MG	G	G	MG	MG	MG	M	G	G	VG
A4	MG	MG	G	MG	MG	G	MG	MG	G	G
A5	M	M	MG	MG	MG	MG	M	MG	MG	MG
A6	L	G	G	VG	G	VG	G	G	VG	MG
. . .										
Expert VII										
	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
A1	M	MG	MG	M	MG	G	MG	G	M	MG
A2	ML	G	MG	M	ML	MG	MG	M	G	MG
A3	MG	M	M	MG	M	MG	M	M	VG	VG
A4	MG	MG	G	VG	MG	G	MG	MG	G	G
A5	M	M	VG	MG	MG	G	M	MG	MG	VG
A6	ML	G	VG	MG	G	G	M	G	G	VG

Source: Authors, based on the expert survey

The highest-ranked alternative is the architecture integrating the Internet of Things and cyber-physical systems (IoT-CPS Integrated DT-A6), with a Q_i value of 0.9541 (Table 7). In line with this result, Peladarinos et al. (2023) point out that integrating different data sources enables more comprehensive monitoring of production conditions and supports decisions on irrigation, fertilisation and crop protection. In this sense, the ranking of alternative A6 is consistent with the importance of integration emphasised in the literature.

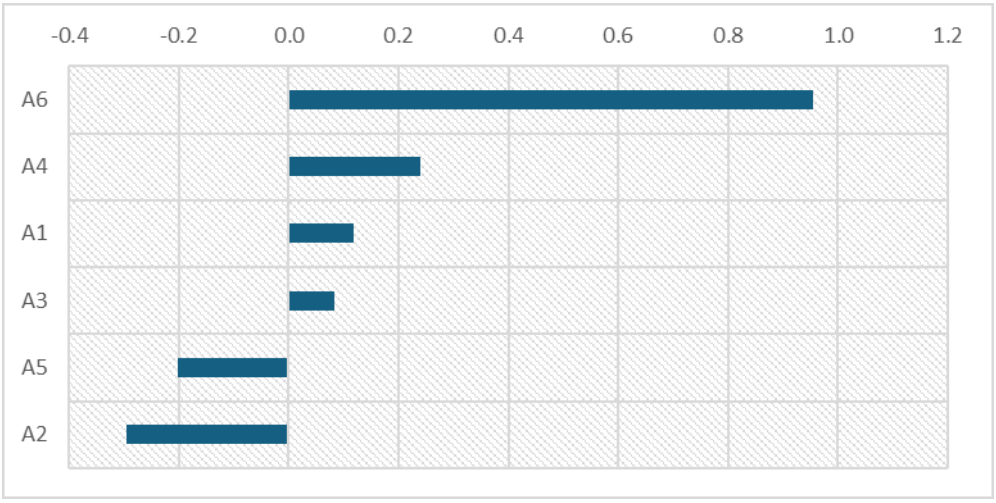
Table 8. Final ranking of alternatives

ID	Alternative	v_{ij}	v'_{ij}	Q_i	Rank
A6	IoT-CPS Integrated DT	0.0089	0.3769	0.9541	1
A4	AI-driven Autonomous DT	0.1581	0.2578	0.2397	2
A1	Cloud-based Digital Twin	0.1853	0.2348	0.1177	3
A3	Hybrid Digital Twin	0.1896	0.2237	0.0824	4
A5	Blockchain-integrated DT	0.2500	0.1663	-0.2011	5
A2	Edge-based Digital Twin	0.2584	0.1404	-0.2958	6

Source: Authors' calculations

The second-place ranking of the AI-driven autonomous architecture (A4; $Q_i = 0.2397$) shows that the high importance of AI readiness is insufficient for this alternative to achieve the best overall ranking. Within the model applied, the combination of all criteria favours alternative A6. Cloud-based architectures rank third (A1; $Q_i = 0.1177$), while hybrid architectures rank fourth (A3; $Q_i = 0.0824$). These should be considered further because of the relatively small difference between their scores (Table 7). Figure 1 below provides a visualisation of the final ranking of alternatives.

Figure 1. Ranking using the fuzzy RAWEC method



Conclusion

This study considers the selection of the most suitable digital twin architecture for precision agriculture. An integrated fuzzy SIWEC-fuzzy RAWEC model was used in the study. The objective was to connect technology, economics and ecology within a single decision-making framework. Six alternatives were evaluated in the analysis. The assessment was based on ten criteria. The opinions of seven experts were used for the assessment. All experts provided their assessments. This enabled multiple aspects to be linked within a single system. The results show that the most important factors are the capacity to integrate artificial intelligence and ease of implementation. This means that experts favour architectures that can readily adapt to new technologies. Architectures that are easily introduced into practice also have an advantage. Costs also have a major influence. Real-time capability is crucial. Scalability and interoperability are also important. This indicates that technology must adapt its performance to the actual needs of users. The lower weights of sustainability and resource efficiency do not mean that these criteria are unimportant. They simply show that the expert panel placed greater emphasis on other aspects.

What could be characterised as the methodological contribution of the paper is the successful application of an integrated multi-criteria modelling framework, while its practical usefulness would lie in supporting agricultural producers, advisory services and investors when considering the introduction of digital solutions. Future research should expand the expert decision-making panel and its composition, and focus on comparing the results with similar ranking methods and validating the approach on farms of different sizes and with different investment and digital capacities.

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Conflict of interests

The authors declare no conflict of interest.

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