A Model to Support Decision-Making in the Generation of Management Zones for Fruit Growing

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Abstract.

Implementation of precision fruit farming faces challenges in accurately defining these zones, mainly because, as the orchard reaches the productive phase, the relevance of soil fertility decreases compared to other phytotechnical and physiological parameters. Correct generation of management zones is crucial for the success of the operation, but the accurate interpretation of the collected data requires highly qualified professionals with years of experience, a gap that limits the adoption of precision fruit farming. The overall objective of this work is to develop a computer-based decision support system (DSS) using a binary decision tree to assist in the generation of management zones in precision fruit farming. This tool aims to increase the accuracy of the process and reduce the dependence on specialized technical expertise, standardizing procedures and minimizing the need for years of experience in management. The system was designed to guide the generation of these zones, considering factors such as plant physiology, climate, and soil fertility. The methodology was based on a perceived demand in the productive sector and used a new algorithm structured on the principle of decision trees, using binary questions and answers (yes or no) in the form of flowcharts. The algorithm was divided into specialties for the generation of management zones. The computational system was planned to use structured programming in Python 3.11 (as the back-end), and the front-end in Django for the creation of the RAG, but ended up being developed using the n8n software, whose code is in JSON, allowing publication on the Web. The system was modeled as an Artificial Intelligence Agent (AI Agent) with a deliberative (goal-oriented) architecture, orchestrated in n8n. This agent is responsible for the coordination and execution of an LLM model (ChatGPT), which compiles the information from the flowcharts and offers the user detailed answers in a guiding text format, with a meticulous step-by-step process, ideal for lay users. For preliminary evaluation purposes, the completed system was subjected to a semi-empirical benchmark, where the URL was informally distributed so that users could interact and verify the consistency of the responses. The feedback from the evaluations, conducted personally, demonstrated that the decision support system is functional, modular, and adaptable. The research confirmed that the combination of binary decision trees with deliberative agents constitutes an effective solution for guiding the process of generating management zones. It is expected that the tool, which acts as a digital manager, can be made available to the general public, possibly through Embrapa, allowing for its future expansion and improvement. In short, the work offers a technological alternative capable of reducing dependence on specialists and democratizing access to data-driven management practices,

contributing to the digitalization and sustainability of agribusiness.

Keywords.
Large Language Models, Precision Agriculture, Digital Agriculture

Introduction

Precision Agriculture (PA) is based on the recognition that agricultural environments are spatially heterogeneous and therefore should not be managed as uniform production units. To address this variability, management zones are commonly established by grouping areas with similar characteristics, allowing site-specific interventions and more efficient resource allocation (Luchiari Júnior et al., 2011; Molin et al., 2020).

In perennial crops, particularly in fruit production systems, the generation of management zones presents additional challenges. During orchard establishment, soil fertility and water availability are among the most important factors influencing plant growth and development. However, as orchards reach their productive phase, the relationship between soil fertility and crop performance progressively weakens. The expansion of root systems, accumulation of reserves in perennial structures, and increasing physiological complexity of mature plants reduce the direct influence of soil fertility on productivity and fruit quality (Childers et al., 1995; Ferree and Schupp, 2003; Gebler et al., 2015). Consequently, management decisions become increasingly dependent on other phytotechnical and physiological variables, such as vegetative vigor, nutritional status, dormancy break, fruit thinning requirements, phytosanitary conditions, and yield potential (Ferree and Schupp, 2003).

The successful implementation of Precision Fruit Growing therefore depends not only on the availability of spatial data, but also on the ability of decision makers to correctly interpret the relationships between environmental variability and crop responses. In practice, this process often requires highly qualified professionals with extensive field experience. The scarcity of such specialists has been identified as one of the major barriers to the broader adoption of precision agriculture technologies in perennial crops, particularly when management zones must be generated from multiple and often conflicting sources of information (Gebler et al., 2024).

Recent advances in Artificial Intelligence (AI) have created new opportunities for the development of Decision Support Systems (DSS) capable of assisting users in complex decision-making processes. Among the available approaches, binary decision trees offer a transparent and interpretable framework for representing specialist reasoning through sequential yes-or-no questions, facilitating user interaction while preserving expert knowledge structures (Quinlan, 1993). Furthermore, intelligent agents supported by Large Language Models (LLMs) have expanded the possibilities for knowledge transfer, allowing users to interact with expert systems through natural language interfaces (Russell and Norvig, 2013).

To address the challenge of management zone generation in Precision Fruit Growing, Gebler et al. (2024) proposed a structured algorithm based on binary decision trees covering different orchard management specialties. Building upon this framework, the present work transformed the original graphical algorithm into a computer-based Decision Support System implemented as a deliberative AI agent. The system combines workflow orchestration, binary decision trees, and a Large Language Model to guide users through the process of defining management zones according to orchard characteristics and management objectives. Therefore, the objective of this study was to develop and evaluate a decision support system capable of assisting users in the generation of management zones for Precision Fruit Growing, reducing dependence on specialized expertise and promoting broader adoption of data-driven management practices.

Materials and Methods

Knowledge Base Development

The knowledge base used in this study was derived from a previously published algorithm developed to support the implementation of management zones in apple orchards under Precision Fruit Growing conditions (Gebler et al., 2024). The original algorithm was constructed from expert knowledge obtained through ex-ante and ex-post evaluations conducted by specialists in different areas of orchard management. The objective was to provide a structured methodology capable of assisting users in the generation of management zones while avoiding the need for extensive previous experience in precision agriculture.

The algorithm was organized into three major operational phases representing the orchard production cycle. Phase I focused on orchard establishment and included management zones related to soil fertility, soil water storage capacity, and topography. Phase II addressed tree formation and vegetative development, including vigor, nutrition, and dormancy-breaking management zones. Phase III focused on production management, including fruit thinning, phytosanitary monitoring, and yield forecasting. Altogether, nine specialized decision modules were incorporated into the system.

Algorithm Structuring

The original graphical flowcharts were converted into Unified Modeling Language (UML) activity diagrams to facilitate computational implementation and standardize the decision logic. The proposed methodology was based on binary decision trees, in which users navigate through a sequence of yes-or-no questions. Depending on the responses provided, the system may indicate that: (i) management zones can be generated; (ii) Precision Fruit Growing is not recommended under the evaluated conditions; or (iii) additional decision modules must be consulted.

Figure 1 presents an example of the UML activity diagram used to represent the decision-making process for management-zone generation. The diagram preserves the original binary-tree structure while providing a standardized representation suitable for software implementation.

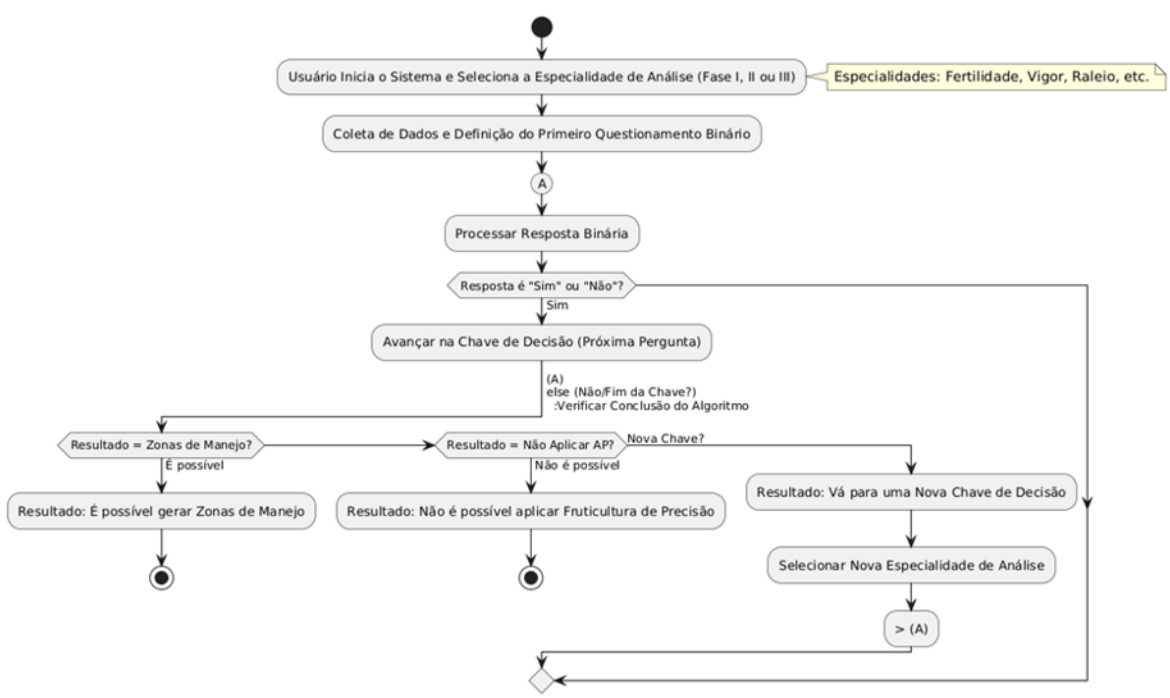

Fig. 1. UML activity diagram representing the binary decision-tree structure used for

management-zone generation in Precision Fruit Growing.

The binary-tree approach was selected due to its transparency, interpretability, and ability to represent expert reasoning in a structured and reproducible manner (Quinlan, 1993).

Decision Support System Architecture

The Decision Support System was implemented as a deliberative Artificial Intelligence agent. The architecture combined workflow orchestration using the n8n platform with a Large Language Model (ChatGPT) responsible for processing user requests and generating explanatory responses.

The workflow receives user questions through a web interface, accesses the knowledge base composed of the decision-tree documents, retrieves the relevant information, and submits the contextualized content to the language model. The AI agent then generates a detailed response describing the recommended decision path and the conditions required for management zone generation.

The complete workflow architecture implemented in n8n is presented in Figure 2. The workflow integrates user interaction, document retrieval, knowledge processing, and response generation through a Large Language Model, forming the operational core of the proposed Decision Support System.

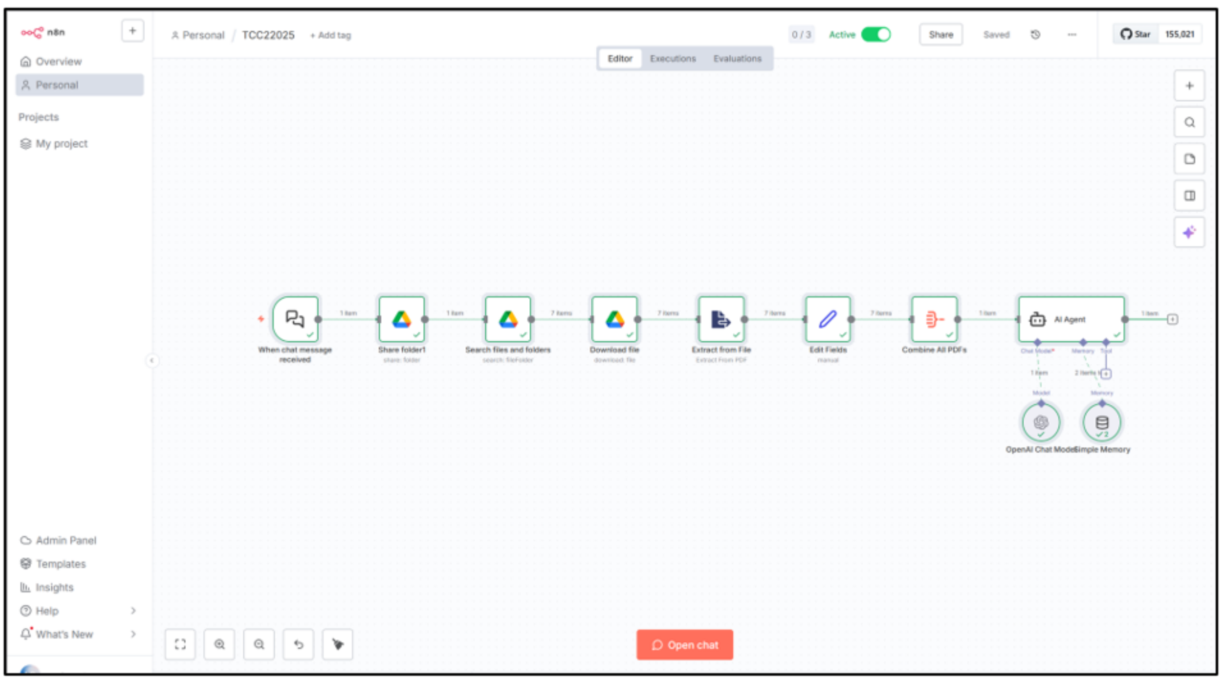

Fig. 2. Workflow architecture of the deliberative AI agent implemented in n8n, integrating the knowledge base, workflow orchestration, and Large Language Model services.

Unlike conventional expert systems that provide only static outputs, the proposed architecture allows interactive communication through natural language, enabling users with limited technical knowledge to navigate the decision process more efficiently.

Preliminary Evaluation

A preliminary semi-empirical evaluation was conducted to verify the operational functionality and consistency of the system. The web application was made available through a public URL and distributed informally to ten volunteer users. The participants represented diverse backgrounds, including fruit growers, agronomists, information technology professionals, and individuals with no previous experience in Precision Agriculture. Participants were asked to interact with the agent and evaluate whether the system was accessible, functional, and capable of providing coherent responses based on the embedded management-zone algorithms.

The evaluation focused on operational performance, response consistency, and usability rather than statistical validation. User feedback was collected through direct interaction with the development team and used to verify the feasibility of the proposed Decision Support System as a tool for supporting management-zone generation in Precision Fruit Growing.

Results and Discussion

The first outcome of this study was the successful transformation of expert knowledge related to management-zone generation into a structured computational framework. The original algorithm proposed by Gebler et al. (2024) was based on graphical flowcharts designed to support decision-making in Precision Fruit Growing. Although effective as a technical reference, its practical application still required users to manually navigate multiple decision paths and interpret the resulting recommendations. By converting these flowcharts into UML activity diagrams and subsequently integrating them into an AI-based architecture, the decision process became more standardized, reproducible, and accessible.

The resulting system incorporated nine management-zone specialties distributed across the orchard production cycle, covering soil-related, physiological, phytotechnical, and production-oriented aspects of orchard management. This organization reflects the complexity of perennial crop systems, where different factors become relevant according to orchard age and management objectives. Unlike annual crops, where soil fertility often remains the dominant decision variable, mature orchards require the integration of physiological and environmental information to support management decisions (Ferree and Schupp, 2003; Gebler et al., 2015). Consequently, the proposed system provides a broader perspective of orchard variability than approaches based exclusively on soil attributes.

A second important result was the successful implementation of the Decision Support System as a deliberative AI agent. The combination of workflow orchestration and a Large Language Model enabled the system to interact with users through natural language while preserving the logical structure of the original decision trees. This approach differs from conventional expert systems, which frequently require users to navigate rigid interfaces or interpret technical outputs without contextual explanations. The proposed architecture allows the agent to act as a digital advisor, guiding users through the reasoning process and explaining the rationale behind each decision pathway.

Figure 3 illustrates a practical example of user interaction with the system. Through a conversational interface, the agent guides users through the decision process and translates technical knowledge into operational recommendations. This capability is particularly important for users with limited experience in Precision Agriculture, as it reduces the complexity associated with the interpretation of management-zone methodologies.

The preliminary evaluation demonstrated that the system was operationally functional and capable of generating coherent responses based on the embedded knowledge base. The preliminary benchmark involved ten volunteer users representing different backgrounds, including growers, agronomists, information technology professionals, and non-specialists. Informal testing confirmed that the platform was accessible through a standard web browser and capable of responding consistently to management-zone-related questions. Although the evaluation was not designed as a formal usability experiment, user feedback indicated that the system successfully translated technical concepts into understandable recommendations, particularly for individuals with limited previous experience in Precision Agriculture.

From a broader perspective, the proposed approach contributes to an important challenge currently faced by Precision Agriculture and Digital Agriculture: the democratization of specialist knowledge. The increasing availability of sensors, geospatial data, and digital platforms has expanded data collection capabilities, but the interpretation of this information remains highly dependent on human expertise (Inamasu et al., 2024). Decision Support Systems based on artificial intelligence may help bridge this gap by transforming expert reasoning into accessible digital services. In this context, the proposed system can be viewed as a first step toward the development of intelligent digital managers capable of supporting producers, consultants, and extension agents during the implementation of Precision Fruit Growing programs.

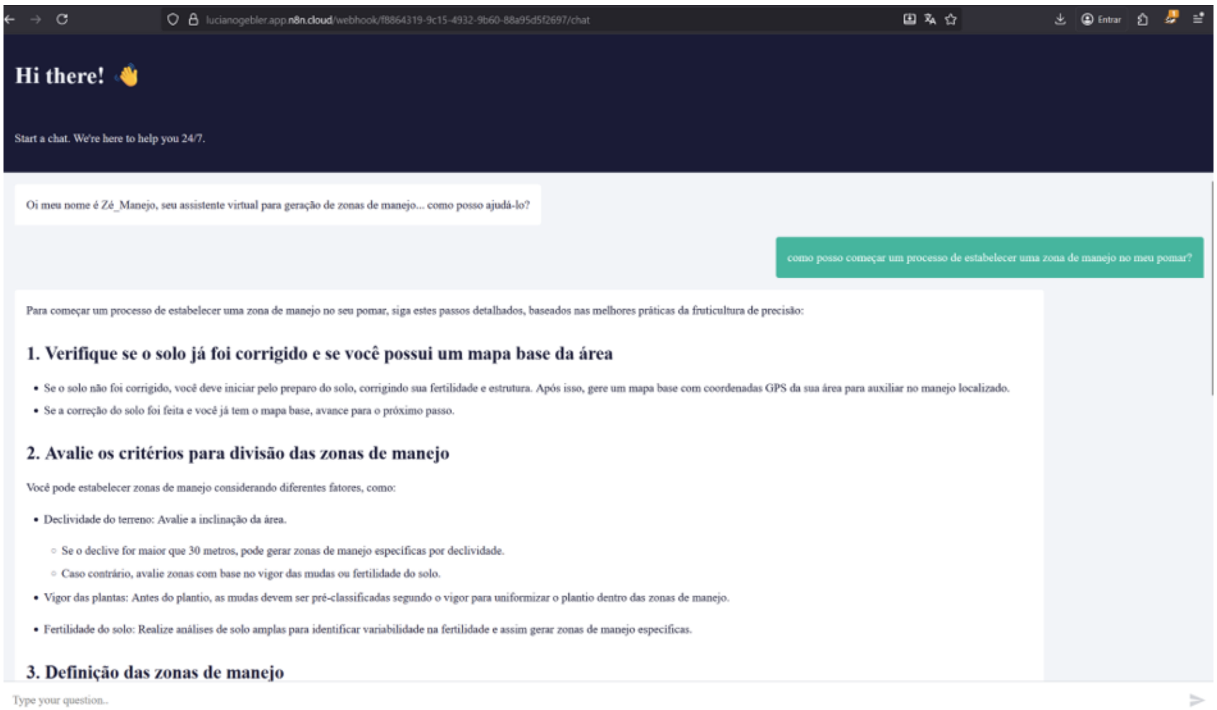

Fig. 3. Example of user interaction with the proposed Decision Support System through the web interface.

Despite these promising results, some limitations should be acknowledged. The current version relies on a predefined knowledge base derived from expert-designed decision trees and does not yet incorporate real-time field data, sensor networks, or machine-learning models. Furthermore, the evaluation was limited to operational verification and qualitative feedback. Future developments should include formal usability assessments, larger validation studies involving different user profiles, and integration with external databases and IoT devices. Such improvements would allow the system to evolve from a knowledge-guided decision-support tool into a more comprehensive digital agriculture platform.

Overall, the results indicate that the combination of binary decision trees, deliberative AI agents, and Large Language Models constitutes a feasible and promising strategy for supporting management-zone generation in Precision Fruit Growing. By reducing dependence on specialized expertise and improving access to structured agronomic knowledge, the proposed system may contribute to the broader adoption of data-driven management practices in perennial crops.

Conclusion

This study demonstrated the feasibility of transforming expert knowledge related to management-zone generation in Precision Fruit Growing into a computer-based Decision Support System. By combining binary decision trees, workflow orchestration, and a deliberative AI agent architecture, the proposed system was able to guide users through complex decision-making processes while preserving the logical structure of specialist knowledge.

The resulting platform successfully integrated nine management-zone specialties covering different phases of orchard management, from orchard establishment to production and harvest planning. The implementation of the system through a conversational interface enabled users to interact with the knowledge base using natural language, reducing the complexity traditionally associated with the interpretation of management-zone methodologies.

Preliminary evaluation indicated that the system is operationally functional and capable of providing coherent recommendations based on the embedded decision algorithms. These results suggest that the proposed approach has potential to reduce dependence on highly specialized professionals, facilitating the adoption of Precision Fruit Growing practices and supporting the broader digitalization of orchard management.

Future developments should focus on formal usability assessments, integration with real-time data sources, sensor networks, and geospatial databases, as well as the incorporation of adaptive learning mechanisms. Such improvements may allow the system to evolve into a more comprehensive digital agriculture platform capable of supporting increasingly complex management decisions in perennial cropping systems.

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References

Childers, N. M., Morris, J. R., & Sibbett, G. S. (1995). Soil management for apples. In N. F. Childers (Ed.), Modern Fruit Science: Orchard and Small Fruit Culture (10th ed., pp. 71–91). AGScience Inc.

Ferree, D. C., & Schupp, J. R. (2003). Pruning and training physiology. In D. C. Ferree & I. J. Warrington (Eds.), Apples: Botany, Production and Uses (pp. 319–344). CAB International.

Gebler, L., Grego, C. R., Vieira, A. L., & Kuse, L. R. (2015). Spatial influence of physical and chemical parameters on management zone definition in apple orchards. Engenharia Agrícola, 35, 1160–1171.

Gebler, L., De Rossi, A., Alves, S. A. M., & Santos, R. S. S. (2024). Algorithm for setting up management zones in precision fruit growing in the apple crop. In Agricultura de Precisão: Um Novo Olhar na Era Digital (pp. 493–508).

Inamasu, R. Y., et al. (2024). Precision Agriculture: historical perspective and continuous transformation. In Agricultura de Precisão: Um Novo Olhar na Era Digital (pp. 9–26).

Luchiari Júnior, A., et al. (2011). Management Zones: theory and practice. In Agricultura de Precisão: Um Novo Olhar (pp. 60–64).

Molin, J. P., et al. (2020). Precision agriculture and the digital contributions for site-specific management of the fields. Revista Ciência Agronômica, 51(spe).

Quinlan, J. R. (1993). C4.5: Programs for Machine Learning. Morgan Kaufmann Publishers.

Russell, S. J., & Norvig, P. (2013). Artificial Intelligence: A Modern Approach. Pearson Education.

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