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Designing Decision-Support Systems for Precision Agriculture: A Methodological Framework for Explainability, Usability, Validation, and Adoption

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Abstract

Decision-support systems are increasingly positioned as mechanisms for translating agricultural data and analytical models into farm-management recommendations, yet their methodological quality cannot be judged through predictive performance alone. This article proposes an original methodological framework for designing and evaluating decision-support systems in precision agriculture. The framework integrates farm-management decision-context definition, stakeholder mapping, data-quality and provenance assessment, model and recommendation-logic documentation, explainability and interpretability requirements, usability and farmer-centered design, validation planning, decision-reliability assessment, adoption-barrier analysis, implementation-condition assessment, human oversight, and iterative feedback. Explainability is treated as a role-sensitive design requirement involving input visibility, output explanation, decision rationale, uncertainty communication, traceability, and appropriate explanation timing and format. Usability is addressed through farmer participation, co-design, workflow integration, accessibility, local relevance, manageable decision-support workload, training, and feedback mechanisms. Validation is extended beyond internal model testing to include external and local validation, calibration, error analysis, field-validation planning, drift monitoring, and review of the complete recommendation pathway. Adoption is interpreted as a contextual and voluntary process shaped by perceived usefulness, trust, affordability, infrastructure, digital capability, interoperability, support, and governance. Human oversight remains necessary because neither technical performance nor explanation quality independently establishes decision reliability. The framework contributes a structured method for coordinating design and evaluation activities while retaining explicit boundaries against claims of guaranteed decision quality, adoption, or deployment readiness.

Keywords Precision agriculture, Explainable AI, Usability, Validation, Decision-support systems, Farmer-centered design

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Introduction

Decision-support systems in precision agriculture can be understood as socio-technical arrangements that connect heterogeneous farm data, analytical processes, user-facing information, and human judgment. Their input foundations may include sensor observations, remote-sensing products, weather records, soil and crop information, machinery data, and farm-management records. These sources are transformed through data infrastructures and analytical procedures before being presented as predictions, alerts, comparisons, optimization outputs, or recommendations. Consequently, a

decision-support system is not equivalent to a prediction model. It includes the surrounding processes through which data are collected, documented, interpreted, communicated, reviewed, and incorporated into farm-management decisions. Smart-farming research has shown that these processes involve not only technical components but also data ownership, organizational relationships, service providers, knowledge intermediaries, and users with different responsibilities and information needs [1].

Digital agriculture similarly extends beyond the adoption of isolated software, sensing devices, or artificial-intelligence models. It involves changes in agricultural knowledge, work organization, decision authority, skills, infrastructure, and relationships among farmers, advisors, technology developers, data stewards, researchers, and platform providers. These social and institutional dimensions influence which farm problems are selected for digital support, whose knowledge is represented in system requirements, how data are governed, and whether users can question or override recommendations. A technically advanced system may therefore remain poorly aligned with local practices, inaccessible to some users, or dependent on organizational arrangements that have not been adequately examined. Treating precision-agriculture decision support as a socio-technical design problem helps reveal these wider dependencies and prevents technical functionality from being mistaken for practical suitability [2].

Agricultural decision-support systems may combine descriptive analytics, prediction models, optimization models, recommendation logic, visualization components, and advisory functions. They can be configured for irrigation scheduling, nutrient-management support, pest or disease risk interpretation, yield assessment, resource allocation, or other farm-management contexts where adequate evidence and locally relevant data are available. However, the existence of a model output does not establish that the resulting advice is understandable, agronomically appropriate, transferable across locations, or reliable under changing field conditions. Agricultural decision-support research has consequently identified continuing challenges involving data integration, interoperability, knowledge representation, model evaluation, interface design, and the translation of analytical results into actionable but appropriately bounded recommendations [3].

This article argues that precision-agriculture decision-support systems should be evaluated through a coordinated methodological process rather than through technical performance alone. Explainability, interpretability, usability, farmer participation, validation logic, uncertainty communication, decision reliability, adoption conditions, governance safeguards, and human oversight must be considered as interconnected design requirements. Responsible smart-farming scholarship further indicates that anticipation, inclusion, reflexivity, and responsiveness are needed when digital systems may redistribute knowledge, influence decision authority, or create new dependencies [4]. The objective of this article is therefore to propose a methodological framework that structures how decision contexts, data inputs, model outputs, explanation requirements, user interfaces, validation procedures, implementation conditions, and feedback mechanisms can be designed and evaluated. The proposed framework supports methodological planning rather than operational prescription and does not independently establish farm-level benefit, user trust, adoption, or readiness for deployment.

Decision-Support Systems in Precision Agriculture

A precision-agriculture decision-support system should begin with a defined farm-management decision rather than with an available dataset or modelling technique. The methodological starting point is to identify who makes the decision, when it is made, which alternatives are available, what evidence is required, what consequences may follow, and which parts of the process should remain subject to human review. Within this structure, a prediction model estimates an outcome or state, an optimization model evaluates alternatives against specified objectives and constraints, a recommendation system translates analytical outputs into possible actions, and an advisory tool communicates information within a broader human decision process. These functions may be combined, but they should remain methodologically distinguishable. Agricultural DSS architectures demonstrate the value of separating data ingestion, analytical processing, model execution, and user-facing outputs so that each layer can be documented and evaluated independently [5].

The user-facing layer is especially important because decision support is delivered through representations rather than through models in isolation. Maps, time series, alerts, ranked options, comparative scenarios, field summaries, and explanatory text can make complex agricultural information easier to inspect, but they can also conceal uncertainty, exaggerate precision, or overload the user. Interface design must therefore determine which information is visible, how units and thresholds are expressed, when warnings appear, how users move between summary and detail, and whether the system permits questions, corrections, or overrides. Reviews of visualization in agricultural decision-support systems indicate that visual form, information organization, interaction design, and human–computer interaction principles influence whether outputs can be interpreted within agricultural tasks [6]. Interface design should accordingly be treated as a methodological component that requires evaluation rather than as a decorative layer added after modelling.

The analytical capacity of agricultural decision support depends on its data foundation. Connected sensing systems can provide observations on soil, crop, weather, water, equipment, and environmental conditions, while remote sensing and farm records may extend spatial, temporal, and management coverage. Yet additional data sources also introduce questions about sampling, calibration, missingness, synchronization, spatial resolution, data ownership, connectivity, security, and interoperability. Data may be technically available but unsuitable for the intended decision because they are stale, poorly localized, inconsistently formatted, or collected under conditions that differ from the intended use context. Agricultural Internet-of-Things research has therefore emphasized that dependable sensing, communication, and integration infrastructures are prerequisites for data-enabled farm applications, while also identifying reliability, interoperability, energy, communication, and security constraints [7].

A methodological distinction is consequently needed between data availability, model capability, recommendation validity, and operational decision support. Irrigation, nutrient, disease, yield, or resource-allocation applications may use similar sensing and analytical infrastructures, but each has different timing requirements, error consequences, validation needs, and expectations for human review. Layered smart-agriculture architectures can support the movement of data from field devices through communication and processing services to user applications, yet the existence of this pipeline does not demonstrate that its recommendations are locally valid or responsibly usable [8]. Across complementary DSS, visualization, and IoT studies, agricultural decision support is described as a layered socio-technical arrangement linking analytical functions, user-facing outputs, and connected data infrastructure [5–7]. The methodological framework proposed here therefore requires explicit documentation of the decision context, input data, data provenance, model purpose, recommendation logic, interface function, uncertainty, intended user, and limits of use before any claim about decision support is made.

Explainability and Interpretability Requirements

Explainability in precision-agriculture decision support concerns how a system communicates the basis, meaning, scope, and limitations of an output to people responsible for interpreting or acting upon it. Interpretability concerns the degree to which relevant aspects of model behavior can be understood, either because the model is inherently inspectable or because an additional explanatory method is applied. Agricultural explainable-AI scholarship suggests that feature attribution, response analysis, interpretable modelling, and other explanation methods can help reveal how models use agricultural data [9]. Nevertheless, an explanation of model behavior is not equivalent to evidence that the model is accurate, calibrated, transferable, agronomically appropriate, or suitable for a particular decision. Explainability should therefore be designed as one component of responsible review rather than as proof of decision quality.

A usable explanation framework must distinguish among model documentation, interpretability, explainability, transparency, and traceability. Model documentation records the model's purpose, development context, inputs, assumptions, version, limitations, and intended users. Input visibility shows which data sources, timestamps, spatial units, preprocessing steps, missing values, and quality indicators contributed to an output. Output explanation clarifies the meaning, unit, time horizon, and scope of a result. Decision rationale connects the output to relevant evidence, constraints, rules, or recommendation logic. Transparency concerns whether these processes and responsibilities can be

inspected, while traceability concerns whether the system can reconstruct how a particular output was produced. General XAI research supports treating these concepts as related but non-equivalent requirements that must be matched to system purpose and stakeholder needs [10].

Explanation quality also depends on the recipient and the decision context. Farmers may need field-specific language, familiar units, visual comparisons, practical cautions, and explanations that connect system outputs to observable conditions. Agricultural advisors may require more detailed access to assumptions, data provenance, model limitations, uncertainty estimates, alternative interpretations, and records of earlier recommendations. Developers and data stewards may need diagnostic explanations for error analysis, drift investigation, and system maintenance. Explanations may be required before a decision, at the point of recommendation, when an abnormal condition is detected, or after an outcome has been observed. Research on human explanation indicates that explanations are commonly selective, contrastive, audience-sensitive, and socially interpreted rather than accepted solely because they expose additional technical detail [11].

The methodological framework therefore requires designers to specify the explanation goal, intended audience, decision stage, information content, presentation format, and evaluation method before selecting an explainability technique. Feature importance may be appropriate for some predictive tasks, while rule summaries, scenario comparisons, input histories, uncertainty intervals, or counterfactual explanations may be more suitable elsewhere. Each method requires evaluation for fidelity, stability, comprehensibility, timing, accessibility, and risk of misinterpretation. Multidisciplinary XAI frameworks support aligning explanation design with user groups, tasks, goals, and iterative evaluation rather than relying on a universal explanation format [12]. Explanation quality is audience- and purpose-dependent, requiring attention to agricultural model behavior, XAI properties, and human explanation needs rather than reliance on a universal explanation technique [9–11]. Human review must remain available where recommendations are uncertain, consequential, or outside documented conditions. **Table 1** summarises explainability and interpretability requirements for decision-support systems in precision agriculture.

Table 1. Explainability and Interpretability Requirements for Precision Agriculture Decision-Support Systems: Model Documentation, Input Visibility, Output Explanation, Decision Rationale, Uncertainty Communication, Confidence Communication, Farmer Interpretability, Advisor Interpretability, Traceability, Human Review, and Explanation Boundaries

Explainability requirement	Core decision-support question	Required evidence or practice	Design function	Potential output	Failure risk	Evaluation need
Model documentation	What model produced the output, for what purpose, and under which assumptions?	Document model purpose, version, development context, input variables, assumptions, intended users, limitations, and excluded uses	Establishes inspectability and responsibility	Model documentation record or agricultural model summary	Hidden assumptions encourage inappropriate reuse	Technical agronomic user review complete
Input visibility	Which data contributed to the output?	Show data source, timestamp, spatial scope, preprocessing, missingness,	Links recommendations to observable evidence	Input summary or provenance panel	Users cannot identify stale, missing, or irrelevant inputs	Comprehensive and targeted relevant testing

		and quality indicators				
Output explanation	What does the result mean in the intended decision context?	Explain unit, range, time horizon, spatial scope, threshold, and intended interpretation	Converts analytical output into decision-relevant information	Plain-language statement, map, chart, or comparison	Technically correct outputs are misunderstood	User comprehension and task t
Decision rationale	Why was a recommendation, alert, or priority produced?	Link relevant inputs, model result, rules, constraints, alternatives, and uncertainty	Supports reasoned human review	Rationale statement or evidence summary	Recommendation appears arbitrary or authoritative	Test whe users c identify basis a limitation
Rule or logic transparency	Can the recommendation logic be inspected?	Document rules, thresholds, optimization objectives, constraints, and exception logic where applicable	Makes recommendation generation traceable	Rule table, decision tree, or objective-and-constraint summary	Hidden logic creates inconsistent or contested advice	Agronomi technic review
Feature importance	Which variables contributed most strongly to a model output?	Use an appropriate importance method, stability checks, and limitation statement	Supports model-behavior inspection	Ranked factors or localized contribution display	Importance is misinterpreted as causality	Fidelin stability, user interpret evaluat
Uncertainty communication	How uncertain is the prediction or recommendation basis?	Present predictive intervals, ranges, scenario variation, data-quality warnings, or uncertainty categories	Reduces false precision	Interval, distribution, warning, or uncertainty label	Point estimates encourage overconfidence	Calibratio comprehen evaluat
Confidence communication	How strongly should the output be relied upon?	Distinguish statistical confidence from operational recommendation confidence	Supports review, escalation, or cautious use	Confidence statement with review trigger	Confidence values are treated as guarantees	Calibrat wording, behavior testin
Interpretability	Can relevant stakeholders	Select interpretable	Aligns model complexity with	Interpretable rule set,	Simplification misrepresents	Fidelity stakeho

	understand model behavior sufficiently for their roles?	models or justified post-hoc methods according to task and risk	scrutiny needs	response profile, or explanation package	model behavior	comprehensive testing
Farmer interpretability	Can a farmer relate the output to field conditions and the current management decision?	Use local terminology, familiar units, contextual comparisons, actionable framing, and limitation statements	Supports contextual sense-making	Field-specific explanation	Explanation is technically valid but practically irrelevant	Farmer-centered evaluation realistic to
Advisor interpretability	Can an agricultural advisor scrutinize the agronomic and analytical basis?	Provide detailed inputs, assumptions, alternatives, uncertainty, provenance, and traceability where advisor involvement is appropriate	Supports professional review and mediation	Advisor-level explanation view	Insufficient detail prevents informed review	Advisor simulation experience assessment
Explanation timing	When should explanation and caution information appear?	Identify pre-decision, at-decision, exception, and post-decision information needs	Matches explanation to workflow stage	Progressive, triggered, or on-demand explanation	Essential caveats arrive too late	Workflow interruption testing
Explanation format	Which representation fits the user, device, and decision?	Compare text, chart, map, icon, rule, scenario, and layered formats	Improves accessibility and comprehension	Multimodal explanation interface	Poor format creates overload or misunderstanding	Comparative usability accessibility testing
Traceability	Can the system reconstruct how a specific output was generated?	Record data version, model version, rules, parameters, timestamp, explanation, and user override	Supports audit and error investigation	Decision and provenance log	Errors cannot be reconstructed or attributed	Auditability record-integrity assessment
Human review	Which outputs require confirmation,	Define review roles, risk triggers,	Preserves human authority and accountability	Review queue, warning, override, or	Automation bias or unreviewed	Scenario testing

	challenge, override, or escalation?	accessible evidence, override controls, and rationale recording		escalation pathway	consequential advice	uncertain abnormal
No explainability-sufficiency boundary	What cannot be inferred from an explanation?	State that explanation does not establish accuracy, calibration, fairness, agronomic validity, trust, or decision quality	Prevents overclaiming	Persistent methodological boundary statement	Explanation is treated as proof of reliability	Verify t users distingu explana from valid

Usability and Farmer-Centered Design

Usability concerns whether intended users can access, understand, operate, and review a decision-support system with acceptable effort and error risk. Farmer-centered design extends this concern by requiring that farmers' decision contexts, practices, knowledge, constraints, and priorities influence system requirements from the beginning. A farmer-centered process should therefore start with needs assessment and contextual inquiry rather than asking users to react only after a technical system has been developed. Interviews, observation, task analysis, seasonal workflow mapping, prototype review, and co-design activities can help identify which decisions require support, what information is already available, how responsibility is distributed, and where additional technology might create burden. Farmer-centric design-thinking research supports iterative processes that connect farmer needs, problem definition, prototyping, evaluation, and revision [13].

Farmer participation must be substantive rather than symbolic. Participatory design should document who was included, whose knowledge shaped requirements, how disagreements were handled, and which design changes followed from user contributions. Representation may need to account for differences in farm scale, production system, experience, language, digital capability, connectivity, equipment, labor organization, and access to advisory services. Local context should influence terminology, units, timing, visualization, alert thresholds, and the interpretation of recommendations. Trust-building also depends on whether users understand how their data are collected, used, shared, and converted into value. Evidence on smart-farming trust indicates that transparency about data practices and benefit distribution can support more accountable relationships, although transparency alone cannot ensure trust [14].

Farm-workflow integration is another central usability requirement. A decision-support system may be difficult to use when it duplicates existing records, requires repeated manual data entry, produces alerts outside relevant decision windows, assumes continuous connectivity, or presents recommendations without sufficient context. Interface design should therefore address navigation, readability, device constraints, accessibility, language, error prevention, alert burden, progressive disclosure, and the balance between summary and detail. Decision-support workload should be evaluated alongside conventional usability dimensions because a system can be technically operable while adding excessive cognitive or administrative burden. Direct farmer inquiry can reveal unmet decision-support needs as well as structural, market, institutional, and operational barriers that cannot be solved through interface modification alone [15].

Training, continuing support, digital inclusion, and feedback mechanisms should be treated as design and implementation conditions rather than as activities deferred until rollout. Users may require role-specific guidance on data quality,

explanation interpretation, uncertainty, override procedures, and the limits of recommendations. Agricultural advisors may support interpretation where their involvement is appropriate and consented to, but their role should be defined so that farmer autonomy and responsibility remain clear. Feedback channels should allow users to report incorrect data, implausible recommendations, contextual changes, usability problems, and observed outcomes, with records showing whether and how the system was revised. Farmer perceptions of usefulness, complexity, compatibility, and support can differ between expectation and experience and may vary across technologies and farm contexts [16]. Usability, participation, and training can strengthen user relevance and adoption readiness, but they do not guarantee voluntary uptake, trust, affordability, infrastructure sufficiency, or sustained implementation.

Validation Logic and Decision Reliability

Validation should begin with the data rather than with the model-performance result. Data-quality validation examines whether inputs are complete, timely, accurately measured, appropriately labeled, spatially and temporally representative, and suitable for the intended decision context. Data-provenance review complements these checks by documenting where data originated, how they were collected, who controls them, which transformations were applied, and whether the resulting records can be traced to a specific version of the system. These procedures are particularly important when prediction models combine heterogeneous sensor, weather, remote-sensing, soil, crop, machinery, or management data. Reviews of crop-yield prediction research demonstrate substantial variation in datasets, feature construction, algorithms, evaluation metrics, and validation practices, illustrating why reported predictive performance cannot independently establish operational decision reliability [17].

Internal validation should estimate how a model performs within its development context while preventing information leakage and respecting temporal, spatial, farm-level, or seasonal dependence. Random data splitting may be inappropriate when neighboring observations, repeated measurements, or records from the same field occur in both development and evaluation sets. Calibration should also be assessed because a model may discriminate among outcomes while producing probabilities or confidence estimates that do not correspond to observed frequencies. External validation then examines whether performance transfers to independent farms, seasons, regions, devices, management systems, or data-collection conditions. Methodological evidence shows that cross-validation strategy can materially alter both apparent performance and the interpretation of model behavior, making validation design an essential component of the claimed evidence rather than a neutral technical detail [18].

Local validation asks whether a model and its recommendation logic remain relevant in the specific context for which decision support is intended. It should consider local soils, crops, climate, management practices, equipment, data quality, decision timing, and agronomic constraints. Where spatial transfer is important, geographically structured holdouts can provide more informative evidence than randomly partitioned observations. Field-validation planning should subsequently specify how a system might be examined prospectively under realistic decision conditions, including the intended comparator, outcome definitions, human-review process, monitoring procedures, and stopping criteria. Research comparing random, spatial, and field-based validation in agricultural prediction demonstrates that evaluation strategy can produce materially different assessments of transferability [19]. Sensitivity analysis may further examine whether recommendations remain stable when relevant inputs, thresholds, assumptions, or optimization constraints are varied.

Decision reliability concerns the complete pathway from data acquisition to human-reviewed recommendation rather than the performance of a prediction model alone. Error analysis should identify where, when, and for whom failures occur, including false alarms, missed events, subgroup errors, implausible recommendations, and errors with different practical consequences. Model-drift monitoring should detect changes in input distributions, relationships between variables, calibration, or observed performance over time. Uncertainty assessment should make predictive ranges, data limitations, and scenario dependence visible, while recommendation review should test agronomic plausibility, scope, contraindications, and the need for escalation. Conformal-prediction research in crop-production decision support illustrates how calibrated uncertainty information may strengthen review, but it does not establish that a recommendation

will be correct or beneficial in a particular farm context [20]. Human oversight and controlled feedback updating therefore remain necessary, and neither completed validation planning nor acceptable model metrics should be interpreted as evidence of deployment readiness.

Adoption Barriers and Implementation Conditions

Adoption should be treated as a contextual, voluntary, and evolving process rather than as the automatic consequence of technical performance. Perceived usefulness, usability, trust, compatibility with farm practices, digital skills, organizational support, and access to relevant information can interact in different ways across technologies and farm contexts. A system may be considered technically capable but still offer limited perceived value because it addresses an infrequent decision, requires excessive data entry, or does not fit the timing and responsibilities of existing work. Empirical research on smart-farming transitions indicates that adoption is shaped by interacting technological, individual, organizational, and contextual conditions rather than by one design attribute alone [21].

Affordability and infrastructure readiness should be examined through the complete conditions required for use. These may include sensing equipment, compatible devices, connectivity, data services, maintenance, technical support, training, subscriptions, integration work, and time spent entering or reviewing information. Farm scale, production system, existing machinery, regional infrastructure, access to advisory services, and previous technology experience may also influence feasibility. Cross-regional evidence on precision-agriculture adoption shows that costs, farm characteristics, information conditions, and perceived benefits contribute to differing adoption patterns [22]. An affordability assessment should therefore identify cost categories and access constraints without assuming profitability or prescribing a particular procurement strategy.

Adoption evidence also requires careful interpretation. Precision-agriculture technologies differ substantially in function, complexity, required investment, and degree of integration, while studies may define adoption as awareness, trial, ownership, partial use, regular use, or use of a specific feature. Aggregated adoption claims can consequently obscure differences among sensing tools, guidance systems, farm-management platforms, prediction services, and decision-support applications. Critical assessments of precision-agriculture adoption evidence emphasize that reported uptake varies with technology definitions, measurement methods, geography, farm structure, and the population being studied [23]. A methodological framework should therefore assess readiness for a clearly defined system and decision context rather than rely on generalized assumptions about digital-agriculture adoption.

Trust and perceived economic value should be assessed as distinct but related conditions. Users may recognize a possible financial or operational benefit while remaining concerned about data control, service-provider accountability, opaque recommendations, system reliability, or loss of autonomy. Conversely, a trusted advisor or provider relationship does not establish that a system is affordable, locally valid, or useful. Research on digital-agriculture adoption indicates that profitability expectations and trust can both shape adoption decisions but should not be treated as interchangeable or sufficient conditions [24]. Adoption readiness is multi-dimensional, reflecting perceived value, economic and structural constraints, farm context, and the way adoption is defined and measured [21–23]. Implementation review should therefore consider training, digital skills, connectivity, interoperability, workflow fit, local relevance, advisor support, farmer autonomy, governance safeguards, and continuing technical assistance. **Table 2** maps usability, validation, decision reliability, adoption barriers, and implementation conditions for precision agriculture decision-support systems.

Table 2. Usability, Validation, Decision Reliability, Adoption Barriers, and Implementation Conditions for Precision Agriculture Decision-Support Systems: User Needs, Co-Design, Farm Workflow Fit, Local Validation, Error Analysis, Model Drift, Trust, Training, Digital Skills, Infrastructure Readiness, Interoperability, Human Oversight, and Adoption Boundaries

Design or implementation component	Core methodological question	Required input, evidence, or condition	Methodological function	Potential output	Failure or barrier risk	Evaluation support needed
User-needs assessment	Which farm-management decision requires support?	Interviews, observation, task analysis, seasonal context, and user-defined priorities	Aligns the system with an actual decision need	User-needs and decision-context specification	Technology addresses a low-priority or incorrectly framed problem	Validation with intended users and relevant experts
Farmer participation and co-design	How will farmers influence requirements and revisions?	Representative participation, prototypes, scenarios, documented feedback, and design-decision records	Incorporates situated knowledge and user priorities	Co-designed requirements and prototype revisions	Token participation or exclusion of relevant groups	Review when participation changed decision
Farm-workflow fit	Where and when will the system be used?	Workflow mapping, decision timing, responsibilities, devices, interruptions, and recordkeeping practices	Integrates support with existing farm work	Workflow-integration plan	Duplicate work, late recommendations, or excessive interruption	Realistic task and workflow evaluation
Accessibility and interface design	Can intended users perceive, understand, and operate the system?	Language, literacy, device, visual, motor, connectivity, navigation, and error-prevention requirements	Supports inclusive interaction	Accessible interface specification	Exclusion, confusion, or accidental action	Accessibility and task completion testing
Data-quality validation	Are input data suitable for the intended decision?	Completeness, accuracy, timeliness, spatial coverage, calibration, and missingness checks	Detects unreliable inputs	Data-quality report and use restrictions	Plausible recommendations are generated from unsuitable data	Continuous data-quality monitoring

Uncertainty and decision-reliability assessment	Is the complete recommendation pathway dependable enough for its intended role?	Predictive uncertainty, calibration, agronomic plausibility, consequence severity, workflow fit, and local evidence	Integrates model evidence with decision context	Context-specific reliability profile	Accurate predictions produce unreliable or impractical recommendations	Multidisciplinary review and prospective evidence
Trust and explainability	Is reliance proportionate to evidence, transparency, and accountability?	Role-appropriate explanation, data controls, reliability evidence, provider responsibility, and limitations	Supports calibrated rather than unquestioning trust	Trust-condition assessment	Blind reliance, blanket rejection, or persuasive explanations	Assess comprehensive reliance, and skepticism separately
Training and digital skills	Can intended users interpret and operate the system appropriately?	Skills assessment, role-based training, examples, limitations, refresher support, and accessible help	Reduces misuse and abandonment	Training and support plan	Misinterpretation, dependency, or exclusion	Evaluate learning retention, and access to support
Affordability and infrastructure readiness	Are the technical and economic foundations for use available?	Devices, sensing, power, connectivity, maintenance, support, data services, and total-cost assessment	Tests implementation feasibility	Infrastructure and affordability profile	Hidden costs, unreliable operation, or unequal access	Technical support and transparent cost review
Connectivity and interoperability	Can data and services exchange information reliably and meaningfully?	Network assessment, offline capability, data formats, semantics, identifiers, permissions, and interfaces	Reduces fragmentation and duplicate entry	Connectivity and interoperability specification	Interrupted service, incomplete data, or vendor dependency	Technical integration and governance agreements

Advisor support and farmer autonomy	Can support be provided without displacing farmer authority?	Defined advisor roles, consent, access controls, explanation depth, override, portability, and appeal procedures	Supports interpretation while preserving agency	Advisor and autonomy protocol	Dependency, coercion, conflicting advice, or unclear responsibility	Role clarification, farmer-controlled permissions
Human oversight	Who reviews, overrides, escalates, or stops system-supported action?	Risk triggers, responsible roles, accessible evidence, override controls, and rationale records	Maintains accountable judgment	Human-review and escalation process	Automation bias or responsibility gaps	Scenario testing and audit of override
Implementation-readiness review	Are technical, human, organizational, and governance conditions jointly adequate for a limited next step?	Evidence register covering validation, usability, support, infrastructure, affordability, security, and governance	Prevents single-metric readiness judgments	Conditional readiness profile and unresolved-gap register	Premature or unsupported implementation	Staged tests with explicit stop and restart criteria
No adoption-guarantee boundary	What cannot be inferred from favorable design and readiness indicators?	Explicit distinction among usability, value, trust, affordability, infrastructure, and voluntary uptake	Prevents deterministic adoption claims	Adoption-boundary statement	Design quality is presented as proof of uptake	Periodic review with intended users
No commercial-readiness boundary	What additional evidence is required for sustained commercial operation?	Maintenance, scalability, liability, security, support, cost, field evidence, and	Separates methodological planning from commercial claims	Commercial-evidence gap register	Conceptual work is presented as market-ready	Independent technical, organizational, financial, and legal assessments

		organizational capacity			
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Proposed Methodological Framework

The proposed framework begins with decision-context definition and stakeholder mapping. Decision-context definition specifies the farm-management question, intended user, timing, available alternatives, consequence of error, required evidence, and boundary between system output and human judgment. The framework can accommodate irrigation, nutrient, pest or disease, yield, and resource-allocation support where these functions are justified by appropriate evidence and locally relevant data, but it does not assume that every application requires the same data, model, explanation, or validation process. Stakeholder mapping identifies farmers, workers, agricultural advisors, developers, researchers, data stewards, service providers, extension organizations, cooperatives, and other affected actors. Reviews of digital agricultural knowledge and advice networks indicate that decision-support technologies operate within wider relationships through which knowledge is produced, interpreted, communicated, and contested [25]. Stakeholder mapping is therefore proposed as a method for defining participation, information access, accountability, and feedback responsibilities.

The second stage evaluates data inputs and documents the analytical and recommendation foundations. Data-input assessment identifies which sensor, remote-sensing, weather, soil, crop, machinery, and farm-management records are necessary and proportionate to the intended decision. Data-quality and provenance review then examines completeness, timeliness, calibration, representativeness, origin, transformation, permissions, ownership, and interoperability. Model documentation specifies the purpose, development domain, variables, assumptions, version, limitations, and excluded uses of prediction or optimization models. Recommendation-logic documentation separately records how model outputs, agronomic rules, thresholds, constraints, or objectives are converted into alerts, priorities, or suggested actions. Ethical analyses of smart farming demonstrate that data control, responsibility, power relations, autonomy, privacy, and benefit distribution are integral to responsible digital-system design [26]. Governance safeguards are consequently embedded within the data and model stages rather than treated as an external compliance layer.

The third and fourth stages define explainability and usability requirements through farmer-centered and participatory design. Explanation requirements are specified according to user role, decision risk, task, timing, and required level of detail. They may include model documentation, input visibility, output explanation, decision rationale, uncertainty and confidence communication, rule transparency, feature importance, traceability, and human-review triggers. Usability requirements address accessibility, interface structure, terminology, device constraints, workload, workflow integration, local context, training, support, and feedback. Co-design links these requirements to iterative prototypes and documented decisions showing how farmer and advisor contributions changed the emerging system. Responsible smart-farming development research supports integrating anticipation, inclusion, reflexivity, and responsiveness throughout the innovation process rather than addressing socio-ethical questions only after technical development [27]. In the proposed framework, these practices are methodological requirements, not evidence that users have approved or will adopt the resulting system.

The fifth and sixth stages address validation, decision reliability, adoption barriers, and implementation conditions. Validation planning proceeds from data checks and internal validation to external and local evaluation, calibration, uncertainty assessment, error analysis, sensitivity analysis where appropriate, field-validation planning, and continuing drift monitoring. Decision-reliability assessment examines whether the entire pathway from data to recommendation is sufficiently supported for a defined role, considering agronomic plausibility, uncertainty, consequence severity, workflow compatibility, and human-review capacity. Adoption-barrier assessment evaluates perceived usefulness, usability, trust, skills, affordability, infrastructure, connectivity, interoperability, support, local relevance, and autonomy. Implementation-condition assessment considers whether the organizations, data arrangements, technical services, governance processes, and maintenance structures required for a limited next step are available. Scholarship on Agriculture 4.0

transition pathways emphasizes that technologies enter diverse social and institutional settings and should not be governed through assumptions of one universal transition pathway [28]. The framework therefore requires context-specific assessment and does not function as a universal design or readiness standard.

The final stage integrates human oversight, feedback updating, practical-implication mapping, and future-research revision. Human-oversight design defines who may review, challenge, override, escalate, or stop a recommendation and what evidence must be available to support those actions. Feedback processes capture user corrections, observed errors, changes in farm context, model drift, explanation failures, usability problems, and outcomes relevant to later evaluation. Material changes to data pipelines, models, rules, interfaces, or intended uses should trigger renewed documentation and validation. Trust-oriented agricultural-AI scholarship further indicates that accountable provider relationships, transparency, farmer autonomy, risk allocation, and benefit distribution must be considered alongside technical properties [29]. The framework consequently retains three explicit boundaries: it does not guarantee decision quality, it does not guarantee adoption, and it does not establish deployment readiness. Table 3 presents the proposed methodological framework for designing decision-support systems in precision agriculture.

Table 3. Proposed Methodological Framework for Precision Agriculture Decision-Support Systems: Decision Context, Stakeholder Mapping, Data Input Assessment, Data Quality, Model Documentation, Explainability, Usability, Farmer-Centered Design, Validation Planning, Decision Reliability, Adoption Barriers, Implementation Conditions, Human Oversight, Feedback, and Claim Boundaries

Framework stage	Core purpose	Required input	Methodological function	Potential output	Validation need	Fa
Decision-context definition	Specify the farm-management problem and intended role of support	Decision question, user, timing, alternatives, consequences, agronomic scope, and intended level of automation	Prevents technology-led or ambiguous objectives	Decision-context and intended-use statement	Review with farmers and relevant domain experts	ad wro or e inte
Stakeholder and user mapping	Identify users, affected actors, responsibilities, and power relations	Farmers, workers, advisors, developers, researchers, data stewards, providers, extension services, and cooperatives	Determines participation, access, accountability, and role-specific requirements	Stakeholder and responsibility map	Check representation, omissions, and conflicts	Rel on gr e
Data-input assessment	Determine which data are necessary and proportionate	Sensor, remote-sensing, weather, soil, crop, machinery, management,	Aligns data acquisition with the decision problem	Data-input specification	Assess relevance, availability, resolution, and timeliness	E ir una pool

		and contextual-data inventory				
Data-quality and provenance review	Establish whether inputs are reliable, traceable, authorized, and current	Quality metrics, source records, collection methods, permissions, transformations, and version history	Controls data-related uncertainty and accountability	Data-quality and provenance dossier	Local checks and continuing monitoring	High standards for data quality or completeness
Data-interoperability assessment	Determine whether required systems can exchange meaningful data	Formats, semantics, identifiers, permissions, interfaces, synchronization, and ownership conditions	Reduces fragmentation and duplicate processing	Interoperability and integration specification	Test exchange accuracy and semantic consistency	Inconsistent data formats or standards
Model documentation	Record what the analytical model does and where it may be used	Model purpose, variables, assumptions, development domain, version, training conditions, and limitations	Supports inspectability and controlled reuse	Model documentation record	Technical, agronomic, and independent review	As-is or in-use documentation
Recommendation-logic documentation	Explain how model outputs become alerts or suggested actions	Rules, thresholds, objectives, constraints, alternatives, exception handling, and escalation logic	Separates prediction from recommendation generation	Recommendation-logic specification	Agronomic and scenario review	Model logic not transparent or explainable
Explainability-requirement definition	Determine what each stakeholder must understand	User roles, decision risk, model type, task, timing, and information needs	Selects explanation content, method, timing, and format	Explanation-requirements specification	Fidelity, stability, comprehension, and accessibility testing	Model not explainable or understandable
Usability-requirement definition	Translate user tasks and constraints into interaction requirements	Needs assessment, workflows, devices, language, accessibility,	Specifies usable interaction and information structure	Usability-requirements specification	Task-based and accessibility evaluation	Usability issues or barriers to use

Human-oversight design	Define review, challenge, override, escalation, and responsibility	Risk classes, named roles, evidence access, stop criteria, override controls, and appeal pathways	Preserves accountable human judgment	Oversight and escalation protocol	Automation bias or responsibility gaps	Systemic exclusion or overreach
Feedback and model updating	Control learning from errors, outcomes, and contextual change	Outcome observations, user corrections, drift evidence, version history, and change requests	Enables accountable iteration	Feedback log and validated update plan	Uncontrolled updating introduces new failure modes	Reactive or ad hoc changes
Practical-implication mapping	Translate framework findings into bounded methodological actions	Stage outputs, evidence gaps, stakeholder priorities, and feasibility constraints	Identifies appropriate next research and design steps	Practical-implication map	Recommendations exceed available evidence	Misaligned or impractical
Future-research updating	Identify unresolved questions and new evidence priorities	Validation gaps, usability findings, adoption evidence, emerging technologies, and monitoring results	Keeps the framework responsive to new evidence	Prioritized research agenda	Framework becomes static or obsolete	Evidence not integrated
No decision-quality guarantee boundary	Prevent inference that framework completion guarantees good decisions	Explicit limitations across data, models, explanations, validation, and oversight	Maintains epistemic caution	Decision-quality boundary statement	Technical evidence is overstated as outcome assurance	Marketing system
No adoption-guarantee boundary	Prevent inference that design quality ensures uptake	Explicit distinction among usability, value, trust, capacity, cost, and voluntary use	Preserves contextual interpretation of adoption	Adoption-boundary statement	Participation or usability is presented as proof of adoption	Contextual misinterpretation

No deployment-readiness boundary	Prevent claims of field validation, certification, or operational readiness	Evidence-gap register covering local, field, safety, maintenance, governance, and support needs	Separates conceptual planning from implementation authorization	Deployment-readiness boundary statement	Proposed framework is overstated as operationally ready	Inc em org as
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Figure 1 presents the proposed methodological framework for designing decision-support systems in precision agriculture, linking decision context, data inputs, explainability, usability, validation, adoption conditions, human oversight, and feedback updating.

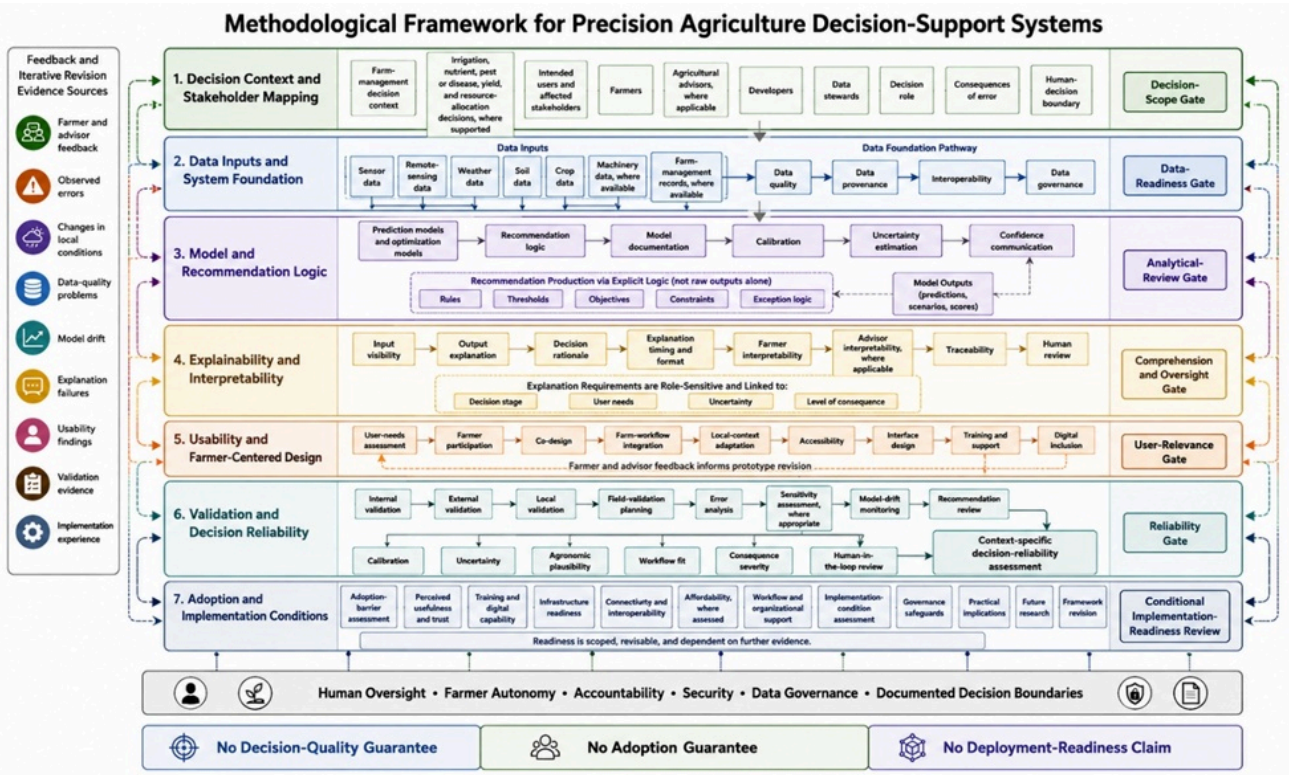


Figure 1. Methodological Framework for Precision Agriculture Decision-Support Systems

Alt-text description:

A conceptual methodological framework showing decision context, stakeholder mapping, data inputs, model documentation, explainability, usability, farmer-centered design, validation, decision reliability, adoption barriers, implementation conditions, human oversight, and feedback planning.

Practical Implications and Future Research

For farmers, agricultural advisors, extension services, and cooperatives, the framework offers a structured way to articulate decision needs, information requirements, workflow constraints, explanation preferences, and acceptable forms of human review. Its practical value lies in supporting questions about whether a system addresses a meaningful decision, whether its outputs can be interpreted in local context, and whether users can identify data limitations, uncertainty, and conditions requiring professional review. Farmer-centered design should remain iterative because early

requirements may change after users interact with prototypes or encounter recommendations in realistic seasonal workflows [13]. Local validation should similarly be planned around relevant farms, seasons, spatial conditions, and management contexts rather than inferred from randomly partitioned development data [19]. These implications are methodological and do not constitute advice about particular crops, treatments, investments, or farm-management actions.

For technology developers, platform providers, researchers, and data stewards, the framework emphasizes separation among data pipelines, analytical models, recommendation logic, explanation components, interfaces, validation evidence, and implementation claims. Explanation methods should be chosen and evaluated according to intended users and decision tasks rather than added as generic interpretability features [12]. Uncertainty information should be calibrated, comprehensible, and linked to review or escalation processes rather than displayed as an unsupported confidence label [20]. Agricultural knowledge and advisory networks should be mapped because data and recommendations are often mediated through multiple organizations and professional roles [25]. Governance review should address responsibility, data control, autonomy, security, and benefit distribution throughout the development lifecycle [26]. These considerations support documentation and research planning but do not prescribe a particular platform architecture, vendor relationship, engineering method, or procurement decision.

Future research should empirically examine how explanation content, interface structure, workflow integration, farmer participation, validation strategy, and oversight arrangements influence comprehension, error detection, appropriate reliance, and sustained use across diverse agricultural settings. Comparative studies are needed to determine when temporal, spatial, farm-level, or seasonal validation designs produce more credible estimates of transferability and decision reliability [18]. Longitudinal research should investigate how system performance, calibration, user needs, trust relationships, infrastructure, and organizational responsibilities change over time. Responsible-innovation approaches can support continuing anticipation, inclusion, reflexivity, and responsiveness as technologies and contexts evolve [27]. Research should also investigate provider accountability, farmer autonomy, data governance, benefit distribution, and the conditions under which trust is warranted rather than merely encouraged [29]. The proposed framework itself requires empirical testing, revision, and comparative evaluation before any claim can be made about its effectiveness or operational suitability.

Conclusion

This article proposes a methodological framework for designing precision-agriculture decision-support systems through coordinated attention to decision context, stakeholder mapping, data quality and provenance, model and recommendation-logic documentation, explainability, interpretability, usability, farmer-centered design, validation logic, decision reliability, adoption barriers, implementation conditions, human oversight, practical implications, future research, and feedback updating. Its central contribution is to reposition decision-support quality as a property of the complete socio-technical pathway through which data are converted into understandable, reviewable, context-sensitive, and responsibly governed support. Predictive accuracy and technical capability remain relevant, but they are insufficient without transparent uncertainty, accessible interfaces, local validation, workflow alignment, user participation, error analysis, continuing monitoring, and accountable human review. The framework is conceptual and supports structured methodological planning rather than operational prescription. It does not establish that a system will improve decisions, earn trust, be adopted, produce farm benefits, satisfy governance requirements, or be ready for deployment.

Acknowledgements

None

Conflict of interest

None

Financial support

None

Ethics statement

None

Received: 01 Feb 2025

Revised: 08 Mar 2025

Accepted: 12 Apr 2025

Published online: 25 November 2025

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