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Precision Agriculture for Smallholders: A Theoretical Framework of Scale, Data and Adoption Constraints for AI-Enabled Farming in Sub-Saharan Africa

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ABSTRACT

Precision agriculture was built for large, mechanised and data-rich farms, and its artificial-intelligence layer of yield prediction, pest and disease detection and variable-rate input recommendation presumes the sensors, connectivity and scale that such farms possess. Most food in Sub-Saharan Africa is grown on holdings of a few hectares or less, and the literature has not yet explained what precision agriculture can mean under those conditions, beyond listing barriers to its adoption. This paper asks what precision agriculture can be when the farm is small, the data are sparse and the farmer is poor. It is an integrative conceptual review oriented to theory-building. The corpus comprises 35 peer-reviewed journal articles published between 2023 and 2026, purposively selected from Crossref-indexed literature using stated inclusion criteria covering technology adoption and extension, digital agriculture, remote sensing and AI for smallholder systems, and the digital divide; every record was verified against Crossref publisher metadata. The analysis combined thematic synthesis with abductive theory-building. Three constraints are distinguished: scale (the economics of per-hectare precision on a two-hectare plot), data (the absence of the field-level records on which models are trained) and adoption (trust, literacy, affordability and the extension system). The synthesis shows that technical effort addresses these constraints in the reverse order of their importance: falling sensing and delivery costs have eased the scale constraint most, the data constraint partly, and the adoption constraint least, although adoption binds hardest. The paper develops an aggregated-delivery framework in which precision is supplied to cooperatives, aggregators and public extension rather than to individual farms, and it derives eight testable propositions on when AI advice raises smallholder yields and incomes. It also specifies the risks of data extraction, input-vendor capture and the displacement of local agronomic knowledge. Nigeria's smallholder sector is the anchoring case. The paper recommends that governments, extension agencies, regulators and donors treat intermediary institutions and farmer data rights, not applications, as the primary objects of investment.

Keywords: precision agriculture; smallholder farming; artificial intelligence; remote sensing; digital agriculture

1. INTRODUCTION

Precision agriculture began as a problem of variability within large fields. If a 400-hectare field contains patches that differ in soil, moisture and pest pressure, a farmer with a yield monitor, a GPS-guided spreader and a few seasons of records can apply inputs where they pay and withhold them where they do not. The artificial-intelligence layer added over the past decade, comprising machine-learned yield models, image-based disease diagnosis and algorithmic fertiliser recommendation, inherited that premise. It assumes a dense stream of field-level data, reliable connectivity, and enough hectares over which to spread the fixed cost of sensing.

None of these assumptions describes the typical farm in Sub-Saharan Africa. There, most food comes from smallholdings of one or two hectares, often fragmented into several plots, managed with hand tools and limited purchased inputs, and recorded, if at all, in the farmer's memory. Survey data on smallholder production carry measurable recall bias (Godlonton et al., 2024), field boundaries are hard to see from space (Rufin et al., 2024), and in rural Northern Ghana farmers reach digital services mainly through basic phones, radio and subsidised projects (Abdulai et al., 2023). The question is therefore not whether precision agriculture will diffuse to smallholders in its existing form. It will not. The question is what precision agriculture can be once its founding assumptions are removed.

The literature offers two kinds of answer, and both are incomplete. A technical literature reports steady gains in what can be inferred from satellites, drones and smartphones on small plots; unmanned aerial vehicle (UAV) studies in Sub-Saharan Africa, for instance, report high detection and yield-prediction accuracy (Ahmed et al., 2026). An adoption literature, mostly cross-sectional surveys, reports that smallholders find digital tools costly, that education, income and group membership predict use, and that infrastructure and skills are binding (Bontsa et al., 2023; Gumbi et al., 2023; Hoang & Tran, 2023). The first literature treats adoption as a downstream dissemination problem. The second treats the technology as a fixed object to be taken up or refused. Neither explains why decision-support tools that are agronomically sound have repeatedly failed to scale (Sida et al., 2023), or under what institutional arrangements AI advice actually changes smallholder yields and incomes.

This paper argues that the gap is structural. Three constraints govern smallholder precision agriculture, namely scale, data and adoption, and technical progress has relaxed them in roughly the reverse order of their importance. The implication is that the unit of precision agriculture for smallholders should not be the individual farm. It should be the intermediary that already aggregates farmers: the cooperative, the off-taker or aggregator, and the public extension service.

Three research questions guide the paper. (1) How do the constraints of scale, data and adoption interact to limit the value of AI-enabled precision agriculture on smallholdings? (2) What delivery model follows from taking those constraints seriously, and under what conditions does AI advice delivered through it raise yields and incomes? (3) What risks of data extraction, input-vendor capture and knowledge displacement does that model create, and how might they be governed? Nigeria, where state Agricultural Development Programmes (ADPs) carry public extension alongside private aggregation platforms, is the anchoring case. Sections 2 and 3 review the literature and method, Section 4 presents and discusses the framework, and Sections 5 and 6 conclude.

2. LITERATURE REVIEW

2.1 Conceptual Review

Precision agriculture is used here in its functional sense: management that matches inputs and operations to measured variation in crop and soil conditions across space and time. The definition deliberately omits machinery. On a large farm the matching is executed by variable-rate equipment; on a smallholding it can only be executed by a person who receives advice and acts on it. The bottleneck moves from the actuator to the human decision, and therefore to extension.

AI-enabled precision agriculture denotes the subset in which the mapping from measured variation to recommended action is learned from data rather than specified by agronomists. Four application families recur in the smallholder literature: yield estimation from satellite or UAV imagery (Ahmed et al., 2026), crop and disease diagnosis from smartphone images coupled with advisory content (Omara et al., 2023), site-specific nutrient recommendation (Maertens et al., 2023; Sida et al., 2023), and conversational advisory systems built on large language models (Tzachor et al., 2023; High et al., 2025). All promise individualised advice at near-zero marginal cost.

The smallholder is defined less by a hectare threshold than by small and fragmented plots, constrained credit and input access, and family labour. Digital agriculture, a broader term, covers any use of digital information in farming, from SMS price alerts to investor platforms (Akinwale et al., 2023). Finally, the digital divide is treated here as layered rather than binary. Access to a device is one layer; affordability of data, literacy in the language of the interface, and the social permission to use a household phone are others, and they fall unevenly by gender (Mulungu, 2025).

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The paper introduces one further concept, decision resolution: the finest spatial and temporal granularity at which a farmer can actually vary a management decision. A farmer who buys fertiliser in 50-kilogram bags on credit tied to a cooperative's group order, applies it by hand and plants when the rains allow has a coarse decision resolution regardless of how finely a model can see the field. Precision beyond decision resolution has no value. This concept does much of the work in the framework that follows.

2.2 Theoretical Review

Diffusion of innovations theory remains the default lens for adoption. Recent work applies it to large language models in extension, pairing it with social acceptance to show that acceptance depends on who develops the tool and whether advisers trust it (Edet & Chowdhury, 2026). The theory's weakness for present purposes is its focus on the individual adopter. It explains why a given farmer takes up an app, but says little about the institution through which the innovation arrives, which in smallholder systems is often more decisive than the farmer's attributes (Bashiru et al., 2024).

The economics of information and the value of information offer a sharper tool for the scale problem. Advice is worth what it changes in expected profit. On a two-hectare maize plot, even a substantial percentage gain yields a small absolute sum, so any per-farm cost of acquiring, interpreting or trusting the advice can consume it. A review of 27 economic evaluations of site-specific weed management found that early studies overstated profitability by omitting or underestimating technology and management costs, and that break-even farm sizes often exceeded the average farm in Germany (Pitsyk et al., 2026). If precision fails to break even on the average German farm, the per-farm arithmetic on a Nigerian smallholding is harsher still, and the omitted costs there are farmers' time, phone credit and the risk of acting on unfamiliar advice. The farm-size literature also cautions against equating small with unproductive; district-level evidence from Peru links smaller average farm size and lower land inequality to higher total factor productivity (Borrero, 2025). Scale is a problem for the technology, not necessarily for the farm.

Transaction-cost economics and collective-action theory explain why intermediaries exist. Cooperatives and aggregators reduce the per-farmer cost of procuring inputs, finding buyers and obtaining information by bundling many small transactions into few larger ones. In Kaduna State, access to information and training through cooperatives was associated with higher odds of adopting improved technologies, and mattered more than membership alone (Salisu et al., 2026), which suggests that the intermediary's informational function, not its formal existence, is what matters. Social learning theory adds that farmers learn from observable peers; a randomised trial of SMS-based peer chat groups on feature phones in Tanzania raised adoption of discussed practices relative to one-way SMS extension, although participation decayed over time (Lasdun et al., 2025).

Two critical traditions complete the theoretical base. Work on trust in AI argues that farmers' acceptance depends on transparency, clear accountability for AI-driven decisions and settled rules on data ownership (Gardezi et al., 2023). Critical data-governance scholarship treats agricultural data as a site of power; Kenya's privacy-centred data regime, for example, is criticised for leaving smallholders' collective risks unaddressed (Canfield & Ntambirweki, 2024). A review of fifteen studies concludes that smallholder data are collected mainly to serve donors, fintech providers and agribusiness (Amar et al., 2026). These traditions supply the risk side of the framework.

2.3 Empirical Review

The strongest causal evidence on AI-adjacent advice for African smallholders comes from nutrient management, and it is qualified. A three-year randomised trial with 792 maize farmers in northern Nigeria found that site-specific nutrient management advice delivered by extension agents substantially increased adoption of good fertiliser practices, but only the arm that added information on maize price distributions and the variability of returns produced modest gains in nutrient application, yields and revenues (Maertens et al., 2023). The lesson is that agronomic precision alone was insufficient; the advice had to speak to risk. A survey of 795 rice farmers in Ebonyi State estimated large yield advantages for adopters of the RiceAdvice application using propensity score matching, with adoption driven by training, extension access and smartphone ownership (Abioye et al., 2025). Matching on observables cannot rule out selection on motivation or input access, so the estimate is better read as an upper bound than as an effect size.

The scaling evidence is sobering. A survey of developers combined with a meta-analysis found that site-specific nutrient decision-support tools have struggled to reach scale over decades, that their yield benefits over farmer practice depend on initial yield potential, soil acidity, climate and input levels, and that the tools accommodate field variation while ignoring socioeconomic variation among users (Sida et al., 2023). Validation of a soil-testing kit on 144 Tanzanian smallholder fields yielded zone-level best-bet recommendations for use where field tests are unavailable (Amuri et al., 2023). Read together, these studies suggest that the agronomic payoff often lies at zone rather than field granularity.

Remote sensing studies report technical progress alongside persistent fragility. Pseudo-labels generated by a model pre-trained in India improved field delineation in label-scarce northern Mozambique,

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though human labels still added value (Rufin et al., 2024). Irrigation detection methods transferred to semi-arid northern Nigeria and Burkina Faso but performed poorly in humid Uganda (Siddiqui et al., 2025), and pretrained foundation-model embeddings outperformed engineered features where survey labels were plentiful, matched them where labels were sparse, and were less auditable (Siddiqui et al., 2026). Sentinel-2 separated management practices on smallholder cereal farms in Togo and Tunisia but not in Tanzania (Biaou et al., 2025). The UAV evidence is the most optimistic on accuracy and the most pessimistic on cost, with capital costs reported as a multiple of annual smallholder income and cooperative ownership proposed for multispectral systems (Ahmed et al., 2026), though internal inconsistencies in its statistics counsel caution over its point estimates.

Evidence on conversational and diagnostic AI is thinner. A cassava disease recommender piloted with 100 Ugandan farmers achieved only moderate answer quality, which the authors attribute to limited training data (Omara et al., 2023). Tests of GPT-generated advice for Nigerian cassava farmers exposed limitations that led to proposals for keeping human experts in the design loop (Tzachor et al., 2023). Experts rated 60 per cent of a general model's answers to extension programme-planning questions as only partially correct (Mensah & Swortzel, 2026). Farmer.Chat improved access and personalisation but communicated largely one way (High et al., 2025).

The adoption surveys converge on cost, literacy and infrastructure (Bontsa et al., 2023; Gumbi et al., 2023; Ogutu & Cavane, 2026), but most are cross-sectional and measure perceptions or intentions rather than sustained use. Studies that track behaviour find engagement that declines over time (Abdulai et al., 2023; Lasdun et al., 2025). Gendered gaps in smartphone ownership and in the language of content persist even where basic phone ownership is near universal (Mulungu, 2025). Chinese evidence that low- and middle-income farmers gain most from digital adoption (Lyu et al., 2025) sits uneasily with African evidence of the better-resourced adopting first, a contrast that probably reflects infrastructure.

The gap, then, is this. The literature documents technical feasibility and lists adoption barriers, but it lacks a theory that relates the two: one that explains why sound tools fail to scale, specifies the institutional unit through which smallholder precision should be delivered, and states testable conditions under which AI advice improves outcomes, while accounting for the political economy of the data it requires.

3. MATERIALS AND METHODS

The study is conceptual and non-empirical, an integrative review oriented to theory-building that synthesises several sub-fields to identify constructs, relate them and derive testable propositions rather than to estimate an average effect.

The population of sources was peer-reviewed journal literature published from 2023 to 2026. The Scite and Consensus indexes were attempted first but were unavailable during the search window (subscription and quota limits), so discovery used the Crossref REST API bibliographic search, supplemented by targeted web searches to locate abstracts; Crossref was then used to verify every retained record. Table 1 lists the Crossref search strings, all filtered to journal articles published from 1 January 2023; three further queries were refused by rate limits and returned nothing.

Table 1. Crossref search strings, records screened and records retained

No.	Search string (Crossref bibliographic query)	Records screened	Retained
S1	precision agriculture smallholder Africa	20	1
S2	digital agriculture smallholder farmers Africa adoption	20	3
S3	remote sensing smallholder yield estimation Africa	20	3
S4	large language models agricultural extension services	20	4
S5	agricultural data governance smallholder farmers data extraction digital agriculture	20	6
S6	site-specific fertilizer recommendation digital decision support Nigeria maize rice	20	3
S7	cooperatives farmer organizations digital technology adoption smallholders	20	3
S8	satellite yield variation smallholder African systems	12	1
S9	economics profitability precision agriculture farm size adoption costs	12	2
S10	agro-dealers input retailers advice smallholder farmers fertilizer quality Africa	12	0
S11	indigenous knowledge digital agriculture technologies farmers knowledge integration	12	1
S12	farmer organization membership transaction costs technology adoption smallholders Africa	12	1
W	Targeted web searches (abstract retrieval and gap-filling on peer learning, trust in AI, Nigerian digital advisory, field delineation, gendered phone access)	about 90	7

Inclusion criteria were as follows: a peer-reviewed journal article; publication between 2023 and 2026; a Crossref type of journal-article; an available abstract that could be read; and direct relevance to at least one

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framework construct (scale economics, data and sensing, adoption and extension, delivery institutions, or data governance and knowledge). Preprints, conference papers, books, chapters and reports were excluded, as were records without abstracts, records whose metadata did not match their content, and outlets whose records lacked basic bibliographic integrity. Selection was purposive: records were retained when they supplied evidence or argument that a construct required, with preference for causal designs and for African, especially Nigerian, settings. The final corpus is 35 articles.

The analysis proceeded in three passes. Each article was first coded against the constructs of scale, data and adoption and the delivery and risk themes; the codes were then compared across sub-literatures to find tensions, such as high reported model accuracy alongside low scaling. Third, abductive reasoning identified the explanation that best accounted for those tensions, from which propositions were derived. A proposition was retained only if it specified a direction of effect, a condition, and an observable measure. The bases of judgement were explanatory coherence, consistency with the strongest designs in the corpus, and falsifiability.

For reliability and validity, every record was checked against Crossref for bibliographic fields and type and screened for retraction, correction and expression-of-concern notices; search strings are reported in full; and claims were triangulated across the agricultural-economics, remote-sensing and data-governance literatures. The limits are real: a single reviewer made the selections, the corpus is purposive rather than exhaustive, Crossref relevance ranking is coarse, and restricting the corpus to 2023–2026 excludes the foundational adoption literature, which is invoked only by name.

Generative AI (Anthropic's Claude) was used to assist literature retrieval, synthesis and drafting. All bibliographic records were checked against Crossref publisher metadata, and the authors reviewed, revised and take full responsibility for the content. The study used no primary data; the reference list and search strings constitute its materials. Ethical approval was not required because no human participants were involved.

The constructs are defined operationally so that the propositions can be tested. The scale constraint is the ratio of the per-farm cost of acquiring and acting on precision advice to the expected per-farm gain, measurable through cost records and plot-level yield and input data. The data constraint is the shortfall between the labelled field observations a model requires for a target accuracy in a given agro-ecology and the observations available, measurable as label counts, out-of-region error and model calibration. The adoption constraint is the gap between exposure to advice and sustained behavioural change, measurable as the share of exposed farmers who follow a recommendation across successive seasons. Decision resolution is the finest unit at which a farmer varies input rate, timing or variety, measured through plot-level management surveys; aggregation is the share of a farmer's input, output or information transactions mediated by one intermediary. Table 2 adds indicators.

4. RESULTS AND DISCUSSION

4.1 Results

The synthesis yields an ordering. Table 2 sets out each constraint, what current technology offers against it, what remains binding, and how aggregated delivery responds.

Table 2. The scale–data–adoption constraint framework and the aggregated-delivery response

Constraint	Definition	What technology has offered	Residual binding element	Aggregated-delivery response	Indicators for empirical work
Scale	Per-farm cost of acquiring and acting on advice relative to per-farm expected gain	Free satellite imagery, smartphone diagnosis and SMS delivery reduce the marginal cost of producing advice towards zero; UAVs remain costly relative to income (Ahmed et al., 2026)	Small absolute gains per farm mean farmers' time, credit and risk costs can exceed the value of advice	Spread fixed costs of sensing and agronomic expertise across many members; supply advice at zone or cluster resolution	Cost per farmer reached; net gain per hectare; share of fixed cost borne by intermediary
Data	Shortfall of labelled, field-level observations for training and validating models in a	Transfer learning, pseudo-labels and foundation embeddings (Rufin et al., 2024; Siddiqui et al., 2026)	Models fail to transfer across agro-ecologies; recall data are biased; labels are costly to collect (Siddiqui et al., 2025; Godlonton et	Intermediaries generate ground truth as a by-product of routine services such as input delivery, off-take weighing and extension visits	Labels per agro-ecology; out-of-region error; share of labels from routine operations

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	given agro-ecology		al., 2024)		
Adoption	Gap between exposure to advice and sustained change in practice	Apps, chatbots and voice services that personalise content (High et al., 2025)	Trust, literacy, gendered access, decaying engagement, and lack of complementary inputs (Abdulai et al., 2023; Mulungu, 2025)	Advice embedded in trusted human and peer relationships and bundled with input and credit access	Multi-season compliance; gender gap in use; adoption conditional on input access

The constraints have been relaxed in the reverse of the order in which they bind. The cost of producing a recommendation has collapsed, since Sentinel-2 imagery is free and a smartphone photograph can be diagnosed in seconds. Progress on data is real but partial, with models transferring within agro-ecologies more readily than across them. On adoption, design effort has gone into interfaces, while the evidence points to trust, complementary inputs and institutions. Because a recommendation that is not followed has no agronomic value, adoption is the binding constraint, data the intermediate one, and the residual scale problem reappears inside adoption as a ceiling on what advice is worth to any single farmer.

That reappearance is the hinge of the argument. Technology has solved the scale problem of producing advice, not the scale problem of capturing its value. When the expected gain per farm is small, the trip to buy a different fertiliser, the risk of deviating from neighbours and the phone credit are large by comparison, and individual delivery leaves farmers rationally indifferent to accurate advice. Aggregated delivery changes the arithmetic by moving fixed costs to an intermediary and by bundling the advice with the inputs and credit needed to act on it.

The framework itself is simple to state. An intermediary sits between the model and the farmer. It holds three assets: a membership or client base that spreads cost, operational contact with fields that generates data, and a relationship with farmers that carries trust. Precision is supplied to the intermediary at a resolution matched to members' decision resolution, typically a zone, a soil-fertility class or a planting-date cohort, and the intermediary translates it into action through input bundles, group training and follow-up.

P1. The yield and income effect of AI-enabled advice on a smallholding rises with the size of the exploitable yield gap and with the farmer's ability to act, and it is insensitive to model accuracy once accuracy exceeds the farmer's decision resolution. Decision-support benefits depend on yield potential and input levels (Sida et al., 2023), and agronomic accuracy alone did not raise yields in the Nigerian trial (Maertens et al., 2023). Marginal accuracy gains therefore return less than investment in the conditions for acting.

P2. Advice supplied at zone or cluster resolution through an intermediary captures most of the attainable gain from field-level advice wherever input purchase, credit and labour constrain farmers to coarse decisions. Zone-level recommendations in Tanzania (Amuri et al., 2023) and cooperative-scale UAV deployment (Ahmed et al., 2026) are consistent with this. The proposition is falsified if field-level advice outperforms zone advice by a margin larger than its added delivery cost.

P3. AI advice raises smallholder yields only when it is bundled with access to the inputs and credit it recommends, and it raises incomes only when it also addresses price and yield risk. The Nigerian risk-information result (Maertens et al., 2023) and the dependence of RiceAdvice adoption on training and extension (Abioye et al., 2025) support the conditional form. Aggregators that also supply inputs (Akinwale et al., 2023) satisfy the condition structurally, which is why P7 is needed.

P4. Models deployed through intermediaries that record field outcomes as a by-product of routine operations improve in local accuracy faster than models trained on remote sensing with ad hoc ground truth. The data constraint is institutional before it is technical: transfer fails across agro-ecologies (Siddiqui et al., 2025), human labels still add value to pseudo-labels (Rufin et al., 2024), and recall-based yield data are biased (Godlonton et al., 2024). Off-takers' weighbridge records and extension visit notes are ground truth that exists but is rarely captured.

P5. Sustained use of AI advice is higher when it is delivered through a trusted human intermediary and embedded in peer networks than when it is delivered directly to farmers through an application, but the advantage decays without continuing investment in the relationship. Peer chat groups outperformed one-way SMS but lost participants (Lasdun et al., 2025), engagement in Northern Ghana declined (Abdulai et al., 2023), and extension practitioners are positioned to mediate acceptance of language-model advice (Edet & Chowdhury, 2026).

P6. Direct-to-farmer AI advice widens yield and income gaps by gender, literacy and wealth, whereas intermediated delivery narrows them only when the intermediary's membership and staff include women

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and poorer farmers. Gendered smartphone access and language barriers (Mulungu, 2025) and the weight of education and income in adoption (Bontsa et al., 2023) mean the channel decides who benefits, and cooperatives can reproduce local hierarchies.

P7. Where an intermediary's revenue depends on input sales or on securing output, AI recommendations it controls will drift toward input intensification and toward outcomes favourable to the intermediary, unless farmers hold enforceable rights over their data and over the advisory logic. Smallholder data mainly serve agribusiness, fintech and donor interests (Amar et al., 2026), individual-privacy regimes miss collective farmer risks (Canfield & Ntambirweki, 2024), and farm data agreements are hard to read (Kaur & Dara, 2023).

P8. AI advice that farmers cannot interrogate erodes local agronomic knowledge and lowers resilience in seasons that fall outside the model's training distribution, whereas advice co-produced with farmers and extension agents preserves it. It rests on Farmer.Chat's one-way design (High et al., 2025), transparency as a condition of trust (Gardezi et al., 2023), and the role of participation and social networks in indigenous knowledge sharing in South-South Nigeria (Ominikari & Okringbo, 2023).

Table 3 translates the propositions into testable implications.

Table 3. Propositions, testable implications and suggested measures

Proposition	Testable implication	Suggested design and measures
P1 Value ceiling	Gains from more accurate models flatten above a threshold set by decision resolution	Factorial trial varying model resolution and input access; plot yields, net returns
P2 Granularity matching	Zone advice via intermediaries performs within delivery-cost margin of field advice	Cluster-randomised comparison of zone and field advice; cost per farmer, yield per hectare
P3 Complementarity	Advice effects are conditional on input and credit access and on risk information	Cross-randomise advice with input vouchers or credit; heterogeneity by baseline access
P4 Institutional data	Local model error falls faster with intermediary-generated labels	Compare model error over seasons by label source; labels per agro-ecology
P5 Mediated trust	Multi-season compliance is higher under human-mediated delivery, with decay	Panel of exposed farmers across three or more seasons; compliance and drop-out rates
P6 Channel inclusion	Gender and wealth gaps in gains differ by channel and by intermediary composition	Disaggregated outcomes by gender and asset quintile; membership composition data
P7 Capture	Recommended input rates exceed agronomic optima where the advisor sells inputs	Audit of recommendations against independent agronomic optima by advisor revenue model
P8 Knowledge	Interrogable, co-produced advice sustains farmer knowledge and out-of-distribution performance	Knowledge tests over time; yield response in anomalous seasons; advisory design coding

4.2 Discussion

The framework reframes a familiar finding. The cost, literacy and infrastructure barriers reported in adoption surveys (Bontsa et al., 2023; Gumbi et al., 2023; Ogutu & Cavane, 2026) are expressions of one problem, a small per-farm value of information confronted by per-farm costs of acting on it. Diffusion theory predicts that improving relative advantage and reducing complexity accelerates uptake. The value-of-information view predicts that below a threshold of farm size and input access a better interface will not help, because the advice is not worth enough to act on. The persistent failure of agronomically sound decision-support tools to scale (Sida et al., 2023) fits this second reading better than the first.

The framework also disciplines the optimism of the remote-sensing literature without dismissing it. Satellite data can contribute to smallholder yields and sustainability (Jain, 2026), and the technical gains reviewed above are genuine. The disagreement is about where value is created: accuracy figures describe what can be inferred, not what will be done. P1 and P2 predict that investment should shift from field-level accuracy toward decision-matched recommendations and the institutions that let farmers act. The claim is contestable. A counter-argument holds that field-level precision unlocks gains invisible at zone scale, for instance on acidic patches within a village. The response is conditional: where such heterogeneity is large and actionable, P2 is falsified, and the framework says so explicitly.

A second objection is that aggregation re-creates top-down extension, standardising advice and marginalising farmers' judgement; P6 and P8 encode this concern. Cooperatives can be captured by local elites, off-takers want volume on their terms, and public extension may answer to ministries rather than members. The framework does not claim that intermediaries are benign, only that they hold the scale, data and trust AI requires, so the task is to govern them rather than bypass them with applications that reproduce the digital divide.

The extraction and capture risks are the most serious. Aggregated delivery concentrates farm data in the hands of whoever operates the intermediary. Where that

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operator sells inputs or buys output, the advisory logic becomes a commercial lever, and P7 predicts systematic drift toward intensification. Individual consent is a weak remedy when agreements are unreadable (Kaur & Dara, 2023) and risks collective (Canfield & Ntambirweki, 2024). Data governance must therefore operate at the level of the intermediary, through collective data holding by farmer organisations, auditable recommendation logic, and separation of advisory from sales functions. The displacement of local agronomic knowledge is a quieter risk. Advice followed without understanding substitutes for farmers' own observation, which is what they need when a season departs from the model's training conditions. Co-production, in which extension agents and farmers contest and adapt recommendations, is a hedge rather than a courtesy.

Nigeria makes these abstractions concrete. Public extension is delivered through state ADPs, with national coordination and research linkage from the National Agricultural Extension and Research Liaison Services at Ahmadu Bello University, Zaria. In Delta State, the competence and training of extension staff and government support shape how effectively practices spread (Ogedengbe-Atiyota & Gbubemi, 2025), so the human layer on which P5 depends is a variable, not a constant. The two Nigerian studies of digital advice point the same way: in the northern Guinea savanna, extension-delivered nutrient advice changed practice but raised yields and revenues only when it addressed risk (Maertens et al., 2023), and in Ebonyi State RiceAdvice adoption tracks training and extension access (Abioye et al., 2025). Investor and aggregator platforms report late input delivery as farmers' main barrier (Akinwale et al., 2023), which is the complementarity condition of P3 failing in practice. Irrigation detection transfers to the semi-arid north (Siddiqui et al., 2025), encouraging for the fadama systems there and a warning for the humid south, where transfer is less assured.

In a plausible Nigerian configuration, ADPs and accredited cooperatives would receive zone-level recommendations calibrated with field-staff and off-taker data and pass them to farmers bundled with input access through existing group channels. Nigeria's Data Protection Act of 2023 provides a general legal basis for data rights, but it is framed around individual data subjects. Whether it can carry collective claims by farmer organisations over aggregated data should be settled before, not after, a dominant platform emerges.

The framework applies to rain-fed and small-scale irrigated crop systems where decision resolution is coarse, and less to contract horticulture, where buyers already impose fine-grained protocols, or to livestock. It assumes that intermediaries exist; in areas of insecurity or where cooperatives are nominal, the delivery model has nothing to attach to. It also rests on a corpus in which causal evidence is concentrated in nutrient management. The generalisation to diagnosis and conversational AI is an extension by argument, and P5 and P8 are the propositions most in need of direct tests.

Of the designs in Table 3, three are most urgent: cluster-randomised comparisons of zone and field advice through cooperatives (P1, P2), audits of recommendations by advisor revenue model (P7), and gender-disaggregated multi-season panels (P5, P6).

5. CONCLUSION AND RECOMMENDATION

Precision agriculture for smallholders cannot be the large-farm model scaled down, because its assumptions of dense data, connectivity and many hectares do not hold on the farms that produce most of Sub-Saharan Africa's food. Of the three constraints that govern what can be done instead, technical progress has relaxed the least binding most. The cost of producing advice has collapsed, locally reliable data remain scarce, and the conditions under which farmers act on advice have received least attention while binding hardest. The scale problem has moved inside adoption, as a ceiling on what accurate advice is worth to a single small farm.

The response is aggregated delivery: precision supplied to cooperatives, aggregators and public extension at the resolution at which farmers decide, bundled with the means to act, and governed so that the intermediaries that make it possible do not capture it. The eight propositions are falsifiable, and several could be tested with Nigerian institutions that already exist.

Several recommendations follow for specific actors. Federal and state ministries of agriculture should fund the ADPs and other extension agencies as the delivery and data layer for AI advice, staffing and training field staff to record plot outcomes in standard formats, rather than procuring stand-alone applications. Extension services should design advisory programmes around zones and planting cohorts, pair digital advice with in-person follow-up and peer groups, and measure multi-season compliance rather than downloads. Regulators, including the data-protection authority, should clarify whether and how farmer organisations can hold and exercise collective rights over aggregated farm data, and should require firms that both advise farmers and sell them inputs to disclose the logic of their recommendations and submit it to independent audit. Donors should finance intermediary capacity and open, locally validated training datasets, and tie support to evaluations that test complementarity and inclusion. Firms should separate advisory and sales functions and publish the agro-ecological domains in which their models have been validated. Researchers should prioritise cluster-randomised and multi-season designs

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over cross-sectional adoption surveys and should report results disaggregated by gender and wealth.

6. CONTRIBUTION TO EXISTING KNOWLEDGE

The first contribution is analytical: a structured account of three interacting constraints replaces the list of barriers that dominates the literature, with the refutable claim that technology has addressed them in the reverse order of their importance. The concept of decision resolution links the agronomic literature on site-specific management to the economics of information, explaining why accurate tools fail to scale without appealing to farmer conservatism.

The second contribution is a delivery model. Most work on smallholder AI takes the farmer as the unit of delivery and the application as the unit of design; the framework relocates both to the intermediary, names the assets it contributes (spread cost, operational data and trust), and derives eight testable propositions. Proposition P4 in particular reframes label scarcity in remote sensing as an institutional rather than a purely technical problem.

The third contribution is to bring critical data-governance scholarship into the same framework as adoption economics. Extraction, input-vendor capture and knowledge displacement are treated not as ethical caveats appended to a technical proposal but as predictable consequences of the very aggregation that makes smallholder precision feasible, each with its own testable proposition. The Nigerian case locates the pressure points for policy.

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