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Climate Information Services and Artificial Intelligence: A Theoretical Account of Forecast Skill, Decision Relevance and Trust in Agricultural Adaptation

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ABSTRACT

Machine-learning weather and climate models now match or exceed conventional numerical prediction on many verification targets at a fraction of the computational cost, and their arrival is being presented as a breakthrough for climate-vulnerable farmers in Africa. Yet the distance between a better forecast and a better adaptation decision remains poorly theorised. This paper aims to explain when, and for whom, artificial intelligence (AI) forecasting can improve agricultural adaptation in West African rain-fed systems. Methodologically, it is an integrative conceptual review leading to theory-building. The corpus comprises 36 peer-reviewed journal articles published between 2023 and 2026, purposively selected through searches of the Crossref and PubMed indexes against stated inclusion criteria, with every record verified against Crossref publisher metadata. The analysis combined thematic synthesis with abductive, analytical theory-building. The paper distinguishes three properties that a climate information service must possess to change outcomes: skill (accuracy at the relevant scale and lead time), relevance (the forecast answers a question the farmer actually faces) and trust (the farmer acts on it). It shows that AI improves the first markedly at medium range while leaving the second and third to national meteorological services, extension systems and intermediaries that are weakest where vulnerability is highest. A forecast-to-decision framework links these properties to planting date, crop and variety choice, input purchase and labour allocation, and yields eight propositions: that the properties are complements rather than substitutes; that medium-range gains translate weakly into onset-dependent decisions; that skill gains are bounded by observation infrastructure; that trust responds asymmetrically to salient misses; that hybrid scientific and indigenous forecasts raise use where local indicators remain intact; that forecast value depends on the capacity to act; that unequal access can widen within-community gaps; and that benefits depend on the institutional delivery channel. The paper recommends that governments, donors and technology firms invest in observation networks, probabilistic communication, co-produced hybrid services and bundled finance, and that evaluations measure decisions and welfare rather than verification scores alone.

Keywords: climate information services; weather forecasting; artificial intelligence; climate adaptation; agricultural decision-making

1. INTRODUCTION

Within the space of roughly two years, global weather prediction acquired a second engine. Data-driven models trained on reanalysis archives began to beat the best operational deterministic systems on most standard verification targets, and to do so at a small fraction of the computational cost (Bi et al., 2023; Lam et al., 2023). Probabilistic and hybrid successors followed, extending the gains to ensemble forecasting and to climate-length simulation (Kochkov et al., 2024; Price et al., 2024). For a region such as West Africa, where most cereals, legumes and roots are grown under rain-fed conditions and where the timing of the first sustained rains decides much of a household's year, the promise is easy to state. Cheaper and better forecasts should mean better planting, fewer failed sowings and less wasted fertiliser.

This paper argues that the promise is real but mis-specified. A forecast does not raise a farmer's welfare by being accurate. It does so only when it is accurate about the variable that governs a pending decision, arrives with enough lead time to change that decision, is believed, and finds a farmer with the means to act differently. The first of these conditions is a property of the model. The others are properties of institutions, intermediaries and household circumstances. Evidence from the climate-services literature already shows that access to information does not translate automatically into use, and that the intensity of use, rather than mere receipt, is what predicts changes in practice (Hagos et al., 2025). Studies of maize farmers in Oyo and Kwara States in Nigeria find that farmers obtain forecasts mainly from radio, neighbours and family, and that the technicality of applying forecast information, weak extension support and language are among the main constraints (Abdulrahman et al., 2025; Ogunjinmi et al., 2024). None of these constraints is addressed by a faster neural network.

The field is therefore at an awkward juncture. Forecasting research reports percentages of verification targets won (Lam et al., 2023; Price et al., 2024). Climate-services research measures uptake, willingness to pay and yields, usually without reference to forecast skill (Bizo et al., 2024; Manzvera et al., 2024). Scholarship on indigenous forecasting documents a partly independent knowledge system that farmers rely on, often because scientific forecasts are judged less usable (Paparrizos et al., 2023). These literatures rarely meet, and no framework tells a meteorological service, donor or technology firm which forecasting improvements will matter for adaptation, and under what conditions.

The purpose of this paper is to supply such a framework. It addresses four research questions. (1) Which properties must an AI-enabled climate information service possess for improved forecasts to change agricultural adaptation decisions? (2) How do these properties map onto the specific decisions that West African rain-fed farmers face? (3) How do AI forecasts interact with indigenous forecasting knowledge? (4) What are the distributional consequences when access to improved forecasts is unequal? Section 2 reviews the conceptual, theoretical and empirical literature; Section 3 sets out the review method; Section 4 presents the framework and propositions and discusses them; Sections 5 and 6 conclude with recommendations and the paper's contribution.

2. LITERATURE REVIEW

2.1 Conceptual Review

A climate information service is understood here as the full chain that runs from observation and modelling, through tailoring and communication, to a decision made by a user. Each link can fail independently: an excellent rainfall forecast sent by text message in a language the farmer cannot read has failed at communication, not modelling.

Three properties of this chain are central. Skill is the accuracy of the forecast relative to a reference, typically climatology or an established model, for a specified variable, spatial scale and lead time. Skill is not a single number. GraphCast reduces average precipitation error relative to physics-based models over the United States yet underpredicts the area of intense rainfall (Radford et al., 2025); whether it is "more skilful" depends on whether the user cares about average error or heavy events.

Relevance is the degree to which the forecast bears on a decision the user actually faces, at the scale and time at which it is faced: onset date or dry-spell risk rather than daily totals, delivered before the decision deadline and in a usable format. The older vocabulary of salience, credibility and legitimacy captures much of this and has recently been applied to hybrid services for smallholders (Paparrizos et al., 2024).

Trust is the user's willingness to act on the forecast. It is shaped by track record, by how uncertainty is communicated, by the messenger and by consistency with other knowledge the user holds. Experiments show that inaccurate forecasts reduce trust, that probabilistic information softens this effect and improves economic decisions, and, less intuitively, that visible revisions can increase trust by signalling uncertainty (Burgeno & Joslyn, 2023). Trust is not credulity; discounting an unreliable forecast is rational.

A fourth concept, actionability, closes the chain. It is the farmer's capacity to change behaviour in response to a forecast, given access to seed, credit, labour and land, and is treated here as a conditioning variable rather than a property of the service.

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Indigenous or local forecast knowledge refers to the system of environmental indicators, such as the behaviour of animals and birds, the flowering of particular trees, wind direction, cloud forms and the phases of the moon, through which farmers anticipate seasonal and short-range weather (Oladele & Amara, 2024; Paparrizos et al., 2023). A hybrid forecast is one in which such indicators are formally combined with scientific forecast output (Sutanto et al., 2025).

2.2 Theoretical Review

Four bodies of theory underpin the framework. The first is the value-of-information model, in which a forecast is worth something only if it can alter an action whose payoff depends on the forecast variable. Value is zero for a farmer who would act identically whatever the forecast said, and rises with the weather sensitivity of payoffs and the flexibility of the decision. Contingent-valuation studies apply this logic implicitly: in Manicaland, Zimbabwe, most maize producers would pay a modest monthly fee for seasonal forecasts, but willingness was lower among an ethnic minority and in remote areas (Manzvera et al., 2024). Stated-choice work in Ghana, Senegal, Mali and Burkina Faso shows that farmers value forecasts most when bundled with seed advisories and drought insurance, and that adding credit makes preferred bundles more attractive (Ouedraogo et al., 2025). Forecasts, on this reading, are complements to the means of acting on them.

The second is technology-acceptance theory. Adapted to multimedia agro-advisory services, the Unified Theory of Acceptance and Use of Technology identifies effort expectancy, self-efficacy and source credibility as determinants of perceived benefit, which predicts use (Mallick et al., 2025). The theory usefully locates part of trust in the source, though it says little about why credibility differs across sources.

The third is the knowledge-systems tradition, which treats scientific and indigenous forecasting as distinct systems that co-production can bring into contact. Hybrid forecasts are argued to raise legitimacy and hence trust (Paparrizos et al., 2024), and adaptation planning to require recognition of knowledge hybridity rather than replacement of indigenous practice (Oladele & Amara, 2024). Nigerian root and tuber farmers, studied through situated learning theory, prefer practices they regard as effective, accessible and inexpensive and remain wary of scientific interventions (Olaniyan & Govender, 2023).

The fourth is the access perspective, which holds that benefits accrue to those who control the means of obtaining and using a resource. It predicts that phone ownership, gender, education and tenure will shape who benefits from forecasts; a systematic review for sub-Saharan Africa finds gender widely studied but intersecting identities rarely analysed together (Khatibu & Kissoka, 2025). None of these theories alone links the technical properties of a forecast to the institutional conditions of its use.

2.3 Empirical Review

The empirical record on AI forecasting is impressive and narrow. Pangu-Weather produced deterministic medium-range forecasts more accurate than the operational system of the European Centre for Medium-Range Weather Forecasts (ECMWF) across all tested variables when verified against reanalysis (Bi et al., 2023). GraphCast outperformed the most accurate operational deterministic systems on 90% of 1,380 verification targets (Lam et al., 2023), FuXi extended comparable performance to fifteen days (Chen et al., 2023), and GenCast beat ECMWF's operational ensemble on 97.2% of 1,320 targets (Price et al., 2024). NeuralGCM, which couples a differentiable dynamical core with learned physics, matched the best methods for weather and tracked climate metrics for decades, though it does not extrapolate to substantially different future climates (Kochkov et al., 2024).

Three limitations recur. Physical consistency is incomplete: one AI model failed to reproduce the rapid early growth of tiny initial perturbations that bounds predictability (Selz & Craig, 2023). Precipitation, the variable that matters most for rain-fed agriculture, is handled less well than pressure fields. And the gains are concentrated in the medium range. At subseasonal lead times of two to six weeks, model skill falls sharply for AI and physics-based systems alike, and recent progress depends on statistical bias correction layered on top of both (Guan et al., 2026). At seasonal range, GenCast forced with persisted sea-surface temperature anomalies captured much of the precipitation response to El Niño and La Niña, but ECMWF's seasonal system retained superior skill in the tropics for near-surface temperature and pressure, and the persisted configuration showed little reliability relative to climatology (Antonio et al., 2026). Even conventional seasonal ensembles show significant rainfall biases and areas of absent skill in parts of East Africa (Tefera et al., 2025).

Two findings bear directly on Africa. A global analysis reports that a seven-day temperature forecast in a high-income country is, on average, about as accurate as a one-day forecast in a low-income country, a gap persisting since 1985 and linked to sparse stations and radiosondes and limited capacity to issue local forecasts (Linsenmeier & Shrader, 2026). Yet FuXi Weather, which assimilates satellite data directly, outperformed ECMWF's high-resolution forecast beyond day one in observation-sparse central Africa (Sun et al., 2025). Read together, the results suggest that AI can narrow the gap where satellites substitute for ground networks, but that the gap is rooted in observation and institutions rather than modelling alone.

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The evidence on whether climate information changes farm outcomes is more mixed. In Senegal, an interactive voice advisory system delivering climate-informed advice in local languages was associated with millet and groundnut yields 41% and 21% higher than in matched control villages, and with lower input and labour costs (Joseph et al., 2026). In Niger and Mali, climate information use was associated with higher per-hectare incomes and reduced time spent on farming (Bizo et al., 2024). Such results are encouraging but rest on matching and survey designs that cannot exclude selection into use. A Campbell systematic review found positive effects of weather and climate information services on women farmers' knowledge and adoption of climate-smart practices, but judged five of eight evaluations at high risk of bias (Saran et al., 2024). Determinants studies are numerous and broadly consistent: access to climate information predicts adaptation among rice farmers in Kebbi State (Solaja et al., 2024) and rain-fed farmers in Ghana (Yeleliere et al., 2023), while in Ethiopia phone ownership and male headship increased access and female headship reduced use (Fikadu et al., 2023). The weakness of this literature is that it treats "climate information" as homogeneous, so it cannot say whether a more skilful forecast would have produced a larger effect.

On indigenous forecasting, a global review identified around 1,350 local environmental indicators, most in Africa and Asia, and found the low usability of scientific forecasts to be the main reason farmers relied on local knowledge (Paparrizos et al., 2023). In northern Ghana, the DROP application's hybrid of local and scientific forecasts detected rain best but raised more false alarms, so its overall performance was below the scientific forecast; farmers nonetheless used it to adjust sowing, weeding and fertiliser timing (Sutanto et al., 2025). In rural South Africa, farmers use phenological and astronomical indicators to time sowing and choose crops, but the disappearance of key indicator species now threatens the system (Magaya & Fitchett, 2026).

The gap is therefore specific. A rapidly advancing forecasting science and a substantial but fragmented climate-services literature have developed in parallel. No existing framework specifies how gains in AI forecast skill propagate, or fail to propagate, through relevance and trust to particular farm decisions, how they interact with indigenous forecasting, or who gains when access is unequal.

3. MATERIALS AND METHODS

The study is a conceptual, non-empirical integrative review aimed at theory-building rather than effect estimation, a design suited to questions that cut across atmospheric science, agricultural economics, extension studies and research on indigenous knowledge.

The population of sources was peer-reviewed journal literature published from 2023 to 2026. Retrieval used the Crossref REST API, queried through its bibliographic search with filters for publication date and journal-article type, and the PubMed index, which covers several of the multidisciplinary journals in which AI forecasting and climate-services studies appear. The Scite, Consensus and Elicit indexes named in the original protocol were inaccessible during the search period, which is reported as a limitation. Crossref was also used to verify every record. The search strings actually run are reported in Table 1.

Table 1. Search strings, indexes and records retained

Index	Search string (date filter 2023 onward; journal articles)	Records screened	Retained
PubMed	(weather forecasting[Title/Abstract]) AND (machine learning OR neural network OR graph neural) AND (Nature[journal] OR Science[journal])	5	3
PubMed	(machine learning[Title] OR artificial intelligence[Title] OR data-driven[Title]) AND (subseasonal[Title] OR seasonal[Title] OR monsoon onset[Title] OR rainfall[Title]) AND forecast*[Title]	6 of 20	2
PubMed	(weather[Title/Abstract] OR climate[Title/Abstract] OR rainfall[Title/Abstract]) AND forecast*[Title] AND (Africa OR African OR Sahel[Title/Abstract])	10 of 57	2
PubMed	(forecast*[Title] OR "climate information"[Title] OR "climate services"[Title] OR "indigenous knowledge"[Title]) AND farmer*[Title/Abstract] AND (Africa OR Ghana OR Nigeria OR Senegal OR Burkina OR Mali OR Niger OR Benin[Title/Abstract])	4 of 15 (2023 onward)	4
PubMed	(forecast*[Title]) AND (farmer*[Title] OR agricultur*[Title] OR smallholder*[Title]) AND (decision* OR adaptation OR welfare OR trust OR use)	14 of 28	0
PubMed	(climate services OR climate information OR agro-advisory OR agrometeorological[Title/Abstract]) AND (smallholder OR farmer*[Title/Abstract]) AND (trust OR gender OR access OR willingness to pay OR co-production)	23 of 43	9
Crossref	query = machine learning weather forecasting global	20	1
Crossref	query.bibliographic = climate information services smallholder farmers Africa	25	3
Crossref	query.bibliographic = local forecast knowledge indigenous weather indicators farmers (has abstract)	25	4
Crossref	query.bibliographic = trust weather forecasts farmers decision (has abstract)	25	4
Crossref	query.bibliographic = artificial intelligence weather models Africa evaluation	25	2

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Crossref	query.bibliographic = onset rainy season forecast West Africa sowing	25	1
Crossref	Model paper named in the protocol (Pangu-Weather), retrieved by DOI	1	1

Inclusion criteria were: a peer-reviewed journal article with a Crossref type of journal-article; publication between 2023 and 2026; an abstract available for reading through Crossref or PubMed; and direct relevance to at least one of the framework's constructs (skill, relevance, trust, actionability) or to indigenous forecasting or distributional access. Exclusion criteria were preprints, conference papers, books, chapters and grey literature; records carrying a retraction or expression of concern; studies of forecasting in unrelated domains such as energy demand or disease incidence; and records whose abstract could not be read. Several relevant articles in *Climate Services* and *Climate and Development* were excluded for the last reason, because their abstracts were not deposited in either index. Selection was purposive. From roughly 230 records screened at title or abstract level, 36 were retained, chosen to cover the forecasting frontier, the evidence on forecast use and impact, indigenous forecasting and the West African and Nigerian context.

Analysis proceeded in three passes. Each article was coded against the four constructs and the farm decisions it concerned. Coded findings were synthesised thematically within and then across sub-literatures, to locate tensions such as that between verification-based and use-based notions of value. Propositions were then derived abductively and retained when they offered the most plausible account of a pattern across at least two sub-literatures and could be tested with observable measures. Bases of judgement were consistency across independent studies, strength of design and plausibility of mechanism.

Reliability and validity were addressed in four ways. Every bibliographic record was checked against Crossref publisher metadata for authors, title, journal, volume, issue, pagination and year, and for update, correction and retraction notices; one record, Pangu-Weather, carries a published correction, which does not affect the claims cited. The search strings are reported verbatim. Findings were triangulated across sub-literatures rather than drawn from any single study. The review was conducted by a single reviewer with purposive selection, so it cannot claim exhaustiveness and is open to selection bias; the propositions should be read as hypotheses rather than established regularities.

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. No primary data were collected; the reference list and the search strings in Table 1 constitute the materials of the study. Ethical approval was not required because the study involved no human participants.

The constructs are defined operationally in Table 2. Skill would be measured with decision-relevant verification metrics at district scale, relevance by the match between products and the decision calendar, trust behaviourally (the share of advisories acted upon) as well as attitudinally, and actionability through access to the inputs and finance needed to change a decision.

4. RESULTS AND DISCUSSION

4.1 Results

The first result is a set of construct definitions with indicators (Table 2), each defined relative to a decision: skill is accuracy for the variable, scale and lead time a decision requires, not accuracy in general.

Table 2. Framework constructs, definitions and indicators for empirical testing

Construct	Definition	Indicators	Where AI currently changes it
Skill	Accuracy of a forecast relative to a reference for a stated variable, spatial scale and lead time	Brier skill score for onset and dry-spell events; hit and false-alarm rates for heavy rain; reliability diagrams at district scale	Large gains for medium-range synoptic fields; smaller and less certain gains for local precipitation, subseasonal and seasonal products
Relevance	Fit between the forecast product and a decision the user faces, in variable, lead time, resolution and format	Share of advisories tied to a named farm decision; lead time relative to decision deadline; language and channel match	Little direct change; depends on tailoring by meteorological services and intermediaries
Trust	User's propensity to act on the forecast, given track record, uncertainty communication, messenger and consistency with local knowledge	Proportion of advisories acted on; stated confidence; change in trust after a salient miss	Indirect and ambiguous; opaque models may weaken forecaster and user confidence
Actionability (conditioning)	User's capacity to change behaviour in response to a forecast	Access to seed, fertiliser, credit, insurance, labour and land	None directly; depends on bundling and markets

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The second result maps forecast properties onto the decisions that dominate the rain-fed calendar (Table 3). The map makes visible a mismatch that the verification literature obscures. The decision with the highest stakes, the planting date, depends on the onset of sustained rains and on the risk of a dry spell after sowing, at village scale and with lead times from days to a few weeks. Onset variability in the western Sahel and Guinea coast dominates variability in demise and drives seasonal length and totals, so that monitoring onset can itself yield a useful seasonal outlook (Jayasankar & Misra, 2025). Medium-range AI forecasts are well placed for the final days before sowing; they are poorly placed for the weeks before, when seed and fertiliser must be purchased.

Table 3. Forecast-to-decision map for West African rain-fed agriculture

Decision	Forecast variable needed	Lead time and scale	Fit with current AI strengths	Binding constraint beyond skill
Planting date	Onset of sustained rains; probability of a dry spell of two weeks or more after sowing	Days to four weeks; village or district	Good for final 1 to 10 days; weak for 2 to 6 weeks, where skill depends on bias correction	Seed in hand; labour for land preparation; trust after false onsets
Crop and variety choice	Seasonal rainfall total and length of season; onset and cessation	One to three months; district or agro-ecological zone	Limited; seasonal AI configurations not yet superior in the tropics	Availability of short-cycle or drought-tolerant seed; market outlets
Input purchase (fertiliser, herbicide)	Seasonal outlook; short-range heavy-rain risk for application timing	Seasonal for purchase; 1 to 5 days for application	Good for application timing; limited for purchase	Credit and prices at time of purchase; input supply
Labour allocation (weeding, harvesting, drying)	Short-range rainfall occurrence and intensity	1 to 10 days; farm	Good for occurrence; heavy rainfall under-represented	Household and hired labour availability; wage peaks

From these two results the paper derives eight propositions.

P1. Skill, relevance and trust are complements in producing adaptation benefit: the marginal welfare gain from an increase in forecast skill is increasing in relevance and trust, and approaches zero where either is low.

If a farmer receives no forecast for the variable governing a decision, or receives it and does not act, better accuracy changes nothing. Evidence that intensity of use, not access, predicts adoption (Hagos et al., 2025), and that the largest reported effects come from services tailored to local crops and languages (Joseph et al., 2026), is consistent with complementarity. In a factorial evaluation, the interaction between a skill improvement and a tailoring or trust-building intervention should be positive.

P2. Where decisions depend on subseasonal and seasonal quantities, notably the onset date and post-sowing dry spells, AI-driven skill gains at medium range will translate weakly into better planting and variety decisions unless accompanied by onset-specific products and statistical correction.

AI is strongest at lead times up to about two weeks (Lam et al., 2023; Price et al., 2024). Beyond that, skill drops steeply and the leading advance is a bias-correction layer applied to AI and dynamical models alike (Guan et al., 2026); at seasonal range AI does not yet surpass established systems in the tropics (Antonio et al., 2026). Holding delivery constant, AI upgrades should improve fertiliser and herbicide timing more than sowing and variety choice.

P3. In data-sparse regions, the realised skill of AI forecasts is bounded by observation infrastructure and by the institutional capacity of national meteorological services; AI narrows the North-South accuracy gap only to the extent that it substitutes satellite observation for missing ground networks and is localised by those services.

The persistent North-South accuracy gap is attributed to observation density and institutional capacity (Linsenmeier & Shrader, 2026). AI models inherit the quality of their initial conditions, and local verification needs the very station networks that are missing. A system that assimilates satellite data directly and performs well over central Africa (Sun et al., 2025) supports the proposition, because it works by relaxing the observation constraint.

P4. Trust responds asymmetrically to forecast performance: a salient miss during a high-stakes decision, such as a false onset that leads to failed sowing, reduces subsequent use by more than an equivalent number of hits increases it, and the asymmetry is smaller when forecasts are communicated probabilistically.

Inaccuracy erodes trust, and probabilistic presentation moderates the loss (Burgeno & Joslyn, 2023). A failed sowing costs seed and labour, which makes such misses

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salient, and deterministic AI products that under-represent heavy rainfall (Radford et al., 2025) are particularly exposed. Because postprocessing methods built for numerical models apply directly to AI output (Trotta et al., 2025), the remedy is institutional rather than technical.

P5. Hybrid services that combine AI or scientific forecasts with indigenous indicators will raise trust and use more than scientific forecasts alone, even when the hybrid is not more skilful, provided that local indicators remain observable; where indicator species or patterns are disappearing, the trust premium of hybridisation will decline.

Hybrid forecasts raised legitimacy and trust in Ghana, Bangladesh and Guatemala (Paparrizos et al., 2024), and farmers in northern Ghana changed field operations using a hybrid application whose verification performance was below that of the scientific forecast (Sutanto et al., 2025). This decoupling of skill and use is the core of the proposition. Its boundary condition is the disappearance of indicator species (Magaya & Fitchett, 2026), which makes hybridisation time-sensitive. AI methods could help verify local indicators against observations, but only under arrangements that keep the knowledge in community hands.

P6. The welfare value of an improved forecast is conditional on actionability: it is greater for farmers with access to the seed, credit, insurance and labour required to change a decision, and bundled services that supply these jointly will produce larger welfare gains per forecast than forecast-only services.

Stated-choice evidence that West African farmers prefer forecasts bundled with seed advisories and drought insurance, and that credit raises the attractiveness of bundles (Ouedraogo et al., 2025), indicates that farmers themselves recognise this conditionality. Nigerian maize farmers report that the technicality of applying forecasts and weak extension are constraints (Abdulrahman et al., 2025; Ogunjinmi et al., 2024), which are failures of actionability as much as of communication.

P7. When access to improved forecasts is unequal, forecast improvement will widen within-community welfare gaps, because the farmers best placed to act on better information are those already advantaged by gender, phone ownership, education, land tenure and proximity to extension.

Access is associated with male headship, phone ownership and education (Abdulrahman et al., 2025; Fikadu et al., 2023), land ownership with forecast use in Oyo State (Ogunjinmi et al., 2024), and willingness to pay is lower among marginalised and remote groups (Manzvera et al., 2024). If better forecasts raise returns to the already-informed, average gains will mask distributional losses. A more speculative mechanism runs through markets: many informed farmers acting on one forecast may raise local demand for seed, fertiliser or hired labour at the same moment, shifting costs onto later buyers. This is untested and offered as a hypothesis.

P8. The adaptation benefit of AI forecasting depends on the institutional channel through which it is delivered: where national meteorological services integrate AI output into their own verified, localised and probabilistic products, trust and relevance will rise with skill; where AI forecasts reach farmers through multiple uncoordinated private channels, conflicting messages will reduce trust in all sources.

Operational meteorologists judge AI systems on interpretability and stability as well as scores, where current systems are weaker (Ramsdale, 2026), and postprocessing and blending let meteorological centres adopt AI incrementally (Trotta et al., 2025). Generative AI advisory tools are likewise argued to help only with human oversight, data sovereignty and infrastructure in place (Gakhar et al., 2026). The proposition predicts lower use where farmers report divergent forecasts from different sources.

4.2 Discussion

The framework reframes the question behind current enthusiasm. What matters is not whether AI forecasts are better, which on many verification targets they plainly are, but which property is binding for a given decision, place and group of farmers. For West African rain-fed agriculture the answer is frequently relevance or trust, and sometimes actionability, rather than skill. This does not diminish the forecasting advance. It locates it.

The propositions sit in some tension with parts of the empirical literature. Large yield and income effects reported for advisory services (Bizo et al., 2024; Joseph et al., 2026) might be read as proof that forecast quality matters a great deal. Yet these services bundled tailoring, local-language delivery and extension contact, so their effects are better read as the joint product of relevance, trust and skill, as P1 predicts. The determinants literature is consistent with the framework but cannot test it, and the high risk of bias in most impact evaluations (Saran et al., 2024) means the evidence base for welfare effects remains thin.

The hybrid-forecasting evidence offers the sharpest challenge to a skill-first view. That farmers in northern Ghana acted on a hybrid forecast with more false alarms than the scientific one (Sutanto et al., 2025) could signal that farmers misjudge skill. More plausibly, legitimacy and familiarity carry independent weight, as the finding that source credibility shapes perceived benefit also suggests (Mallick et al., 2025). The obvious counter-argument is that trust built on familiarity is fragile and may lock in inferior forecasts. The framework

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accommodates this by making trust responsive to track record (P4): hybridisation is a route to initial trust, verification the route to keeping it.

The Nigerian case makes the argument concrete. The Nigerian Meteorological Agency (NiMet) issues an annual Seasonal Climate Prediction that typically gives expected onset and cessation dates and dry-spell outlooks for zones ranging from the Sahel and Sudan savannas to the humid south, a product that is, in the framework's terms, highly relevant. Its reach depends on state Agricultural Development Programmes and their extension agents, whose weakness is the constraint farmers in Oyo State rate highest (Ogunjinmi et al., 2024). Farmers in Kwara State draw forecasts mainly from friends, family and personal experience (Abdulrahman et al., 2025), and rice farmers in Kebbi State show low intensity of adaptation despite the influence of climate information on their choices (Solaja et al., 2024). Indigenous practices among root and tuber farmers in southern Nigeria remain preferred partly because of distrust of scientific interventions (Olaniyan & Govender, 2023). An AI upgrade to the forecasts underpinning NiMet's products would improve the skill link. Unless it is accompanied by investment in station networks, local verification, probabilistic communication in Hausa, Yoruba, Igbo and other languages, and extension capacity, the framework predicts that its effect on planting decisions for sorghum, millet, maize or yam will be modest and unevenly distributed.

Boundary conditions limit the framework. It is built for rain-fed systems with one dominant onset decision; bimodal systems along the Guinea coast and irrigated rice schemes have different calendars. It treats the meteorological service as the natural locus of integration, which may not hold where private providers are more trusted. And foundation models used directly to generate advice raise accountability questions the reviewed literature only begins to address (Gakhar et al., 2026).

Future research should test the propositions directly: factorial field experiments varying forecast skill independently of tailoring and delivery (P1, P8), trust panels around verified hits and misses (P4), comparisons of hybrid services where indicator systems are intact and degraded (P5), and measurement of local input prices and wages after widely shared forecasts (P7).

5. CONCLUSION AND RECOMMENDATION

Machine-learning weather models are a genuine scientific advance, but one that acts on a single link of a longer chain. For a West African farmer deciding when to sow, what to plant, when to buy fertiliser and when to call on labour, the forecast must be skilful for the right variable and lead time, relevant to the decision as faced, and trusted enough to act upon, and the farmer must have the means to act. AI improves skill most at medium range and least at the subseasonal and seasonal ranges that govern several high-stakes decisions. Relevance and trust depend on institutions that are weakest where vulnerability is greatest. The eight propositions translate this into testable expectations about complementarity, infrastructure limits, trust dynamics, hybrid knowledge, actionability, inequality and institutional channels.

For government ministries and national meteorological services, including NiMet and its counterparts in the region, the priority is to integrate AI output into existing verified, probabilistic and localised products rather than to treat it as a replacement, and to direct savings in computing cost towards the observation networks on which local skill depends. Ministries of agriculture and state extension services should treat the translation of onset and dry-spell forecasts into decision advice as a core extension function, delivered in local languages and through radio, voice and trusted intermediaries.

Donors and development finance institutions should fund bundled services that combine forecasts with seed, credit and insurance, and should require evaluations to report welfare effects disaggregated by gender, tenure and remoteness. Technology firms releasing open AI models should partner with national services rather than bypass them, publish regional verification for African precipitation and onset, and avoid issuing farmer-facing forecasts that conflict with official products. Regulators and communication authorities can support this by setting minimum standards for the disclosure of forecast provenance and uncertainty. Researchers should design studies that separate the effect of forecast skill from the effect of delivery, and should work with communities to document and verify indigenous indicators under arrangements that protect community ownership of that knowledge.

6. CONTRIBUTION TO EXISTING KNOWLEDGE

The paper makes three contributions. First, it offers a skill-relevance-trust framework, with actionability as a conditioning variable, that connects the verification-based evaluation of AI weather models to the use-based evaluation of climate information services. The two literatures have so far proceeded with different metrics and almost no cross-citation; the framework supplies a common vocabulary and defines each construct relative to a farm decision.

Second, it provides a forecast-to-decision map for West African rain-fed agriculture that identifies where current AI strengths align with the decision calendar and where they do not. The map shows that the planting-date

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decision, the most consequential in the calendar, falls largely in the subseasonal range where AI's comparative advantage is weakest, and it identifies the non-forecast constraints that bind each decision.

Third, it derives eight testable propositions, several of which run against prevailing assumptions. The claim that hybrid services can raise use without raising skill, the claim that trust is asymmetric in its response to misses, and the claim that improved forecasts can widen within-community inequality under unequal access each generate specific, measurable predictions. Together they move the debate from whether AI forecasts are better to the institutional conditions under which better forecasts improve adaptation, and for whom.

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