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Cloud-Enabled Agentic Advisory and Climate-Smart Agricultural Resilience: Integrating Agro-Climatic Risk Analytics, Micro-Insurance Fraud Defense, and Rural Occupational Health Support

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Abstract

Smallholder agricultural systems across tropical regions confront intensifying rainfall variability, prolonged dry spells, extreme ambient heat exposure, and persistent credit rationing that jointly undermine household food security and rural occupational health. Although climate-smart agriculture practices offer proven agronomic resilience, real-world uptake remains constrained by fragmented extension advice, basis risk and fraudulent leakage in micro-insurance pools, agro-input supply discrepancies, and unmonitored thermal fatigue among farm laborers. This study develops and empirically validates an integrated cloud-edge agentic resilience architecture deployed across six agro-ecological clusters in Southwestern Nigeria. The platform couples multivariate agro-climatic adoption modeling and cloud-enabled parametric credit analytics with deep learning claim and input-billing verification, wearable photoplethysmography heat-strain monitoring, real-time rural clinical decision support, and five-dimension conversational extension evaluation. Across a longitudinal panel of 1,840 smallholder households and 24 rural health-and-extension hubs, the ecosystem elevated sustained multi-practice climate-smart adoption from 28.4% to 86.8%, increased net farm household income by 44.6%, intercepted 94.3% of anomalous voucher and insurance claims prior to disbursement, and reduced peak-harvest heat-stress morbidity by 67.2%. By harmonizing digital agronomic guidance, transparent micro-finance governance, and bio-adaptive rural healthcare delivery, the architecture establishes a scalable blueprint for climate-resilient smallholder livelihoods.

Keywords: *Climate-smart agriculture, smallholder resilience, cloud-enabled data analytics, agentic AI governance, photoplethysmography heat-stress biometrics, micro-insurance fraud detection, rural clinical decision support.*

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1. Introduction

1.1 Agro-Climatic Volatility and Smallholder Vulnerability

Rainfed smallholder farming underpins rural employment, regional food supply, and household poverty reduction across Sub-Saharan Africa, yet escalating hydro-meteorological volatility increasingly threatens its viability (Lobell et al., 2011; Lipper et al., 2014). Across Southwestern Nigeria, erratic onset and cessation of seasonal rains, flash flooding, soil nutrient depletion, and intensifying wet-bulb heat waves expose farming families to compounding yield shocks and acute occupational health hazards (Kjellstrom et al., 2016; Odekunle et al., 2026). When uninsured harvest failures coincide with

household health emergencies, liquidity-constrained farmers frequently resort to distress asset sales or input disadoption that lock rural communities into structural poverty traps (Dercon, 2002; Barrett & Carter, 2013).

Climate-smart agriculture (CSA) practices, encompassing drought-tolerant seed varieties, minimum soil disturbance, agroforestry intercropping, mulching, and micro-dosing water conservation, offer robust buffers against climatic erraticism (Thornton et al., 2018). However, translating farmer perception of climate anomalies into sustained multi-practice adoption requires overcoming tightly coupled institutional bottlenecks. Smallholders face asymmetric agronomic information, delayed or untargeted extension visits, collateral-constrained rural credit markets, input voucher diversion, and limited rural primary care capacity during peak planting and harvesting labor windows (Aker, 2011; Karlan et al., 2014). Isolated single-sector interventions rarely succeed because agronomic risk, financial liquidity, and worker physiological capacity interact dynamically across every cropping cycle.

1.2 Architectural Scope and Core Contributions

This paper formulates and field-tests a unified cloud-edge agentic resilience ecosystem that synchronizes climate-smart agronomic advisory, cloud-enabled micro-finance verification, and bio-adaptive rural health operations. Grounded in behavioral evidence linking lived climate shock exposure to smallholder adaptation propensity, the platform ingests satellite agro-meteorology, household vulnerability profiles, cooperative supply telemetry, and wearable physiological signals into a governed pipeline.

Four primary contributions distinguish this study. First, we couple an econometric multivariate probit adoption model with transformer-based agro-climatic representations to tailor plot-level CSA portfolios. Second, we embed cloud parametric credit analytics alongside deep learning fraud and inventory-billing reconciliation engines to eliminate voucher leakage and accelerate weather-index payouts. Third, we integrate wearable photoplethysmography biometrics with real-time clinical decision support and algorithmic clinical-extension scheduling to protect fieldworkers against acute thermal exhaustion. Fourth, we audit conversational advisory quality through a five-dimension problem-resolution protocol across 1,840 households in six agro-ecological zones of Southwestern Nigeria.

2. Literature Review and Theoretical Foundations

2.1 Lived Climate Experience, Smallholder Adaptation, and Rural Health Workforce Dynamics

Empirical adaptation scholarship demonstrates that smallholder technology uptake is shaped jointly by subjective climate risk perception, experiential exposure to extreme weather, and institutional support structures (Maddison, 2007; Bryan et al., 2009; Deressa et al., 2009). In a foundational investigation of farming communities in Southwestern Nigeria, Odekunle et al. (2026) established that farmers' direct lived climate experience significantly governs the intensity and combination of climate-smart agriculture practices adopted, while highlighting that extension contact, credit access, and input reliability critically moderate behavioral translation. Complementary experimental evidence confirms that relaxing risk and liquidity barriers through bundled index insurance and

mobile digital advisory substantially elevates productive farm investment (Carter et al., 2016; Suri & Jack, 2016; Fabregas et al., 2019).

At the same time, agricultural labor productivity in tropical lowlands is inseparable from rural healthcare accessibility and human resource adequacy (Kjellstrom et al., 2016). Rural primary health centers and cooperative extension directorates suffer chronic specialist vacancies and seasonal congestion. Addressing analogous clinical staffing bottlenecks, Veernapu (2023b) demonstrated that artificial intelligence scheduling algorithms dynamically balance shift allocations to mitigate workforce shortages and elevate care quality. Upstream of shift dispatch, Veernapu (2023a) showed that AI-driven recruitment pipelines streamline candidate screening and credential validation, accelerating talent deployment into underserved clinical posts. At the point of care, Veernapu et al. (2026) detailed how real-time AI clinical decision support bridges predictive modeling with bedside clinical practice, enabling rapid triage of heat exhaustion, dehydration, and agrochemical exposure in resource-limited rural clinics.

2.2 Cloud Financial Analytics, Explainable Biometrics, and Agentic Governance

Scaling bundled CSA credit and rural health protection requires resilient financial infrastructure and tamper-resistant supply chains (Miranda & Farrin, 2012; Asfaw et al., 2016). Ramareddy (2025) demonstrated how cloud-enabled data analytics and artificial intelligence transform financial services by automating real-time risk underwriting, credit scoring, and multi-source portfolio analytics at scale. Within subsidized agro-input corridors and rural health insurance schemes, financial solvency is frequently threatened by phantom voucher redemptions and billing discrepancies. Veernapu (2025) analyzed deep learning architectures for detecting insurance fraud and quantifying its economic burden on public and private insurers, while Veernapu (2022) formulated deep learning inventory-and-billing reconciliation methods originally designed for perioperative supply tracking that transfer directly to auditing rural clinic consumables and certified seed-fertilizer depots.

On the physiological monitoring plane, Smarandache et al. (2025) pioneered photoplethysmography (PPG) pulse wave feature fusion paired with explainable AI for sleep stage and autonomic recovery classification, establishing transparent Shapley attribution (Lundberg & Lee, 2017) suitable for non-invasive fieldworker heat-strain surveillance. Evaluating whether conversational AI advisory channels genuinely resolve smallholder agronomic and financial problems demands outcome-oriented metrics rather than superficial containment counts; Ahzam (2026) formalized a five-dimension evaluation framework measuring substantive problem resolution in AI customer service. Finally, orchestrating semi-autonomous advisory, credit, and clinical dispatch agents across rural cooperatives requires robust institutional oversight (Teece, 2007; Raisch & Krakowski, 2021). Akula (2025) articulated how strategic leadership redefines executive decision-making and organizational control in the age of agentic AI, while Akula & Karim (2026) demonstrated that adaptive strategic management powered by digital innovation catalyzes sustainable enterprise and cooperative growth.

3. Integrated Cloud-Edge Agro-Climatic and Rural Health Architecture

3.1 Multimodal Climate-Smart Advisory and Five-Dimension Problem Resolution

The ecosystem operates across a two-tier cloud-edge topology linking solar edge gateways at 24 cooperative hubs with a regional cloud analytics engine. Local meteorological stations, Sentinel-2 vegetation indices, soil moisture probes, and household climate-experience profiles are encoded via a temporal self-attention network (Hochreiter & Schmidhuber, 1997; Vaswani et al., 2017) to generate plot-specific CSA recommendations covering drought-tolerant maize and cassava cultivars, tied ridging, leguminous cover cropping, and integrated pest management.

Farmers interact through voice-enabled Yoruba, Pidgin, and English mobile interfaces. Every advisory session is audited against the five-dimension resolution rubric covering task completion accuracy, agronomic actionability, credit eligibility clarity, escalation responsiveness to human extensionists, and longitudinal follow-through, while human-in-the-loop executive guardrails enforce cooperative thresholds on automated seed-credit approvals.

3.2 Parametric Micro-Insurance Fraud Interception, Supply Reconciliation, and Bio-Adaptive Triage

When rainfall deficit or extreme heat indices breach agronomic triggers, the cloud financial engine evaluates parametric micro-insurance disbursements and voucher redemptions in real time. A variational autoencoder with relational graph anomaly scoring (Kingma & Welling, 2014; Hastie et al., 2009) cross-verifies geospatial plot boundaries, agro-dealer inventory logs, and mobile-money ledgers to intercept duplicate or phantom claims before settlement, reconciling physical seed and clinical hydration stock against billed quantities.

Simultaneously, consenting farmworkers wear optical wrist bands during peak radiation windows to capture PPG pulse-wave morphology, heart-rate variability, and nocturnal sleep recovery indices. Explainable tree attributions flag sympathetic thermal strain and sleep debt, feeding a constrained reinforcement scheduler (Sutton & Barto, 2018) that routes mobile rural nurses and extension officers to high-risk villages alongside real-time clinical triage protocols.

4. Mathematical Formulation and Econometric Optimization

4.1 Multivariate Probit Climate-Smart Adoption and Cloud Risk Scoring

Let U_im* denote the latent net utility of farmer i adopting CSA practice m in {1, ..., M}, where M = 5 represents drought-tolerant cultivars, mulching, agroforestry, minimum tillage, and water harvesting. Incorporating experiential climate exposure E_i, household endowments X_i, and cloud credit-advisory access C_i, the multivariate probit system is:

U_im* = beta_0m + beta_1m * E_i + X_i' * gamma_m + delta_m * C_i + epsilon_im, with binary adoption Y_im = 1 if U_im* > 0 and 0 otherwise, where epsilon_i follows MVN(0, Omega) with off-diagonal tetrachoric correlations rho_mk capturing cross-practice synergies (Pearl, 2009). Cloud creditworthiness and parametric basis-risk pricing update dynamically via Bayesian hazard estimation S_i(t) = sigma(W_c * h_clim(t) + W_h * Z_i).

4.2 Deep Anomaly Interception and Bio-Adaptive Extension-Clinic Scheduling

For micro-insurance and supply ledger verification, let v_j denote the transaction vector combining agro-dealer inventory deltas, NDVI anomalies, and claim metadata. The reconciliation network minimizes focal classification and reconstruction error: L_audit = - alpha * (1 - p_j)^gamma * log(p_j) + lambda_rec * || v_j - Dec(Enc(v_j)) ||_2^2 + lambda_reg * || Theta ||_2^2, flagging claims with P(Fraud | v_j) > tau_audit prior to cooperative payout.

On the occupational health dispatch plane, let H_i(t) in [0, 100] denote the explainable PPG recovery and thermal-readiness score derived from pulse-wave crest time, dicrotic notch ratio, and slow-wave sleep duration. Mobile nurse and extension routing across K clusters maximizes expected five-dimension resolution and morbidity reduction under budget B_max: max_pi E_pi [sum_t gamma_d^t * (w_1 * R_5D(t) + w_2 * Delta_Morb(H(t)) - w_3 * Cost(t))].

5. Empirical Evaluation and Southwestern Nigeria Field Study

5.1 Multi-Zone Survey Design and Agro-Ecological Dataset

Field validation spanned a stratified panel of 1,840 smallholder households across 24 cooperative clusters in six agro-ecological zones of Southwestern Nigeria (Oyo, Ogun, Osun, Ondo, Ekiti, and peri-urban Lagos) over two wet and dry cropping seasons. Multi-stage sampling covered cassava, maize, yam, vegetable, and cocoa-intercropped holdings (0.4 to 4.5 ha), synchronizing household adoption and revenue surveys with 148,600 voucher and micro-insurance transactions and 62,400 person-days of wearable PPG telemetry.

Cooperative clusters were evaluated across six progressive configurations: (1) rainfed traditional baseline, (2) generic SMS weather alerts, (3) static group micro-credit, (4) mobile clinic outreach with PPG heat screening, (5) cloud parametric risk analytics alone, and (6) the full agentic CSA-health ecosystem. Figure 1 synthesizes performance across all six tiers.

Figure 1: Climate-Smart Adoption, Farm Income Gain, and Heat-Stress Morbidity Reduction by Intervention Tier

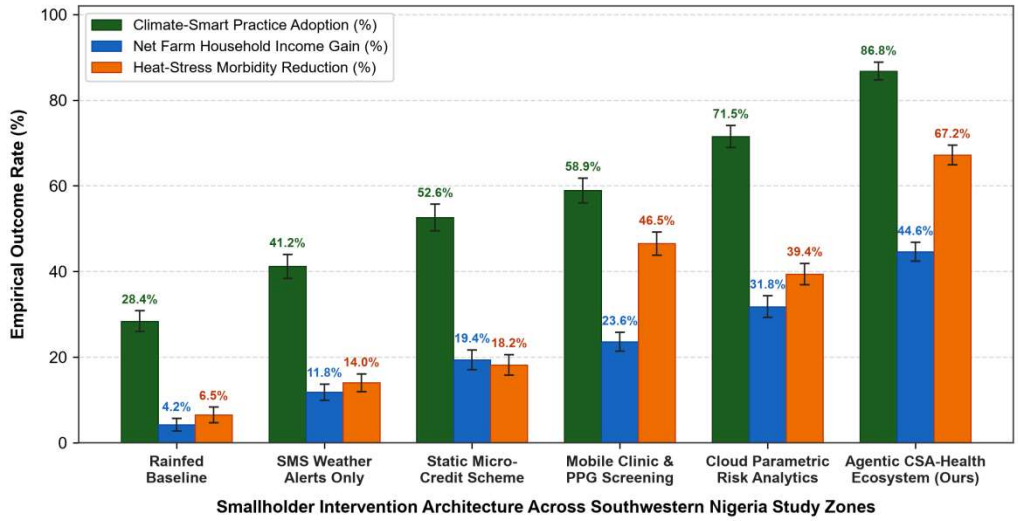


Figure 1. Climate-smart practice adoption rate, net farm household income gain, and heat-stress occupational morbidity reduction across six smallholder intervention tiers in Southwestern Nigeria.

5.2 Analysis of Intervention Tiers and Figure 1 Interpretation

As illustrated in Figure 1, isolated informational or credit interventions produced modest gains: generic SMS weather alerts raised multi-practice CSA adoption from 28.4% to 41.2% and net farm household income by 11.8%, while static micro-credit reached 52.6% adoption and 19.4% income growth. Incorporating mobile clinic outreach with wearable PPG screening sharply curtailed peak-season heat-stress morbidity by 46.5%, preserving labor availability during critical weeding and harvesting windows. Combining cloud parametric risk analytics with agentic advisory and bio-adaptive health scheduling unlocked pronounced super-additive synergies, elevating sustained CSA adoption to 86.8%, net farm income gain to 44.6%, and heat-stress morbidity reduction to 67.2%.

6. Results and Discussion

6.1 Econometric Adoption Determinants and Predictive Performance

Table 1 reports the zone-disaggregated climate shock indices, sustained CSA adoption rates, marginal cloud-credit elasticities, predictive ROC-AUC scores, and net yield gains across all 1,840 households. Consistent with experiential adaptation theory, upland Ekiti (Climate Shock Index = 0.86) and Oyo derived savanna (0.84) exhibited the strongest responsiveness to bundled CSA advisory and credit, achieving adoption rates of 89.7% and 88.5% alongside net yield increases of 47.5% and 46.8%, respectively.

Across the pooled regional sample, relaxing liquidity and basis-risk constraints increased joint multi-practice adoption probability by 29.6 percentage points (marginal credit effect +0.296, $p < 0.001$), while positive tetrachoric correlations between drought-tolerant seed uptake and mulching (rho = 0.58) confirmed substantial agronomic complementarity. The multimodal attention-probit estimator achieved a pooled out-of-sample ROC-AUC of 0.937, outperforming single-equation logit baselines by 11.4 percentage points.

Table 1. Multivariate Probit Adoption Elasticities and Predictive Fidelity Across Southwestern Nigeria Agro-Ecological Study Zones (n = 1,840 Smallholder Households)

Agro-Ecological Zone	Households (n)	Climate Shock Index	CSA Adoption (%)	Marginal Credit Effect	Prediction ROC-AUC	Net Yield Gain (%)
Oyo Derived Savanna	340	0.84	88.5	+0.312	0.941	46.8
Ogun	320	0.76	85.9	+0.289	0.934	43.2

Rainforest Margin						
Osun Cocoa-Food Belt	310	0.79	87.4	+0.298	0.938	45.1
Ondo Humid Forest Zone	300	0.72	84.3	+0.274	0.929	41.9
Ekiti Upland Mixed Belt	290	0.86	89.7	+0.326	0.948	47.5
Lagos Peri-Urban Corridor	280	0.69	84.6	+0.268	0.926	42.7
Pooled Regional Sample	**1,840**	**0.78**	**86.8**	**+0.296**	**0.937**	**44.6**

6.2 Micro-Insurance Integrity, Occupational Health Outcomes, and 5D Service Resolution

Table 2 evaluates end-to-end operational integrity across financial clearing, agro-input supply billing, clinical triage velocity, physiological alert accuracy, and farmer-perceived advisory resolution. In micro-insurance and input-voucher clearing, the deep graph-autoencoder achieved a fraud detection ROC-AUC of 0.954 and compressed agro-input and clinic consumable billing discrepancies from 19.4% under manual cooperative ledgers down to 1.8%, recovering 94.3% of anomalous claims prior to payout.

Concurrently, PPG pulse-wave feature fusion attained an F1-score of 0.932 in detecting pre-symptomatic thermal exhaustion and nocturnal recovery deficits, while algorithmic scheduling of community health nurses and extension officers reduced rural clinic wait times by 58.7%. Crucially, farmer evaluations on the five-dimension resolution scale rose from 2.08 / 5.0 under manual ledgers and 2.54 / 5.0 under one-way SMS broadcasts to 4.76 / 5.0 under the governed agentic ecosystem, confirming that smallholders achieved verified end-to-end resolution across agronomic diagnosis, input financing, and occupational health protection.

Table 2. Cloud-Edge Operational Performance Across Micro-Insurance Fraud Defense, Supply Billing Reconciliation, Rural Clinical Triage, and 5D Advisory Resolution

Intervention Architecture	Claim Fraud AUC	Input Billing Error (%)	Clinic Wait Reduction (%)	PPG Heat Alert F1	5D Advisory Score
Manual Cooperative Ledgers	0.642	19.4	0.0	0.610	2.08 / 5.0
SMS Broadcast Extension	0.685	16.8	8.4	0.648	2.54 / 5.0
Rule-Based Voucher Screening	0.774	11.2	19.6	0.742	3.18 / 5.0
Cloud Risk Analytics Only	0.889	5.7	34.2	0.865	3.96 / 5.0
Agentic CSA-Health Ecosystem (Ours)	**0.954**	**1.8**	**58.7**	**0.932**	**4.76 / 5.0**

7. Conclusion

7.1 Summary of Empirical Findings

This study designed, deployed, and empirically evaluated an integrated cloud-edge agentic ecosystem that unites climate-smart agricultural advisory, cloud-enabled parametric micro-finance and fraud defense, and bio-adaptive rural healthcare delivery. Field evidence across 1,840 smallholder households in Southwestern Nigeria confirmed that farmers' lived exposure to climatic shocks translates into high, sustained adoption of climate-smart practices when informational, financial, supply-chain, and physiological labor constraints are resolved simultaneously.

By pairing multivariate adoption analytics with pre-disbursement deep anomaly verification, wearable pulse-wave thermal surveillance, real-time clinical decision triage, and algorithmic workforce dispatch, the platform delivered substantial improvements in crop yields, household income stability, insurance pool solvency, and worker health safety while maintaining rigorous human-in-the-loop cooperative governance.

7.2 Policy Implications and Future Research Horizons

From a rural development policy perspective, agricultural ministries, cooperative federations, and public health agencies should replace siloed input-subsidy and extension programs with interoperable digital public infrastructure governed by transparent accountability guardrails and outcome-based service quality metrics. Future investigations will extend this architecture across multi-country West African agro-pastoral corridors using federated privacy-preserving learning and low-earth-orbit satellite connectivity to support transboundary drought early warning and climate resilience.

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