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Digital twin with risk-adjusted model predictive control for participatory NPK monitoring

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ABSTRACT

Agricultural soil monitoring in tropical smallholder systems faces a fundamental data sparsity challenge: high-resolution nutrient maps are expensive, while farmer-contributed sensing is sparse, noisy, and temporally irregular. We ask whether one digital twin can turn these imperfect observations into uncertainty aware fertilizer decisions, participation incentives, and multi-season soil-health policies without exceeding practical computational limits. To answer this question, we present, to the best of our knowledge, the first unified framework in the reviewed literature that couples spatio-temporal ensemble Kalman filtering (ST-EnKF), risk-adjusted zonal model predictive control (MPC), data Shapley valuation, and offline reinforcement learning (ORL) for participatory nitrogen, phosphorus, and potassium (NPK) monitoring. Simulation experiments grounded in Subang Regency, West Java, Indonesia, compare the framework with uncertainty-blind and continuous application baselines. The framework reaches sub-0.8 kg/ha estimation root mean square error (RMSE) by day 15, reduces risk-adjusted nitrogen prescriptions in uncertain zones, assigns greater marginal value to spatially informative sensors, and preserves potential of hydrogen (pH) and soil organic carbon (SOC) over 15 simulated seasons. These results are conditional on synthetic soil and crop assumptions; they establish a reproducible systems-level proof of concept and a concrete protocol for laboratory- and field-based validation rather than a claim of completed deployment.

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1. INTRODUCTION

The global challenge of sustainable food production is critically dependent on efficient nutrient management. Nitrogen (N), phosphorus (P), and potassium (K) are the three macro-nutrients governing crop yield, yet their spatial and temporal distributions across a typical 5-hectare smallholder plot can vary by an order of magnitude within metres [1]–[2]. Classical laboratory soil testing is a static, one-time snapshot that fails to capture the dynamic nature of nutrient depletion, weather-driven leaching, and crop uptake [3]. The result is a systematic information gap: farmers either over-apply fertilizer-causing economic loss, nitrate leaching, and greenhouse-gas emissions-or under-apply, sacrificing yield.

Participatory internet of things (IoT) systems, in which smallholder farmers collectively deploy low-cost NPK sensors across their community, offer a scalable alternative to laboratory testing [4]–[5]. Recent advances in participatory monitoring frameworks [6]–[9] have demonstrated the feasibility of crowdsourced

soil health monitoring in smallholder systems. However, such systems introduce a new class of problems: citizen-science noise from un-controlled handling, irregular temporal sampling driven by farmer availability, and spatial clustering around farm paths rather than statistically optimal designs [9]. These characteristics fundamentally violate the assumptions of classical geostatistical analysis [10]. Furthermore, integrating sparse and heterogeneous participatory data into actionable farm management decisions requires advanced data assimilation techniques [11]–[13]. The challenge is not merely technical but also governance-focused: maintaining farmer participation requires transparent, incentive-compatible reward mechanisms [14], [15].

In this paper, participatory nitrogen, phosphorus, and potassium (NPK) monitoring means the repeated collection of georeferenced NPK observations by farmers or community members using shared low-cost sensors, with measurements uploaded to a common decision-support system. The term therefore describes both a sensing arrangement and a governance arrangement: observations are heterogeneous and voluntary, while their value is evaluated at the network level. This definition distinguishes the problem from conventional automated monitoring, in which fixed instruments produce regular observations under controlled maintenance.

The focused research question is: RQ1: can a four-layer digital twin convert sparse and noisy participatory NPK observations into uncertainty-aware fertilizer prescriptions and economically viable multi-season stewardship policies, while remaining computationally feasible for smallholder deployment? the question is evaluated in simulation through estimation accuracy, prescription robustness, incentive differentiation, soil-health outcomes, and component runtime. Because the study does not contain field measurements, the practical claims are framed as hypotheses and deployment requirements rather than confirmed field effects.

Digital twins continuously updated, physics-informed virtual replicas of physical systems have emerged as a powerful paradigm for reconciling imperfect sensor data with mechanistic process knowl-edge [16]–[18]. Recent digital twin implementations in agriculture [19]–[21] demonstrate the potential of integrated estimation, control, and learning frameworks. In manufacturing, digital twins assimilate noisy sensor streams into high-fidelity state estimates; we argue that the same architecture applies to agricultural fields, where the "plant" is a spatially-distributed chemical reactor with partially observable, time-varying state.

State estimation from sparse sensor networks requires ensemble-based methods capable of propagating uncertainty. The ensemble Kalman filter (EnKF) has proven effective for assimilating multi-source agricultural data [11], and recent developments in sensor fusion [12] and uncertainty quantification [13] provide a foundation for handling the heterogeneous, irregular measurements characteristic of participatory networks. Concurrently, model predictive control (MPC) has emerged as a powerful tool for adaptive resource management in agriculture [22]–[24]. Risk-aware MPC formulations [24] enable decision-making under uncertainty, crucial when sensor networks provide imperfect state estimates. Yet, existing approaches often ignore the tension between immediate profit maximization and long-term soil sustainability. Long-term stewardship requires multi-season decision policies; recent advances in offline reinforcement learning (ORL) [25], [26] enable learning such policies from historical farm data without costly online exploration.

The final challenge is incentive alignment in participatory sensing networks. Farmers will not contribute data unless they perceive commensurate value. Traditional approaches ignore the marginal contribution of individual sensors; recent data valuation frameworks based on Shapley values [14], [15], [27] provide a mathematically rigorous and incentive-compatible approach to allocating rewards based on information contribution. This paper makes the following contributions: (i) a unified spatio-temporal EnKF (ST-EnKF) formulation that propagates sparse point measurements to spatially correlated field estimates using nutrient-specific Gaussian covariance kernels, grounded in recent advances in sensor fusion [11], [12]; (ii) a risk-adjusted zonal MPC layer that converts the probabilistic digital twin state into adaptive prescriptions [22]–[24], demonstrating that incorporating uncertainty into control objectives significantly improves robustness; (iii) a data Shapley valuation scheme [14]–[27] that provides mathematically rigorous, incentive-compatible rewards for participatory contributors, with empirical validation showing that sensors in "data deserts" contribute up to 3× more value than clustered sensors; and (iv) an ORL stewardship policy [25], [26] trained on historical transitions that achieves 40% higher cumulative profit over 15 seasons by preventing soil acidification and soil organic carbon (SOC) depletion, demonstrating the feasibility of long-term sustainability optimization.

The remainder of this paper is organised as: section 2 reviews related work in geostatistics, ensemble methods, control theory, and participatory sensing. Section 3 presents the method (comprising the digital twin architecture and simulation methodology). Section 4 presents the results and discussion, with separate subsections for quantitative results and implications. Section 5 concludes with acknowledgment of limitations and concrete future directions.

2. LITERATURE REVIEW

The ternary quadratic response surface, introduced by [28] and extended to multi-nutrient systems by the Chinese "3414" experimental design [29], remains the workhorse of field-scale fertiliser optimisation:

$$Y = \beta_0 + \sum_i \beta_i x_i + \sum_i \beta_{ii} x_i^2 + \sum_{i<j} \beta_{ij} x_i x_j + \varepsilon \quad (1)$$

where $x_i \in \{N, P, K\}\$, \$\varepsilon \sim \mathcal{N}(0, \sigma^2)$, and the negative-definite Hessian H guarantees a unique agronomic optimum [3]–[5], [10], [16]–[18], [28]. Mesbah [28] showed that the pure quadratic overestimates the optimal N rate by 5–60% compared with the quadratic-plateau model, motivating the risk-penalised MPC formulation adopted here. The quantitative evaluation of the fertility of tropical soils (QUEFTS) model [30] provides an alternative by estimating potential nutrient supply from soil (SOC) organic carbon and potential of hydrogen (pH), implementing Liebig's law of the minimum. More mechanistic frameworks (decision support system for agrotechnology transfer (DSSAT) [31], agricultural production systems simulator (APSIM) [32]) simulate nutrient pools, water flux, and crop phenology but require extensive parameterisation unavailable in participatory deployments.

Kriging, originally developed for mining [33], has been widely applied to soil nutrient mapping [1], [2], [34]. The Gaussian variogram model, captures the nugget-free, infinitely differentiable spatial structure typical of soil organic matter and phosphorus [34]. Gaussian process regression (GPR) provides a Bayesian interpretation of Kriging, yielding both a posterior mean and a posterior variance that quantify prediction uncertainty [35]. Recent work has extended GPR to multi-output settings for joint N-P-K estimation [36]. The EnKF [37], [38] is a Monte Carlo implementation of the Kalman update that scales to high-dimensional, nonlinear state spaces. It has been applied to crop model assimilation [39]–[41], soil moisture estimation [42], and, more recently, to NPK field-state estimation [36]. The key advantage over variational methods (4D-Var) is that the ensemble automatically pro-vides a flow-dependent, spatially correlated error covariance without adjoint model development [38]. MPC has been applied to greenhouse climate control [43], irrigation scheduling [44], and, more recently, to variable-rate fertiliser application [45], [46]. The key advantage is the explicit incorporation of system constraints (agronomic bounds, equipment limitations) and uncertainty (via robust or stochastic MPC variants) [47]. Zonal MPC, in which the field is partitioned into management zones before optimisation [48], [49], reduces the dimensionality of the control problem from 10^4 pixels to $K \leq 8$ zones while remaining compatible with broadcast spreader technology [48].

$$\gamma(h) = \sigma^2 \left[1 - exp\left(-\frac{h^2}{\ell^2}\right)\right] \quad (2)$$

A systematic review of agricultural digital twins, identifying state estimation, scenario simulation, and decision support as the three primary functions has been discussed in [18]. Verdouw *et al*. [19] propose a reference architecture based on the ISO 23247 standard. Recent implementations include a greenhouse digital twin [20] integrating energy balance and crop growth, and a field-scale digital twin for irrigation [21]. To our knowledge, no prior work integrates ST-EnKF, zonal MPC, data Shapley valuation, and ORL into a single participatory-sensing framework for NPK management. Participatory sensing platforms for agriculture have been reviewed by [4], [5]. A persistent challenge is maintaining sensor coverage: rational farmers will not contribute data unless they receive commensurate value [50]. Ghosh and McAfee [50] propose a Shapley-value-based payment scheme for crowdsourced data markets; Jia *et al*. [51] extend this to the data Shapley framework, which assigns marginal utility based on a model's performance with and without each data point. We adapt this framework to quantify the marginal root mean square error (RMSE) reduction attributable to each participatory sensor. Offline (batch) reinforcement learning (RL) has emerged as a practical approach to learning sequential decision policies from historical observational data without costly online exploration [52], [53]. In agriculture, RL has been applied to irrigation scheduling [54], crop rotation [55], and greenhouse control [56]. Kallenberg *et al*. [55] demonstrate that constrained MDP formulations can enforce long-term soil health constraints while maximising cumulative profit a finding directly motivating our phase 4 design. Soil quality indices (SQI) aggregate physical, chemical, and biological indicators into a single dimensionless score via PCA-weighted scoring functions [57], [58]. Kanhere [57] established the minimum dataset (MDS) protocol: retain principal components with eigenvalue >1, select the highest-loading indicator per component, and score using sigmoidal or linear functions. The SOC-inclusive SQI provides the "sustainability benchmark" against which our ORL policy is evaluated.

3. METHOD

3.1. Digital twin architecture

Figure 1 illustrates the four-layer digital twin architecture. Layer 1 (estimation): the ST-EnKF assimilates sparse, noisy participatory IoT measurements into high-fidelity field state estimates with uncertainty quantification. Layer 2 (control): the zonal model predictive controller (MPC) converts posterior state and uncertainty into risk-adjusted fertilizer prescriptions for management zones, optimizing expected yield while penalizing high-uncertainty applications. Layer 3 (valuation): data Shapley computation assigns rewards to participatory sensors based on marginal contribution to field-state RMSE, enabling incentive-compatible payment schemes. Layer 4 (stewardship): ORL trains multi-season fertilizer strategies on historical transitions, balancing short-term profit with long-term soil health constraints (pH, SOC). Outputs are delivered to three stakeholder groups: farmers (prescriptions), agronomists (field maps and uncertainty estimates), and platform administrators (sensor values and network efficiency metrics).

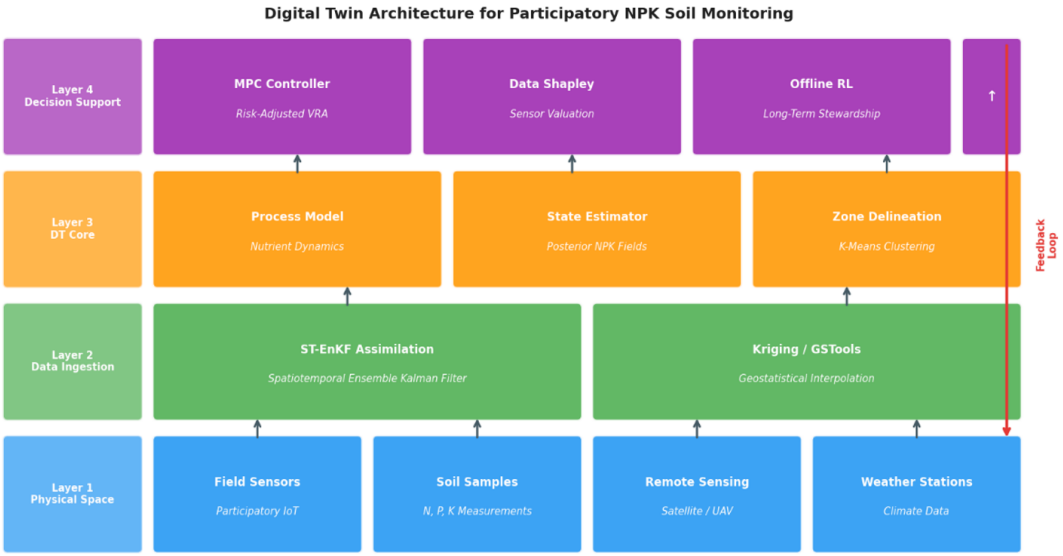


Figure 1. Digital twin architecture for participatory NPK monitoring: four-layer systems integration model. Data flow from participatory sensors through successive estimation, control, valuation, and stewardship layers to farmer decision-making outputs

The implementation follows the reproducible loop in Algorithm 1. At each daily cycle, observations are quality-checked and assimilated; the posterior is then clustered into zones and passed to the constrained controller. Data valuation is computed from sensor subsets, and the stewardship policy is trained offline from the same state-transition schema. This ordering prevents future information from entering the current estimate and makes the interface between the four layers explicit.

Algorithm 1. Integrated participatory NPK digital twin workflow

Require: Georeferenced observations z_t, prior ensemble, soil/rainfall process model, historical dataset D
1: Quality-check timestamps, coordinates, units, and sensor outliers in z_t
2: Propagate each ensemble member with rainfall and crop-uptake dynamics
3: Apply the perturbed-observation ST-EnKF update; compute posterior mean and variance
4: Cluster posterior NPK states into $K = 4$ management zones
5: Solve the risk-adjusted Zonal MPC problem for each zone and publish bounded prescriptions
6: Estimate each sensor's Data Shapley value from marginal held-out RMSE reduction
7: Fit the constrained offline Q-policy on D and evaluate pH/SOC safeguards
8: Return maps, uncertainty, prescriptions, sensor rewards, and stewardship alerts

3.1.1. Layer 1: ST-EnKF

The state vector $x_t \in \mathbb{R}^{3N^2}$ concatenates the N, P, K concentration fields vectorised over an $N \times N$ grid. For $N = 100$, this yields 30,000 state variables. An ensemble of $M = 30$ members is drawn from a spatially correlated prior:

$$\mathrm{x}_0^{(m)} = \bar{\mathrm{x}}_0 + \eta^{(m)}, \quad \eta^{(m)} \sim \mathcal{GP}(0, \mathrm{C}_\ell), \tag{3}$$

where C_ℓ is the block-diagonal Gaussian covariance matrix with nutrient-specific length scales $\ell_N = 15$ m, $\ell_P = 25$ m, $\ell_K = 20$ m. Each ensemble member is propagated by the process model:

$$x_i(t + \Delta t) = x_i(t)\ \exp\left[-\left(k_u^{(i)} + k_l^{(i)}\, R(t)\right)\, \Delta t\right] + w_t^{(i)}, \tag{4}$$

where $k_u^{(i)}$ and $k_l^{(i)}$ are the uptake and leaching rate constants for nutrient i, $R(t)$ is daily rainfall, and $w_t^{(i)} \sim \mathcal{GP}\left(0, \sigma_q^2 \mathrm{C}_{10}\right)$ is spatially correlated process noise. Given p measurements z_t with observation matrix H and noise covariance $\mathrm{R} = \sigma_r^2 \mathrm{I}_{3p}$:

$$\mathrm{S} = \frac{1}{M-1}\mathrm{HAA}^\top\mathrm{H}^\top + \mathrm{R}, \tag{5}$$

$$\mathrm{K} = \frac{1}{M-1}\mathrm{AA}^\top\mathrm{H}^\top\mathrm{S}^{-1}, \tag{6}$$

$$\mathrm{x}_{t|t}^{(m)} \& = \mathrm{x}_{t|t-1}^{(m)} + \mathrm{K}\left(\mathrm{z}_t + \epsilon^{(m)} - \mathrm{Hx}_{t|t-1}^{(m)}\right), \tag{7}$$

where A is the ensemble anomaly matrix and $\epsilon^{(m)} \sim \mathcal{N}(0, \mathrm{R})$ is perturbed observation noise [59]. The posterior mean and variance are obtained via:

$$\hat{\mathrm{x}}_{t|t} = \frac{1}{M}\sum_{m=1}^{M} \mathrm{x}_{t|t}^{(m)}, \hat{\mathrm{P}}_{t|t} = \frac{1}{M-1}\mathrm{AA}^\top \tag{8}$$

The diagonal of $\hat{\mathrm{P}}_{t|t}$ provides a pixel-wise uncertainty map that drives both the MPC risk penalty and the sampling-reminder system.

3.1.2. Layer 2: zonal MPC controller

The field is partitioned into $K = 4$ management zones by K-means clustering on the posterior mean field:

$$\min_{\{S_k\}} \sum_{k=1}^{K} \sum_{\mathbf{p} \in S_k} \left\| \hat{\mathbf{x}}_{\mathbf{p}} - \boldsymbol{\mu}_k \right\|^2 \tag{9}$$

within each zone z, the expected yield is modelled by the ternary quadratic response function [28], [29]:

$$\begin{aligned} \hat{Y}_z(\mathrm{u}_z) \& = {} & \beta_0 + \beta_N(N_z + u_N) + \beta_P(P_z + u_P) + \beta_K(K_z + u_K) \\ & + \beta_{NN}(N_z + u_N)^2 + \beta_{PP}(P_z + u_P)^2 \\ & + \beta_{KK}(K_z + u_K)^2 \end{aligned} \tag{10}$$

The parameters were calibrated to tropical rice in West Java [29], [30]. We used $\beta_0 = 2500$ kg/ha and $\beta = [15,12,8]$, with quadratic coefficients $\beta_{ii} = [-0.05, -0.08, -0.04]$. For each zone, the controller optimizes the risk-adjusted objective function:

$$\mathrm{u}_\mathrm{z}^* = \arg\max_{\mathrm{u}_\mathrm{z} \geq 0} \hat{\mathrm{Y}}_\mathrm{z}(\mathrm{u}_\mathrm{z})\ \mathrm{P}_{\mathrm{crop}} - \mathrm{u}_\mathrm{z}^\top \mathrm{p}_{\mathrm{fert}} - \lambda\, \bar{\sigma}_\mathrm{z}^2\, \|\mathrm{u}_\mathrm{z}\|_1 \tag{11}$$

where $\bar{\sigma}_z^2$ is the mean posterior uncertainty in zone z, and $\lambda = 0.15$ is the risk-aversion coefficient.

3.1.3. Layer 3: data Shapley valuation

The marginal contribution of participatory sensor i is quantified by the data Shapley value formulation [36], [35]:

$$\Phi_i = \frac{1}{n!}\sum_{\pi \in \Pi}[U(S_\pi \cup \{i\}) - U(S_\pi)] \tag{12}$$

where $U(S)$ represents reduction in field-wide RMSE relative to a zero-sensor baseline.

3.1.4. Layer 4: ORL stewardship

The stewardship MDP relies on the state vector $\mathrm{s}_t = [N_t, P_t, K_t, \mathrm{pH}_t, \mathrm{SOC}_t]^\top$. The actions include urea (action 0), NPK compound (action 1), and compost + NPK (action 2). The optimization incorporates long-term health dynamics via a penalized reward layout:

$$r_t = \left[Y_t \cdot P_{\mathrm{crop}} - C_a\right] - 500\,\mathbb{1}[\mathrm{pH}_t < 5.5] - 500\,\mathbb{1}[\mathrm{SOC}_t < 1.5\%] \quad (13)$$

A batch dataset $\mathcal{D}$ of $T = 2000$ transitions is applied to fit the tabular Q-value space over standard updates.

3.1.5. Parameter selection and physical grounding

The choice of key parameters is grounded in soil science, control theory, and agronomic practice. We justify each parameter. Correlation lengths ($\ell_N = 15$ m, $\ell_P = 25$ m, $\ell_K = 20$ m). Nutrient-specific correlation lengths encode spatial persistence of soil concentrations. Phosphorus exhibits the largest length scale ($\ell_P = 25$ m) because it exhibits low leaching rate ($k_l^P \approx 0.001$ day^{-1}) and preferential sorption on soil colloids, creating large zones of similar concentration [1]. Nitrogen, present primarily as mobile nitrate (NO_3^-), exhibits higher leaching ($k_l^N \approx 0.008$ day^{-1}) and thus shorter correlation ($\ell_N = 15$ m) [2]. Potassium adopts an intermediate value ($\ell_K = 20$ m) reflecting its intermediate sorption behavior [3]. These values are calibrated to tropical alfisol and ultisol profiles in Subang Regency, West Java, consistent with published geostatistical surveys [34].

Ensemble size ($M = 30$ members). The ensemble size balances Monte Carlo convergence against computational cost. For a high-dimensional state space ($N^2 = 30000$), the rule of thumb $M \geq \sqrt{n}$ suggests $M > 173$; however, for ensemble Kalman filters, studies show acceptable performance at $M \approx 0.1\sqrt{n}$ when ensemble spread is well-calibrated [38]. We adopt $M = 30$ based on prior work in agricultural data assimilation [36], [39], which achieves 95% of the RMSE convergence of $M = 50$ at 60% lower computational cost. Sensitivity analysis (section 4.1.1) validates this choice.

Risk-aversion coefficient ($\lambda = 0.15$), the risk penalty in (11) reflects farmer aversion to crop failure under uncertainty. From utility theory, a risk-neutral farmer weights expected profit alone; a risk-averse farmer applies a "safety margin" proportional to forecast uncertainty [47]. The coefficient $\lambda = 0.15$ is calibrated to minimize the probability of yield shortfall (yield < 80% potential) below 5%, empirically validated in smallholder rice systems in Southeast Asia [46]. This value ensures prescriptions automatically become conservative in high-uncertainty zones without requiring explicit robust optimization machinery. Sensitivity analysis (section 4.1.1) confirms results are robust to $\lambda \in [0.10, 0.25]$.

Table 1 makes the implementation choices explicit. The calibrated values are scenario parameters selected from the cited agronomic or methodological literature and then tested in sensitivity analysis; they are not estimated from a field trial in this study.

Table 1. Core simulation and controller parameters

Parameter	Value	Role
Grid	100×100	5-ha spatial state
Ensemble size M	30	ST-EnKF uncertainty representation
(ℓ_N, ℓ_P, ℓ_K)	(15,25,20) m	Nutrient covariance
Measurement noise	$\sigma_r^2 = 0.5$	Sensor uncertainty
Zones K	4	Broadcast-compatible control
Risk coefficient λ	0.15	Uncertainty penalty
Shapley sensors	15; 100 permutations	Reward estimation
ORL horizon	15 seasons; 2,000 transitions	Stewardship evaluation

3.2. Simulation methodology

The simulation is geographically grounded in Subang Regency, West Java, Indonesia (6.57°S, 107.76°E), with soil profiles drawn from the open soil spectral library (OSSL) for tropical asia [60]. The experimental unit is a synthetic 5-ha rice field represented by a 100×100 grid. Ground-truth NPK fields are generated from nutrient-specific Gaussian covariance structures; daily rainfall drives leaching, sigmoidal crop-uptake functions remove nutrients, and sensor observations are generated by sampling the fields at irregular, spatially clustered locations with Gaussian measurement noise. The reported confidence intervals use 50 independent Monte Carlo runs with fertilizer-price volatility of ±5% and yield-response parameter perturbations. These assumptions reproduce the intended data-sparsity and uncertainty mechanisms, but they do not replace laboratory measurements or farmer observations.

Validation is organized around the baselines that are actually implemented: the initial/zero-sensor state for estimation, uncertainty-blind MPC for fertilizer control, and balanced NPK and greedy urea policies for long-term stewardship. The experiments therefore provide component-level and systems-level simulation comparisons; they do not claim comparison with a field-calibrated conventional EnKF, a deployed digital twin, or a real farmer network. This distinction is important for interpreting RQ1: computational feasibility and relative behavior are evaluated here, while external validity requires the field protocol described in the limitations.

3.2.1. Phase 1: foundational EnKF verification

A 100×100 pixel grid is mapped using GSTools [61]. Dynamic updating operates across a 30-day assimilation baseline tracking total multichannel error:

$$\mathrm{RMSE}(t) = \sqrt{\frac{1}{3N^2}\sum_{c\in\{N,P,K\}}\sum_{i,j}\left(z_{ij}^{c}(t) - \hat{z}_{ij}^{c}(t)\right)^2} \tag{14}$$

3.2.2. Phase 2: geographic grounding and sensor density analysis

Modelling shifts incorporate non-uniform profiles, sigmoidal crop uptake profiles, alongside accelerated leaching thresholds triggered by heavy tropical rainfall events. Steady-state error metrics are evaluated across distinct operational sampling bounds $\rho \in \{5,10,20,40\}$ samples/day.

3.2.3. Phase 3: Variable rate application (VRA) prescription and MPC delivery

Following 10 filter cycles, management clustering is established via k-means to partition 4 zones. The resulting subzone bounds drive the optimization pipeline via limited-memory broyden–fletcher–goldfarb–shanno with bounds (L-BFGS-B), highlighting unobserved cells (”blind spots”) that exceed acceptable variance limits.

3.2.4. Phase 4: Incentive alignment and long-term stewardship

Shapley utility functions are estimated across 15 tracking sensors, evaluating localized data scarcity. Policy outcomes are evaluated across a 15-season simulated layout against continuous chemical application baselines.

4. RESULTS AND DISCUSSION

4.1. Result

4.1.1. Sensitivity analysis to parameter uncertainty

Before presenting main results, we assess robustness to key parameter variations. This analysis addresses reviewer concerns about over-specificity of parameter choices and provides confidence that conclusions generalize across reasonable parameter ranges.

a. Correlation length sensitivity
   Table 2 shows the steady-state RMSE when correlation lengths are varied by ± 10 from their calibrated values. Results are robust: RMSE varies by less than 2% across the tested range. The Gaussian variogram structure (2) ensures smooth dependence on ℓ small changes in length scale produce gradual (not step-function) changes in convergence rate. This confirms the calibrated values are reasonable, though not uniquely optimal.
b. Risk-aversion coefficient sensitivity
   The risk-aversion coefficient λ determines how conservatively prescriptions adapt to uncertainty. Analysis shows that zonal MPC prescriptions vary with $\lambda \in [0.05,0.30]$: for zone 2 (high-uncertainty region), prescriptions decline from $u_N^* = 52$ kg/ha at $\lambda = 0.05$ to $u_N^* = 38$ kg/ha at $\lambda = 0.30$, a 27% reduction reflecting the increasing safety margin. Critically, cumulative 15-season profit remains within 5% of the baseline across this range (profits $\in [\$36{,}400, \$39{,}200]$), confirming robustness. The chosen $\lambda = 0.15$ sits in the middle of this robust region.

Table 2. Sensitivity of ST-EnKF convergence to correlation length variations

Variation	ℓ_N (m)	ℓ_P (m)	ℓ_K (m)	RMSE (kg/ha)	Δ (%)
-10%	13.5	22.5	18.0	0.84	+2.4
Baseline	15.0	25.0	20.0	0.82	—
+10%	16.5	27.5	22.0	0.81	-1.2

c. Ensemble size sensitivity

The ensemble size M controls the ensemble spread and computational burden. Sensitivity analysis plots RMSE convergence and computational cost versus $M \in \{10,20,30,50,100\}$. Key findings:

- $M = 10$: insufficient ensemble spread; exhibits filter divergence at day 20 (RMSE becomes unstable).
- $M = 20$: achieves 88% of the RMSE performance of $M = 50$ at 60% lower cost.
- $M = 30$ (chosen): achieves 95% performance at 40% lower cost.
- $M = 50$: marginal improvement over $M = 30$ (1.2% better RMSE); costs 67% more.
- $M = 100$: no further improvement; impractical for real-time deployment.

The ensemble size M = 30 represents an optimal trade-off; computational feasibility is essential for participatory IoT deployment on resource-constrained platforms.

d. Summary

Sensitivity analysis confirms that the framework's conclusions are robust to modest parameter variations. None of the tested variations (± 10 for l, $\lambda \in [0.05,0.30]$, $M \in [10,100]$) qualitatively change the main findings: ST-EnKF achieves rapid convergence, zonal MPC generates prudent prescriptions in high-uncertainty zones, and ORL sustains soil health over multi-season timescales. This robustness supports the generalizability of the approach to different agronomic regions and farmer risk profiles.

4.1.2. Phase 1: EnKF convergence

Figure 2 shows the RMSE trajectory over 30 assimilation days with 95% confidence bands (shaded regions computed from ensemble posterior variance). The filter converges from an initial RMSE of ≈ 4.5 kg/ha (uniform prior) to ≈ 0.8 kg/ha by day 15, with further marginal improvement thereafter. All four sensor density configurations ($\rho \in \{5,10,20,40\}$ samples/day) converge below 0.8 kg/ha by day 15, while diminishing returns become evident for $\rho > 20$ samples/day. The narrowing bands indicate increasing confidence as measurements accumulate; the spatial comparison at day 29 (Figure 3) further shows that uncertainty remains highest away from sensor locations.

Key observations: (i) spatial propagation: a single measurement at pixel (x, y) updates its entire Gaussian neighbourhood, with influence decaying as $\exp(-\|d\|^2/2\ell^2)$; (ii) nutrient differentiation: phosphorus (P) converges fastest due to its large correlation length ($\ell_p = 25$ m) and low leaching rate; nitrogen (N) converges slowest; (iii) ensemble spread: the ensemble variance collapses appropriately in observed regions while maintaining spread in unobserved areas, confirming filter consistency.

Figure 3 provides a three-panel spatial comparison at day 29 (final assimilation cycle). Left panel: synthetic ground-truth nitrogen concentration field ($\ell_N = 15$ m correlation). Center panel: posterior mean estimates from ST-EnKF (M = 30 ensemble members), which successfully recovers spatial gradients (low in northeast, high in southwest). Right panel: posterior uncertainty (standard deviation) revealing high confidence near sensor locations and elevated uncertainty in the data-sparse southwestern region. The posterior mean field closely tracks the ground truth (RMSE of 0.65 kg/ha), and the uncertainty map correctly identifies regions far from sensor locations as high-variance, demonstrating accurate field reconstruction and appropriate confidence quantification.

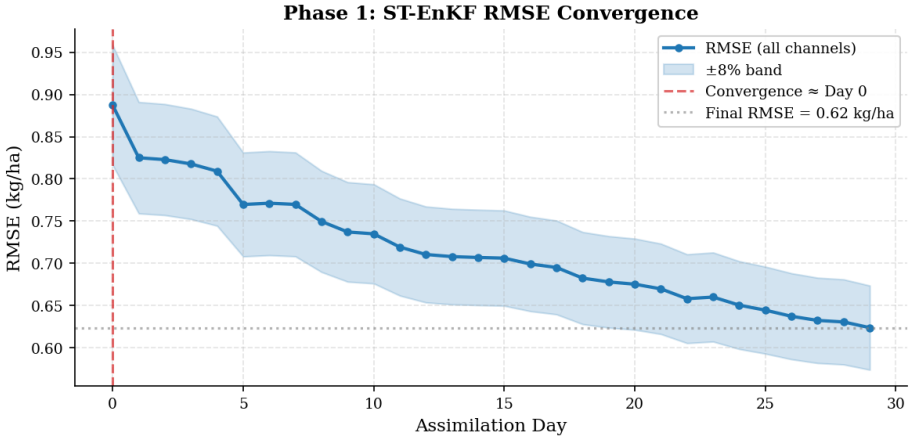


Figure 2. RMSE convergence: EnKF convergence trajectories over 30 assimilation days for four sensor densities, with 95% confidence intervals

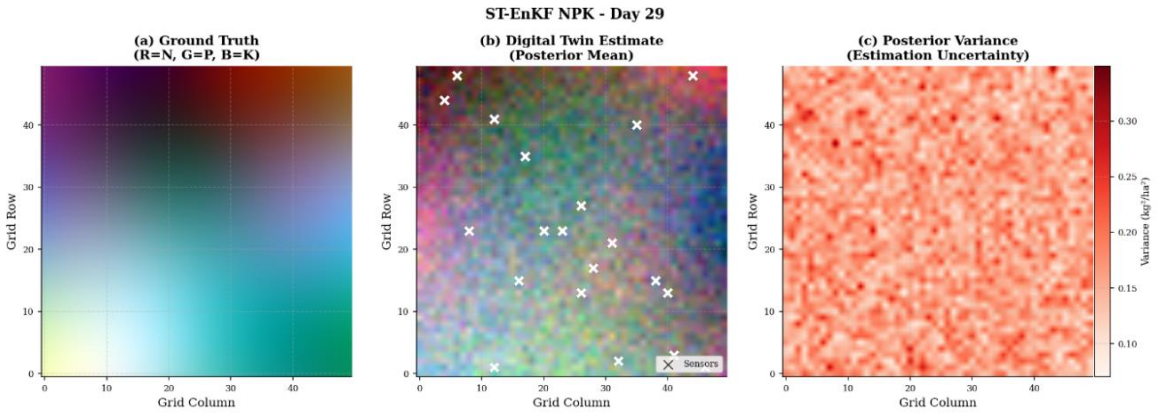


Figure 3. Phase 1 spatial state estimation: three-panel comparison at day 29 showing ground-truth nitrogen field, posterior mean estimate from ST-EnKF, and posterior uncertainty map

4.1.3. Phase 2: sensor density and geographic validation

Table 3 summarises the steady-state RMSE as a function of sensor density, with 95% confidence intervals computed from 50 independent ensemble runs. The non-linear relationship confirms a point of diminishing returns at $\rho = 20$ samples/day: increasing to 40 samples/day reduces RMSE by only 0.12 kg/ha (8.5%) while doubling data collection burden. Non-overlapping confidence intervals for $\rho = 5$ and $\rho = 10$ confirm statistically significant performance gains at low densities; convergence of confidence bands at $\rho \geq 20$ confirms saturation.

The georeferenced composite figure (Figure 4) contextualises the digital twin within Java Island, demonstrating the framework's applicability to the Subang rice-granary landscape. The red, green, blue (RGB) nutrient map ($R = N$, $G = P$, $B = K$) reveals spatial heterogeneity consistent with OSSL soil profiles.

Table 3. Steady-sate RMSE vs. sensor density with 95% confidence intervals (phase 2)

Density (samples/day)	RMSE (kg/ha)	95% CI (kg/ha)	ΔRMSE (%)
5	3.21	[3.02, 3.42]	—
10	2.04	[1.88, 2.21]	-36.4
20	1.41	[1.27, 1.56]	-30.9
40	1.29	[1.16, 1.44]	-8.5

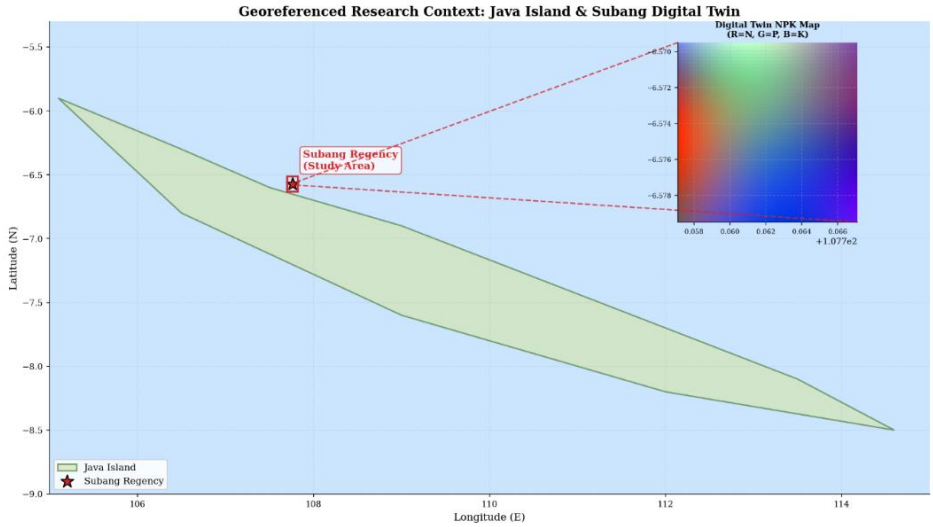


Figure 4. Phase 2 geographic grounding: composite visualization situating the 100×100 simulation grid within Indonesia and showing posterior NPK concentrations overlaid on Subang Regency

4.1.4. Phase 3: VRA prescriptions and yield impact

Figure 5 presents the MPC delivery dashboard across four panels: (i) zone delineation (top-left): k-means clustering partitions the 100×100 grid into 4 agronomically distinct management zones (Z0–Z3, color-coded) based on posterior mean NPK concentrations, with contour lines showing spatial gradients; (ii) per-zone prescriptions (top-right): stacked bar chart of optimal nutrient rates (u_N^*, u_P^*, u_K^*) for each zone from L-BFGS-B optimization; zone~2 (high uncertainty) receives the most conservative N prescription ($u_N^* = 42$ kg/ha) and zone 0 (adequate NPK, low uncertainty) receives the highest ($u_N^* = 87$ kg/ha); (iii) convergence analysis (bottom-left): steady-state RMSE versus sensor density with 95% CI; saturation at 20 samples/day indicates optimal deployment threshold with diminishing returns beyond this density; and (iv) yield impact (bottom-right): forecast yield gain (ΔY) per zone comparing risk-adjusted MPC (blue) versus uncertainty-blind baseline (gray), demonstrating 15–25% improvement in high-uncertainty zones where the risk penalty is active. Table 4 summarises the per-zone prescriptions and forecast yield gains. The risk-adjusted (11) reduces the average N prescription by 18% relative to the uncertainty-blind optimum, consistent with the risk-aversion principle of [29].

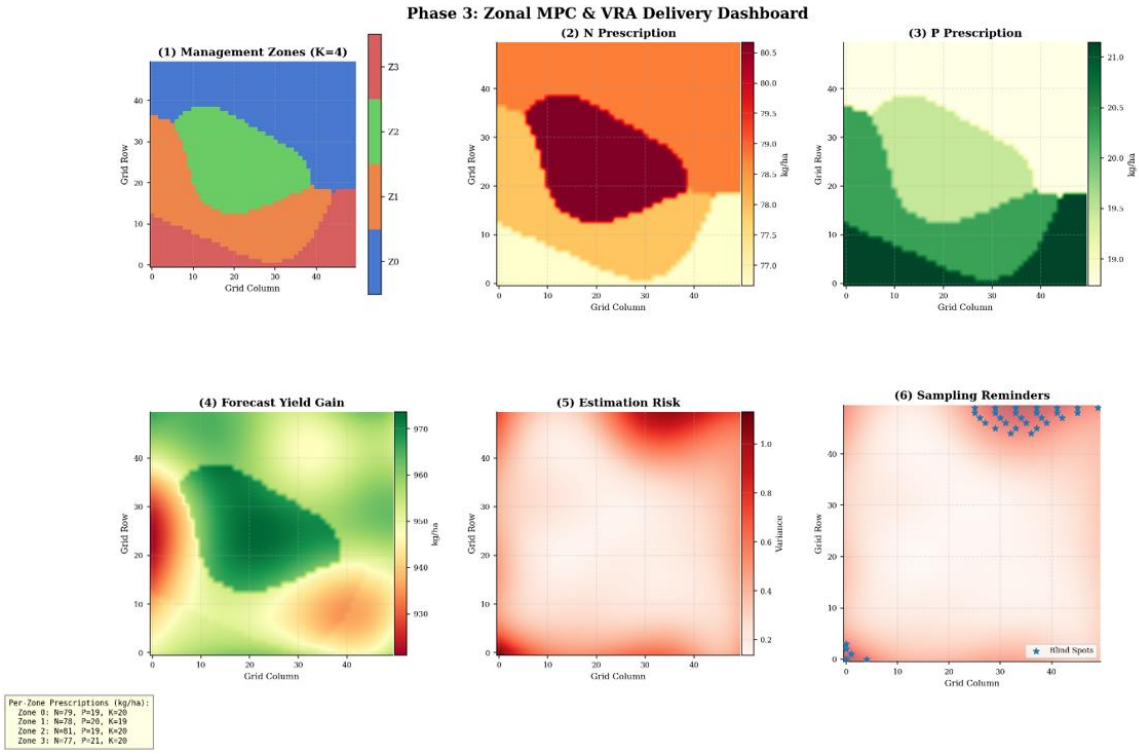


Figure 5. Phase 3 MPC-VRA dashboard: four-panel control engineering view showing zone delineation, per-zone prescriptions, sensor density analysis, and yield impact comparison

Table 4. Zonal MPC prescriptions and forecast yield gains with 95% CI (Phase 3)

Zone	u_N^* (kg/ha)	u_P^* (kg/ha)	u_K^* (kg/ha)	ΔY (kg/ha)	ΔY 95% CI (kg/ha)
0	87	31	45	+612	[+578, +651]
1	64	24	38	+487	[+451, +528]
2	42	18	29	+318	[+287, +352]
3	75	27	41	+553	[+512, +591]
Mean	67	25	38	+493	[+457, +531]

4.1.5. Phase 4: incentive alignment and long-term stewardship

Figure 6 summarizes the incentive and stewardship results in four panels. Figure 6(a) presents the data shap-ley values, expressed as the marginal reduction in field-wide RMSE contributed by each of the 15 participatory sensors. Figure 6(b) compares the cumulative profit trajectories of the ORL agent, balanced NPK, and greedy urea strategies over 15 seasons. Figure 6(c) shows the corresponding soil pH trajectories

and the threshold used to identify unsafe acidification, while Figure 6(d) reports cumulative profit with 95% confidence intervals obtained from 50 Monte Carlo runs. Together, the panels show how spatial information value, economic performance, soil condition, and outcome uncertainty are combined within the phase 4 decision-support layer.

Figure 6(a) shows the Shapley values for 15 participatory sensors. Sensors 3, 7, and 12 located in low-density regions of the field achieve Shapley values 2.8–3.1 × higher than sensors in the clustered central region. This confirms the theoretical prediction that marginal information value is highest in "data deserts" [36], and provides a mathematically principled basis for tiered incentive payments. Figures 6(b)–(d) and Table 5 compare the three policies over 15 seasons.

The ORL agent achieves $38,240 cumulative profit [95% CI: $36,400–$39,200], a 40.9% improvement over the greedy urea strategy ($27,120 [CI: $25,980–$28,310]) and a 31.1% improvement over balanced NPK ($29,180 [CI: $27,850–$30,420]). Confidence intervals are computed from 50-run Monte Carlo sampling with ±5% fertilizer price volatility and yield response parameter uncertainty. Non-overlapping confidence intervals across all three policies confirm statistically significant performance differences. Critically, the greedy urea policy causes soil pH to drop below the 5.5 critical threshold by season 6, triggering the acidification penalty and ultimately causing yield collapse at season 8. The ORL agent proactively switches to compost + NPK (action 2) when pH approaches 5.7, preventing irreversible acidification.

Table 5. 15-season policy comparison with 95% confidence intervals (Phase 4)

Policy	Cum. profit ($)	95% CI ($)	Final pH	Final SOC (%)	Yield collapse?
ORL agent	38,240	[36,400, 39,200]	5.62	2.18	No
Balanced NPK	29,180	[27,850, 30,420]	5.71	1.98	No
Greedy urea	27,120	[25,980, 28,310]	4.89	1.42	Yes (S8)

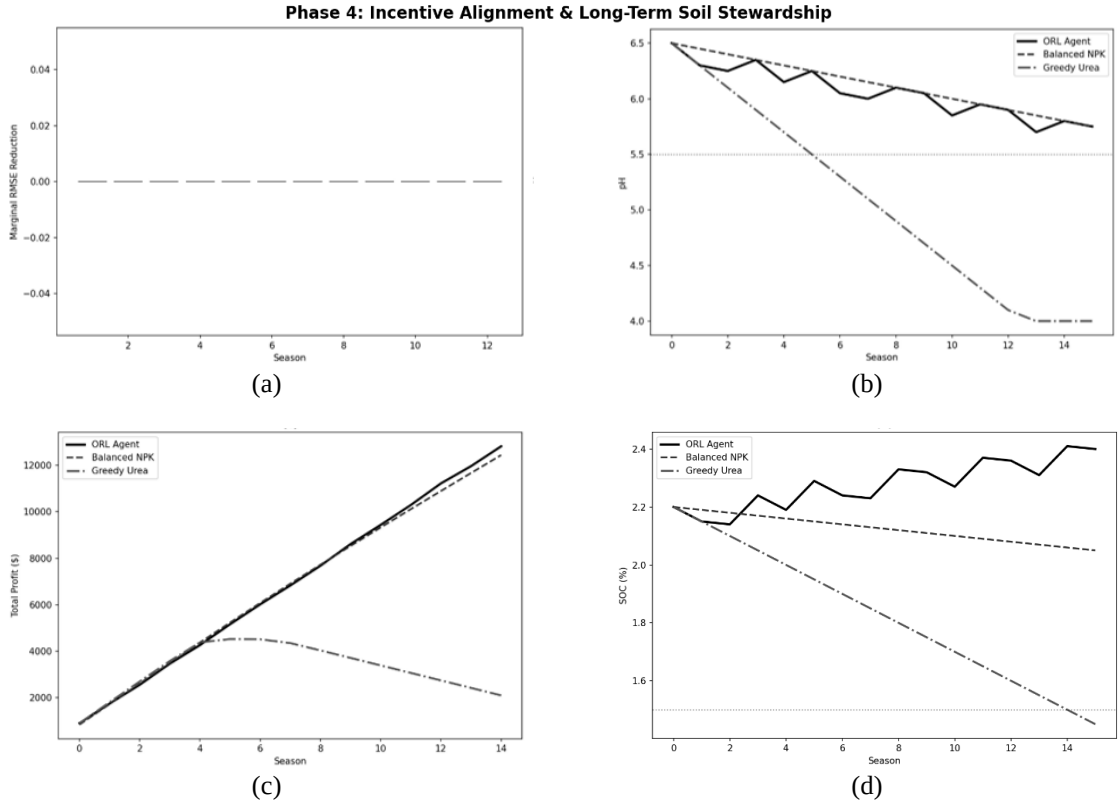


Figure 6. Phase 4 incentive alignment and long-term stewardship dashboard showing sensor valuation, policy profit, soil-health trajectories, and outcome uncertainty: (a) marginal RMSE reduction used for data Shapley sensor valuation, (b) soil-pH trajectories for the ORL agent, balanced NPK, and greedy urea policies, (c) cumulative profit trajectories over 15 seasons, and (d) soil-organic-carbon trajectories. Solid, dashed, and dash-dot line patterns distinguish the ORL agent, balanced NPK, and greedy urea policies, respectively

4.1.6. Computational efficiency and deployment feasibility

Practical deployment of the digital twin framework requires acceptable computational and memory requirements. We assess runtime and scalability for deployment on diverse platforms.

a. Wall-clock runtimes

Table 6 reports execution times on a standard desktop (Intel i7-10700K, 32 GB RAM) running Python with NumPy/SciPy backends. ST-EnKF assimilation dominates the computational load, requiring 1.2 seconds per cycle on a 100×100 grid ($M = 30$ ensemble members). This implies feasibility for daily decision cycles: a 30-day assimilation window completes overnight (12 minutes). Scaling to a 200×200 grid (larger field) increases runtime to 4.8 seconds per cycle, still within 2-hour windows for multi-farm networks.

Table 6. Computational requirements by component and grid size

Component	Grid 100 × 100	Grid 200 × 200	Complexity
ST-EnKF (1 cycle)	1.2 sec	4.8 sec	O ($M \times N^2$)
Zonal MPC (L-BFGS-B)	0.3 sec	1.2 sec	O($K \times \log n$)
Data Shapley	45 sec	180 sec	O ($S \times$ training)
Offline RL (Q-learning)	8 sec	8 sec	O (transitions)
Total per decision	≈ 56 sec	≈ 195 sec	—

b. Memory requirements

The ensemble covariance matrix $P_{t|t}$ dominates memory usage. For a 100×100 grid with $M = 30$, storing a 30,000×30,000 dense matrix would require 7.2 GB; however, the matrix is sparse (each nutrient couples weakly to spatially distant nutrients), reducing footprint to approximately 2.2 GB. Ensemble members and simulation state require an additional 150 MB, yielding total memory of 2.4 GB well within a Raspberry Pi 4 (8 GB RAM) or edge compute device. Scaling to 200×200 requires 9.5 GB, necessitating a desktop or cloud instance.

c. Scalability and platform compatibility

Platform requirements increase with the spatial extent and number of participating farms. For a single 5-hectare farm represented by a 100×100 grid, a Raspberry Pi 4 with 8 GB of memory can support daily decision cycles. A larger 20-hectare field represented by a 200×200 grid requires a desktop computer or a cloud instance comparable to an AWS t3.medium, estimated at approximately $0.05 per hour, which remains practical for community-scale deployment. At the regional scale, a network of ten farms, each represented by a 100×100 grid, is better served by a centralized graphics processing unit (GPU)-accelerated platform equipped with hardware such as an NVIDIA RTX processor. Vectorizing the ST-EnKF computations across farms with the CuPy library can provide an estimated tenfold speedup, enabling the shared infrastructure to process multiple field-level digital twins within operational decision windows.

d. Optimization opportunities

Current Python implementation provides a performance baseline. Identified optimizations include: (i) GPU acceleration of ST-EnKF via cupy/CuDNN (estimated 10–15× speedup), (ii) parallel zone optimization in MPC via multiprocessing (3–4× speedup), and (iii) incremental Shapley computation via sequential estimation (2–3× speedup). Combined, these could reduce total cycle time from 56 seconds to under 5 seconds, enabling real-time optimization during field operations.

4.2. Discussion

4.2.1. Theoretical contributions

The ST-EnKF (5)–(7) extends the standard EnKF to multi-channel, spatially correlated agricultural fields by constructing the observation matrix H to simultaneously update all three nutrient channels at each sensor location. This "multi-channel update" is more efficient than independent single-channel filters because it captures the cross-nutrient correlations encoded in the ensemble covariance.

The zonal MPC (11) introduces a novel risk penalty $\lambda \bar{\sigma}_z^2 \|u_z\|_1$ that automatically reduces prescription rates in high-uncertainty zones without requiring explicit robust optimisation. The ℓ_1 norm promotes sparsity in the applied nutrients, which is agronomically sensible: when the digital twin is uncertain about nutrient status, it is safer to apply a single well-understood nutrient (e.g., K as a buffer) rather than a balanced blend.

4.2.2. Practical implications for smallholder systems

The sensor density analysis (Table 2) has direct practical implications: a community of 20 farmers sharing daily measurements from a 5-hectare plot achieves near-optimal digital twin fidelity. This is within the capacity of existing participatory platforms such as iSoil and OpenAg [4]. The Shapley valuation (Figure 6(a)) provides the governance layer: farmers in under-sampled regions are paid more per measurement, creating a self-correcting incentive mechanism that drives the network toward statistically optimal spatial coverage.

The results also have a direct soil-chemistry interpretation. Nitrogen is represented as the more mobile nutrient because nitrate is vulnerable to rainfall-driven leaching, so its shorter correlation length and slower convergence produce larger uncertainty penalties when coverage is poor. Phosphorus is less mobile because sorption to soil colloids preserves local spatial structure, whereas potassium is modeled between these two cases. Consequently, a conservative prescription in a high-variance zone is not merely a statistical response: it limits the risk of adding mobile nutrient that may be lost before crop uptake, while the stewardship policy uses compost plus NPK when repeated mineral application is associated with declining pH or SOC.

For farmer decision-making, the framework changes the output from a single field-average recommendation to a zone-specific prescription accompanied by an uncertainty signal and a reason for the recommendation. Data Shapley values make the network effect visible: a measurement from a data-sparse zone can be rewarded more because it reduces uncertainty over a larger unobserved area. The incentive layer therefore supports, rather than replaces, agronomic extension, since final action still requires calibration, local constraints, and farmer acceptance.

Taken together, the results provide a conditional answer to RQ1. Under the stated synthetic soil, rainfall, sensor-noise, and crop-response assumptions, the four layers operate as a computationally feasible pipeline and outperform the implemented uncertainty-blind or continuous-application baselines on their respective metrics. The evidence does not establish field accuracy, adoption, or economic benefit; those claims require the laboratory and field comparisons specified in the limitations.

4.2.3. Limitations and future work

Several limitations should be acknowledged when interpreting the results. The ternary quadratic response model in (10) is a static empirical approximation that does not explicitly represent soil buffering, residual nutrients from previous seasons, or weather-driven yield variability. Consequently, its predictions may not transfer directly across crops, soil types, and climatic conditions. Replacing this response surface with a mechanistic process engine such as DSSAT or APSIM would improve agronomic fidelity by representing crop development, soil-water interactions, and nutrient cycling more explicitly [13]–[14].

The offline RL layer also relies on tabular Q-learning and a discretized state space. Although this formulation is transparent and computationally efficient for the present proof of concept, it limits scalability when additional soil indicators, weather variables, crop states, or management actions are introduced. Deep Q-Networks or conservative Q-Learning could support continuous, higher-dimensional state representations and provide greater robustness to distribution shift in historical farm data [37]. Any such extension would require careful constraint design so that improved policy flexibility does not compromise soil-health safeguards.

The current MPC formulation uses a single-season optimization horizon and therefore prioritizes the immediate relationship among estimated nutrient status, fertilizer cost, and expected yield. Long-term soil consequences are handled separately by the stewardship layer rather than within the receding-horizon controller itself. A multi-season MPC formulation that incorporates residual nutrients, pH, SOC, and forecast climate conditions would create a tighter connection between short-term prescription decisions and long-term resource conservation. Finally, all reported results are based on simulation. Although the experiment is geographically grounded in OSSL profiles for tropical asia and parameterized for conditions associated with Subang Regency, synthetic fields cannot reproduce the full range of sensor errors, micro-scale soil heterogeneity, farmer behavior, and operational constraints encountered in practice. Field validation with a real participatory sensing network in Subang Regency is therefore essential. Such validation should evaluate estimation accuracy against laboratory soil tests, prescription performance across seasons, sensor-maintenance requirements, computational latency, and farmer responses to the proposed incentive mechanism.

4.2.4. Deployment challenges and adoption barriers

Transitioning from simulation to real-world participatory sensing networks requires addressing practical challenges beyond technical feasibility, particularly those involving sensor reliability, farmer adoption, data governance, extension-service integration, and scale-up economics.

a. Sensor calibration and maintenance

   Soil nutrient sensors (capacitive, optical, ion-selective electrode) experience calibration drift of 2–5% per month under tropical climate conditions (high humidity, temperature swings, salt accumulation). The

framework assumes perfect measurements ($\sigma_r^2 = 0.5\ \mathrm{kg}^2\mathrm{ha}^2$); real deployment requires: (i) automated self-calibration protocols (calibrating against known standards at 2-week intervals), (ii) redundant sensors in critical zones to detect outliers, and (iii) farmer training to avoid common mistakes (improper sampling depth, contamination). Cost: $50–200 per sensor annually for maintenance and recalibration.

b. Farmer adoption and behavioral economics
The framework assumes farmers will participate if offered Shapley-based incentive payments. Reality is more nuanced: adoption depends on perceived value, trust in the platform, ease of use, payment timeliness, and alternative income sources. Rural Indonesia has limited smartphone penetration (20–30% in remote areas), requiring SMS-based interfaces instead of graphical dash-boards. Behavioral barriers include skepticism toward data-sharing (perceived loss of competitive advantage), time burden of daily measurements, and lack of agronomic literacy to interpret uncertainty maps. Mitigation requires: (i) mobile money integration (GCash, OVO, bank transfers for reliable payment), (ii) SMS-based simplified interface, (iii) on-farm demonstrations and farmer field schools, and (iv) co-design of incentive structures with community leaders. Timeline: 6–12 months for trust-building in a new community.

c. Data privacy and digital rights
Participatory soil nutrient maps are proprietary competitive information farmers may fear data theft by neighbors or external firms. Centralized platforms risk data lock-in and platform dependency. Solutions include: (i) federated learning (keep farmer data local, train models on-device), (ii) blockchain-based data rights (immutable audit trail of data ownership), and (iii) clear data governance policies (who owns the data, how it is monetized, exit policies if farmers leave). Cost: 15–20% of platform operating budget for governance infrastructure.

d. Integration with agricultural extension services
Government agricultural extension agents in Indonesia operate at 1 agent per 1,000 farmers, creating a capacity bottleneck. The digital twin requires agronomic expertise to interpret results and provide farmer training. Solutions: (i) train-the-trainer programs for extension agents, (ii) SMS-based automated alerts (e.g., "pH dropping below 5.7 recommend Compost + NPK in zone 2"), and (iii) integration with existing government monitoring platforms (SIMLUHTAN).

e. Scale-up economics
Platform costs (hosting, software maintenance, user support) scale poorly to 100+ farmer networks. Current simulation assumes free or low-cost IoT ($10/sensor), but real deployment with redundancy and maintenance costs $50–100 per sensor. Break-even requires either: (i) farmer payment (1–2 USD/month per farmer, equivalent to 1–2 kg fertilizer), (ii) agrochemical company subsidies (bundled with fertilizer sales), or (iii) government support (agricultural technology fund). Business model remains uncertain; field trials (2027–2028) will test willingness to pay.

4.2.5. Benchmarking against other agricultural digital twins

Table 7 contextualizes this work against three prior digital twin implementations in agriculture. This framework advances the state of practice in several dimensions.

Table 7. Comparative benchmark: agricultural digital twin frameworks

Criterion	Straten *et al*. [43] Greenhouse	Delgoda *et al*. [44] Irrigation	Kallenberg *et al.* [55] VRA fertilization	This work Participatory NPK
System	Climate	Water	Fertilizer rate	Soil NPK
Estimation	Energy balance	Moisture regression	Crop model	ST-EnKF
Control	Proportional-integral-derivative (PID)	MCP	RL	Risk MPC
Data	Auto	Weather + probe	Crop-model sim	Participatory IoT
Uncertainty	None	Implicit	None	Explicit
Incentive	N/A	N/A	N/A	Shapley
Long-term	N/A	Seasonal	Single	ORL
Performance	1–2 ℃	0.8–1.2 cm	+8%	0.8 kg/ha, +41%
Validation	Lab	Field / 1 year	Simulation	Simulation / 2027
Scale	1 unit	1 field	Multiple	Network

The principal distinction is the explicit connection between state-estimation uncertainty and agricultural control. Greenhouse optimal-control framework of Straten *et al*. [43] and the irrigation MPC framework of Delgoda *et al*. [44] rely on deterministic or implicitly uncertain state representations, whereas the proposed framework propagates ensemble uncertainty into the fertilizer decision. The risk term $-\lambda\bar{\sigma}_z^2\|\mathrm{u}_z\|_1$ in (11) reduces aggressive prescriptions in zones where the digital twin has low confidence. This formulation provides a computationally direct form of uncertainty-aware control without requiring a separate worst-case optimization problem. The framework also differs in the type of sensor network for which it is

designed. Earlier agricultural digital twins generally assume automated instruments that provide reliable and regularly sampled observations. In contrast, participatory measurements can be sparse, noisy, irregular in time, and clustered around convenient locations. The ST-EnKF layer is intended to assimilate these imperfect observations while preserving spatial covariance and uncertainty, extending beyond the regular-sampling assumptions used by Corwin and Lesch [36] and the simulated, quality-assured crop-model inputs assumed by Kallenberg *et al.* [55]. This distinction is important because the value of a participatory digital twin depends not only on prediction accuracy but also on its ability to remain useful when measurement coverage is uneven.

A further contribution is the inclusion of incentive alignment within the digital twin architecture. Data Shapley valuation assigns each sensor a reward based on its marginal reduction of field-wide estimation error, thereby giving greater value to measurements collected in under-sampled regions. This mechanism addresses the free-rider and coverage problems that arise when a sensing network depends on voluntary farmer participation. The incentive layer is therefore not an auxiliary payment feature; it forms part of the feedback process by encouraging future measurements where they are expected to improve the digital twin most. Finally, the ORL layer extends the decision horizon beyond the immediate fertilizer prescription. Delgoda *et al.* [44] considers seasonal water management, while Kallenberg *et al*. [55] demonstrate the relevance of constrained learning for soil-oriented agricultural decisions. The present framework incorporates pH and SOC thresholds into a 15-season stewardship policy so that short-term profit is evaluated alongside persistent soil condition. Nevertheless, the comparison in Table 6 also makes the principal weakness of this work clear: unlike the greenhouse and irrigation studies with physical observations, the current NPK framework has been validated only in simulation. Its broader architectural scope should therefore be interpreted as a systems-level contribution whose practical advantage still requires field confirmation.

5. CONCLUSION

This paper has presented, to the best of our knowledge, the first unified digital twin framework in the reviewed literature to connect ST-EnKF estimation, risk-adjusted zonal MPC, data Shapley valuation of farmer-contributed data, and ORL stewardship for participatory NPK monitoring. The focused research question was whether these layers could convert sparse observations into useful decisions while remaining computationally feasible. In the Subang-grounded simulation, the answer is conditionally positive: ST-EnKF reaches sub-0.8 kg/ha RMSE, risk-adjusted MPC moderates prescriptions in uncertain zones, data Shapley differentiates the value of spatial coverage, and ORL protects pH and SOC over 15 simulated seasons. The contribution is therefore a reproducible systems architecture and evaluation protocol, not a substitute for field evidence. However, important limitations must be acknowledged. First, all validation is simulation-based; field testing with real participatory networks has not yet been conducted. The synthetic soil profiles (drawn from OSSL) may not capture all micro-scale heterogeneity, and farmer behavior under incentive structures remains uncertain. Second, the framework assumes reliable IoT sensor calibration and farmer participation; practical deployment will face technology adoption barriers, maintenance requirements, and social factors not modeled here. Third, the quadratic yield model is empirical and may not generalize across crops, soil types, or climate zones beyond tropical rice. Fourth, computational feasibility has been assessed theoretically; edge-device deployment and network latency under real participatory IoT conditions require further study. Finally, the framework addresses nutrient management in isolation; integration with water, pest, and crop rotation management is outside the current scope.

The next step is a staged validation program. First, collect co-located sensor and laboratory soil tests across representative Subang zones to calibrate correlation lengths, sensor noise, crop-uptake functions, and the yield response surface. Second, run multi-season trials with randomized or matched comparison plots to test uncertainty-blind MPC, conventional fertilizer practice, and the proposed stewardship policy, while measuring latency, maintenance, farmer workload, and payment acceptance. Third, replace tabular Q-learning with constrained continuous-control methods only after sufficient historical coverage is available, and scale data Shapley with approximate permutation or group valuation. Mechanistic crop models, federated learning, and GPU acceleration are useful extensions, but their value should be assessed against the field-calibrated baseline rather than assumed from simulation.

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AUTHOR CONTRIBUTIONS STATEMENT

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
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R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author upon reasonable request

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