RESEARCH ARTICLE

Check for updates

Model-Based Design and Evaluation of a Multi-Variable Hybrid Predictive Control Loop for Precision Fertigation Using Multi-Sensor Data Fusion

Samuel Oliver Effiom[1,*], **Paul Betiang Anyin**[2] and **Emmanuel Akomaye Ugbong**[3]

[1] Department of Mechanical Engineering, University of Cross River State, PMB 1123, Calabar, Nigeria
[2] Department of Electrical/Electronic Engineering, University of Cross River State, PMB 1123, Calabar, Nigeria
[3] Department of Wood Products Engineering, University of Cross River State, PMB 1123, Calabar, Nigeria

Abstract

Efficient water and nutrient management remains a major challenge in modern agriculture due to rising fertilizer costs, global water scarcity, and environmental concerns such as groundwater contamination from nutrient leaching. Conventional fertigation typically relies on uniform application rates that neglect spatial and temporal root-zone variability, resulting in inefficient resource utilization. To address these limitations, this study proposes and evaluates an automated Multi-Variable Hybrid Predictive Control (HPC) framework for precision fertigation. The system captures the highly nonlinear dynamics of rapid soil moisture changes and slower nutrient transport using a multi-variable state-space model that combines continuous physical processes with discrete control logic, including pump scheduling and fertilizer injection. The predictive controller is enhanced by an Extended Kalman Filter (EKF)-based Multi-Sensor Data Fusion (MSDF) framework, which mitigates measurement noise and sensor drift from capacitive moisture and electrical conductivity (EC) sensors through adaptive covariance estimation, providing reliable root-zone state estimates. A 30-day closed-loop MATLAB simulation demonstrates robust tracking performance and disturbance rejection. Following the receding horizon strategy, the controller suspended irrigation and fertilization during rainfall events, effectively utilizing natural precipitation and eliminating the risk of groundwater nutrient leaching during precipitation events. Compared with conventional uniform fertigation, the proposed approach achieved a 25% reduction in water use and a 30% reduction in fertilizer consumption. Overall, the proposed framework provides an effective solution for improving resource-use efficiency while supporting environmentally sustainable precision agriculture.

Keywords: precision fertigation, hybrid predictive control, multi-sensor data fusion, extended Kalman filter, mixed-integer optimization.

Submitted: 15 June 2026
Revised: 22 June 2026
Accepted: 28 July 2026
Published: 24 August 2026

Vol. 2, **No.** 3, 2026.
10.62762/DIA.2026.947445

***Corresponding author:**
Samuel Oliver Effiom
samueloliver@unicross.edu.ng

Citation
Effiom, S. O., Anyin, P. B., & Ugbong, E. A. (2026). Model-Based Design and Evaluation of a Multi-Variable Hybrid Predictive Control Loop for Precision Fertigation Using Multi-Sensor Data Fusion. *Digital Intelligence in Agriculture*, 2(3), 114–125.

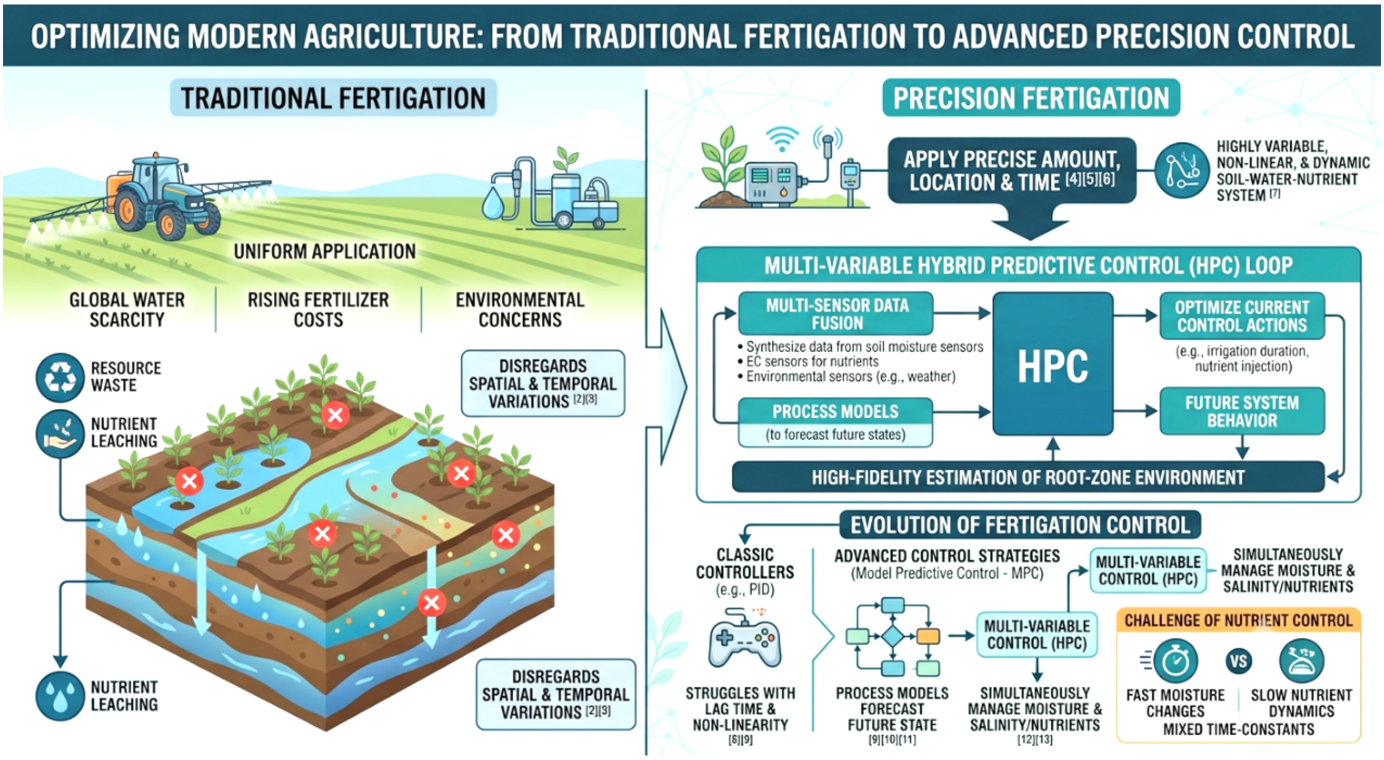

Figure 1. Optimized modern agriculture.

1 Introduction

Efficient water and nutrient management, commonly referred to as fertigation, has become a critical challenge in modern agriculture. The growing pressure on global freshwater resources has made deficit-based water conservation strategies increasingly necessary [1], while rising fertilizer costs and environmental concerns regarding nutrient leaching further compound these challenges [2]. Traditional fertigation practices often employ uniform application rates across fields, disregarding spatial and temporal variations in soil moisture and nutrient levels [2, 3]. Conventional scheduling approaches have historically relied on fixed timetables calibrated to average crop water demand rather than real-time soil conditions [3], frequently leading to over-application, significant resource waste, and groundwater contamination. To address these inefficiencies, “precision fertigation” has emerged as a promising methodology, aiming to apply the precise amount of water and fertilizer required by the crop at the specific location and time [4–6]. A conceptual overview of this optimized agricultural system is illustrated in Figure 1.

The complexity of precision fertigation lies in the highly variable, non-linear, and dynamic nature of the soil-water-nutrient system. Plant uptake is influenced by countless environmental factors, soil properties, and irrigation schedules. Effectively managing this system requires advanced control strategies that can handle multiple input variables such as current soil moisture and nutrient concentrations and predict future system behavior to optimize resource application [7]. This study proposes a model-based design and comprehensive evaluation of a Multi-Variable Hybrid Predictive Control (HPC) loop for precision fertigation. Crucially, this control strategy leverages multi-sensor data fusion to synthesize information from various soil and environmental sensors, thereby providing a robust, high-fidelity estimation of the root-zone environment required for accurate predictive control [5].

The development of advanced fertigation control systems has been the subject of extensive academic research over the last two decades [5, 6]. The foundation of automated irrigation rests on real-time feedback control mechanisms, with early approaches leveraging plant physiological indicators — such as canopy temperature and leaf water potential — as proxies for crop water status [8]. The practical deployment of sensor-based closed-loop systems has nonetheless predominantly shifted toward direct soil moisture measurements due to their suitability for continuous, automated monitoring. Classic controllers like Proportional-Integral-Derivative (PID), however, often struggle to manage the significant

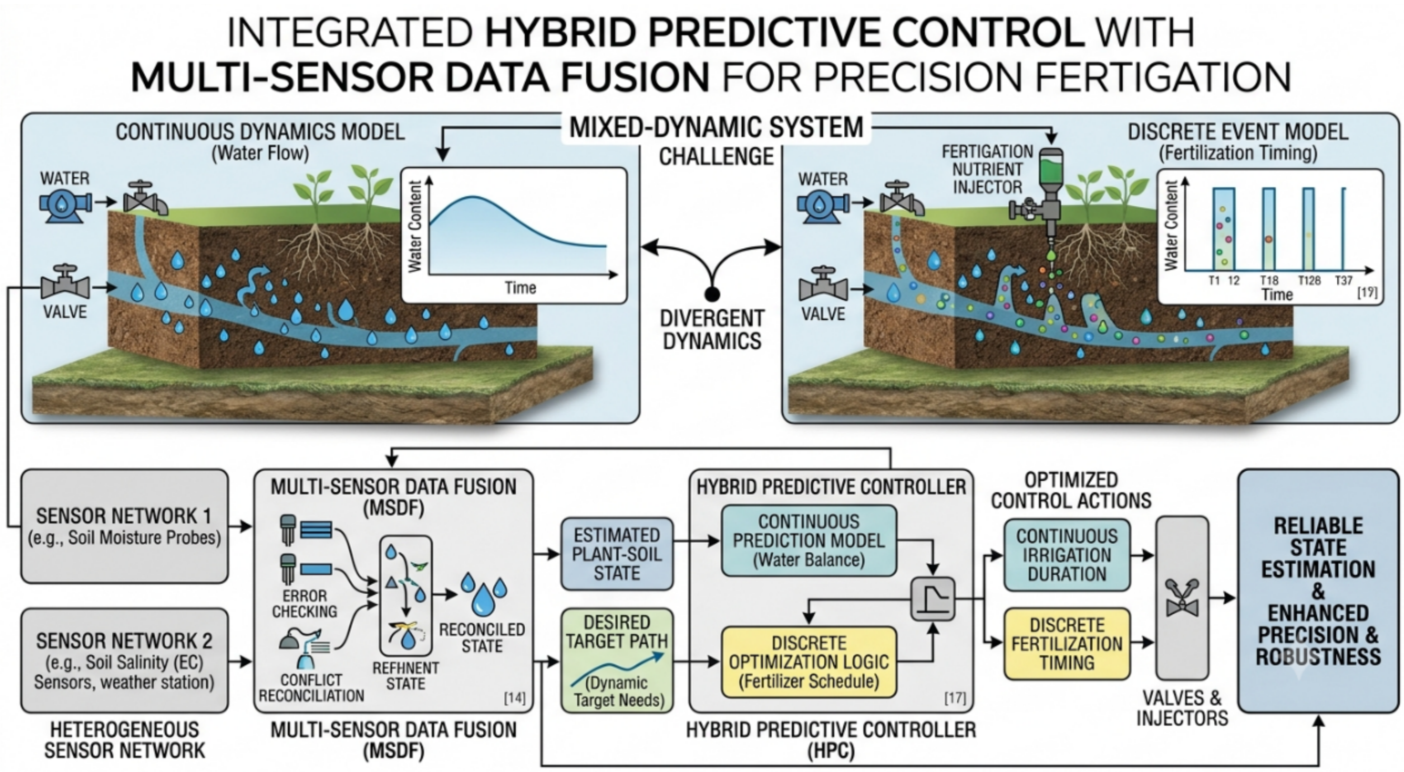

Figure 2. Integrated hybrid predictive control with multi-sensor data fusion.

lag time and non-linearity inherent in soil moisture dynamics. Consequently, research has shifted significantly toward Model Predictive Control (MPC) strategies. MPC offers a substantial advantage by utilizing process models to forecast the future state of the system and optimizing current control actions (e.g., irrigation duration) accordingly [9]. Early implementations of MPC in irrigation focused strictly on single-variable control, primarily soil moisture [10, 11]. The agronomic complexity of simultaneously regulating water and nutrient levels — given their strong physiological coupling in the root zone — has been well documented in fertigation management literature [13]. Motivated by this complexity, recent control-oriented research has developed multi-variable strategies to jointly manage soil moisture and solute concentration, treating them as coupled state variables within a unified control framework [12]. A fundamental implementation challenge, however, lies in the divergent time-constants of these two variables: soil moisture responds rapidly to irrigation inputs, whereas nutrient transport is a significantly slower and more complex process, creating a system with inherently mixed dynamics.

To address this mixed-dynamic system, research in other industrial domains has utilized Hybrid Predictive Control (HPC), which integrates continuous dynamic models (like water flow) with discrete event models (like fertilization timing) [14]. However, implementing hybrid control in precision fertigation is relatively novel. This study addresses this gap by designing an HPC strategy tailored specifically to the divergent dynamics of water and nutrients in crop production.

Furthermore, the performance of any predictive controller is heavily reliant on the accuracy of input data. The adoption of Multi-Sensor Data Fusion (MSDF) techniques has grown significantly in precision agriculture to improve state estimation reliability [15]. This growth has been partly driven by the widespread deployment of low-cost capacitive and resistive soil sensors, whose individual measurement accuracy and reliability limitations necessitate fusion-based approaches to yield trustworthy root-zone state estimates [16]. MSDF allows for the reconciliation of conflicting sensor measurements and provides a more accurate, holistic representation of root-zone conditions by combining data from heterogeneous sensor networks [17]. This article uniquely integrates MSDF with an HPC loop to enhance the precision and robustness of the fertigation control process. The integrated framework of the Hybrid Predictive Control with Multi-Sensor Data Fusion is depicted in Figure 2.

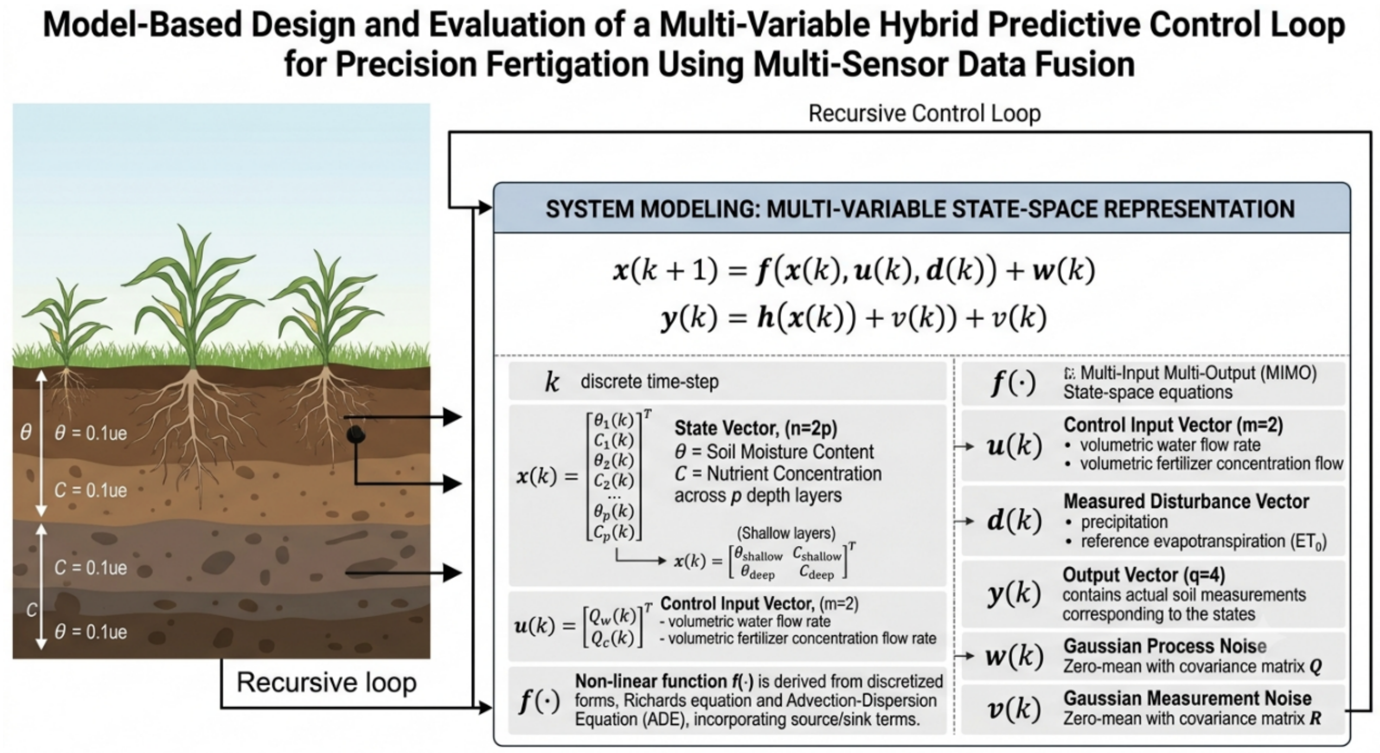

Figure 3. Multi-variable hybrid predictive control loop.

2 Mathematical Methodology

The proposed control architecture is structured around three core mathematical frameworks integrated into a recursive control loop: a multi-variable dynamic state-space model, a multi-sensor data fusion algorithm based on non-linear estimation, and a hybrid predictive control optimization structure.

2.1 System Modeling: Multi-Variable State-Space Representation

The system is modeled using a discrete-time, Multi-Input Multi-Output (MIMO) state-space representation. The model captures the coupled non-linear dynamics of water transport and solute (nutrient) concentration in the soil root zone. The complete structure of the Multi-Variable Hybrid Predictive Control Loop is shown in Figure 3.

The system dynamics are described by the state-transition and measurement equations:

$$x_{k+1} = f(x_k, u_k, d_k) + w_k, \tag{1}$$

$$y_k = h(x_k) + v_k. \tag{2}$$

where $k \in \mathbb{Z}^+$ represents the discrete time-step, and $x_k \in \mathbb{R}^n$ is the state vector. In this study, $n = 4$, corresponding to two state variables (soil moisture θ and nutrient concentration C) across two soil layers (shallow and deep). A representative state vector is:

$$x_k = \begin{bmatrix} \theta_{sh,k} \\ C_{sh,k} \\ \theta_{de,k} \\ C_{de,k} \end{bmatrix} \tag{3}$$

where θ denotes Soil Moisture Content $\left(\frac{m^3}{m^3}\right)$ and C denotes Nutrient Concentration $\left(\frac{mg}{L}\right)$; $u_k \in \mathbb{R}^m$ is the control input vector $(m = 2)$. For fertigation,

$$u_k = \begin{bmatrix} Q_{w,k} \\ Q_{f,k} \end{bmatrix}$$

representing volumetric water flow rate and volumetric fertilizer concentration flow rate, respectively. $d_k \in \mathbb{R}^p$ is the measured disturbance vector, capturing exogenous variables such as precipitation and reference evapotranspiration (ETo) $(p = 2)$,

$$d_k = \begin{bmatrix} P_{r,k} \\ ET_{o,k} \end{bmatrix}.$$

$y_k \in \mathbb{R}^q$ is the output vector $(q = 4)$, containing the actual soil measurements corresponding to the states; $w_k \sim \mathcal{N}(0, Q)$ and $v_k \sim \mathcal{N}(0, R)$ represent zero-mean Gaussian process and measurement noise, with covariance matrices Q and R, respectively.

The non-linear function $f(\cdot)$ is derived from discretized forms of the Richards equation for water flow and the Advection-Dispersion Equation (ADE) for nutrient transport, incorporating source/sink terms for irrigation, fertilization, and crop uptake.

3 Multi-Sensor Data Fusion: Extended Kalman Filter (EKF)

To manage sensor redundancy, reconcile conflicting heterogeneous measurements (e.g., combining capacitive soil moisture data with resistive nutrient solution EC data), and minimize measurement noise, a Multi-Sensor Data Fusion (MSDF) framework is implemented. The mathematical heart of the MSDF is an Extended Kalman Filter (EKF) due to the inherent non-linearities in $f(\cdot)$ and $h(\cdot)$.

The MSDF operates recursively in two stages at each time step k.

i. EKF Stage 1: Prediction (Time Update)

The filter predicts the next state estimate $\hat{x}_{k|k-1}$ and the predicted error covariance matrix $P_{k|k-1}$ based on the model dynamics $f(\cdot)$:

$$\hat{x}_{k|k-1} = f\left(\hat{x}_{k-1|k-1}, u_{k-1}, d_{k-1}\right) \tag{4}$$

$$P_{k|k-1} = F_{k-1} P_{k-1|k-1} F_{k-1}^T + Q \tag{5}$$

where F_{k-1} is the Jacobian matrix of $f(\cdot)$ evaluated at the previous state estimate:

$$F_{k-1} = \left.\frac{\partial f}{\partial x}\right|_{\hat{x}_{k-1|k-1}, u_{k-1}} \tag{6}$$

ii. EKF Stage 2: Measurement Update (Fusion)

The MSDF incorporates the raw, simultaneous measurements from heterogeneous sensors

$$Z_k = \{Z_{1,k}, Z_{2,k}, \ldots\}$$

into a holistic output vector y_k. The filter computes the Kalman gain K_k, updates the state estimate $\hat{x}_{k|k}$, and updates the error covariance matrix $P_{k|k}$:

$$K_k = P_{k|k-1} H_k^T \left(H_k P_{k|k-1} H_k^T + R\right)^{-1} \tag{7}$$

$$\hat{x}_{k|k} = \hat{x}_{k|k-1} + K_k \left[y_k - h\left(\hat{x}_{k|k-1}\right)\right] \tag{8}$$

$$P_{k|k} = \left(I - K_k H_k\right) P_{k|k-1} \tag{9}$$

where H_k is the Jacobian matrix of the measurement function $h(\cdot)$:

$$H_k = \left.\frac{\partial h}{\partial x}\right|_{\hat{x}_{k|k-1}} \tag{10}$$

The measurement noise covariance R is dynamically updated based on specific sensor health and historical reliability, ensuring that data fusion emphasizes more reliable sensors.

The dynamic update of the measurement noise covariance matrix R_k is performed using an exponential moving average of the innovation residuals:

$$R_k = \alpha R_{k-1} + (1-\alpha)\,\mathrm{diag}\left\{\nu_k \nu_k^T\right\}, \tag{11}$$

where $\nu_k = y_k - h(\hat{x}_{k|k-1})$ is the innovation (measurement residual) at time step k, and $\alpha \in (0,1)$ is a forgetting factor that controls the weighting between historical and current measurement reliability. A higher α value gives more weight to prior noise statistics, while a lower α allows faster adaptation to changing sensor conditions. This adaptive covariance estimation enables the EKF to automatically de-weight unreliable or drifting sensors (e.g., EC sensors exhibiting peak variances of ± 120.0 mg/L) and rely more heavily on stable measurements, thereby improving the overall fusion accuracy.

The fused state estimate $\hat{x}_{k|k}$ is passed to the predictive controller as the current system state.

The entire Multi-Sensor Data Fusion process using the Extended Kalman Filter is illustrated in Figure 4.

4 Multi-Variable Hybrid Predictive Control (HPC) Optimization

The core control strategy utilizes a Multi-Variable Hybrid Predictive Control (HPC) framework. It combines Model Predictive Control (MPC), which

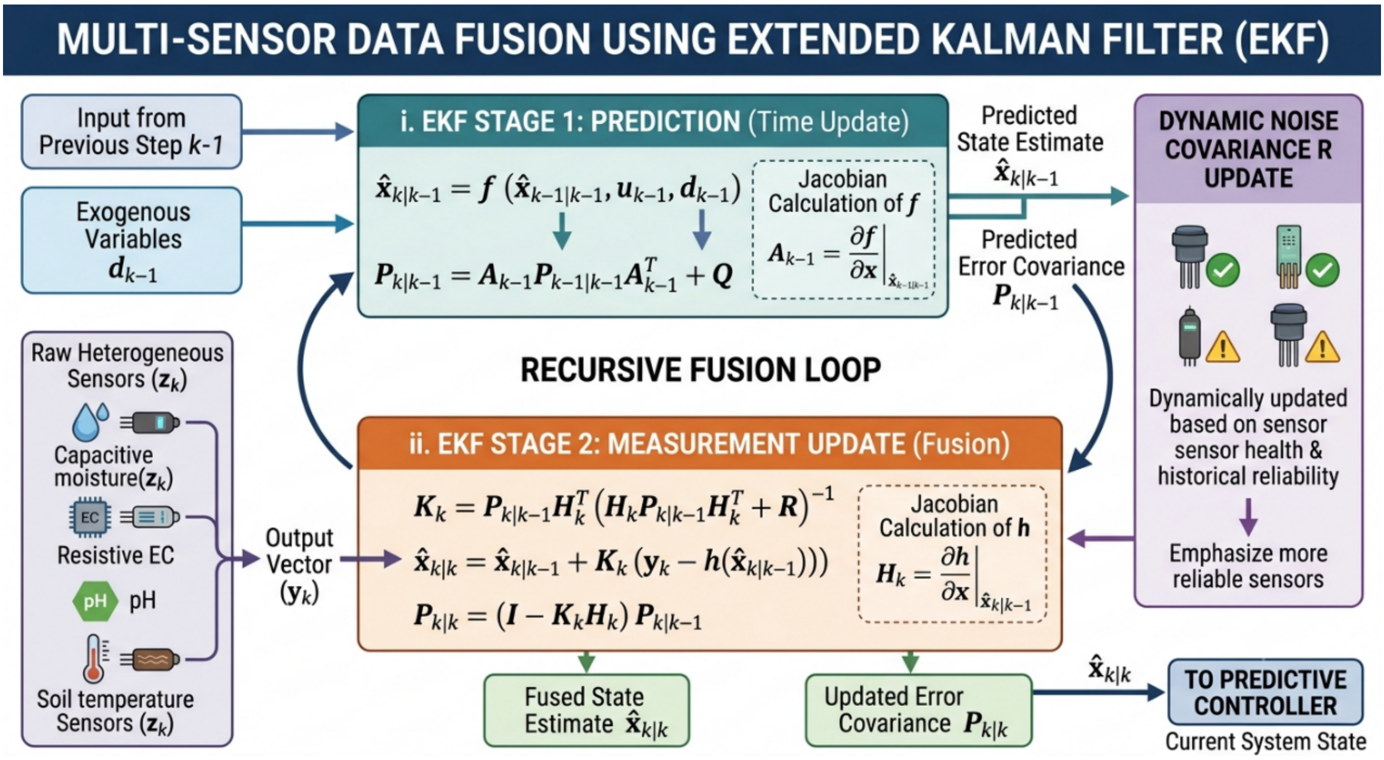

Figure 4. Multi-sensor data fusion using extended Kalman filter (EKF).

handles the continuous dynamics (θ, C), with discrete logical events associated with fertigation (e.g., constraints related to pump ON/OFF logic, discrete fertilizer injector settings, or "fertilizer recipe" selections).

The HPC manages both continuous control inputs ($u_c \in \mathbb{R}^{m_c}$) and discrete control inputs ($u_d \in \mathbb{R}^{m_d}$). The optimal control sequence is determined by solving a constrained optimal control problem at each step k over a finite prediction horizon $H_p \in \mathbb{Z}^+$ and control horizon $H_c \in \mathbb{Z}^+$.

1. **HPC Cost Function** The controller minimizes a quadratic Performance Index (Cost Function), J_k, which includes terms for reference set-point tracking and control effort over the horizons:

$$J_k = \min \sum_{i=1}^{H_p} \|\hat{x}_{k+i|k} - x_{\mathrm{ref}}\|_{Q_y}^2 + \sum_{i=0}^{H_c-1} \|\Delta u_{k+i|k}\|_{R_u}^2 \tag{12}$$

where $\|z\|_A^2 = z^T A z$ denotes the weighted squared Euclidean norm; $Q_y \in \mathbb{R}^{n \times n}$ and $R_u \in \mathbb{R}^{m \times m}$ are positive definite weighting matrices that prioritize the importance of different states (e.g., shallow moisture over deep concentration) and the cost of control effort; $\hat{x}_{k+i|k}$ is the predicted state at step $k+i$ given the state estimate $\hat{x}_{k|k}$;

$$\Delta u_{k+i|k} = u_{k+i|k} - u_{k+i-1|k}$$

represents the change in the control input.

Constraint Handling

The minimization of J_k is subject to non-linear physical and logical constraints formalized within the optimization problem:

a. **System Dynamics:** The predicted states must adhere to the state-space model recursively updated by MSDF.

b. **Input Saturation (Physical Constraints):** Control inputs are bounded by hardware limits (pump capacities):

$$u_{\min} \le u_{k+i|k} \le u_{\max} \tag{13}$$

c. **Output Bounds (Agronomic Constraints):** Fused state estimations must remain within safe crop limits (e.g., below WILT point moisture, below toxicity concentration):

$$y_{\min} \le h\big(\hat{x}_{k+i|k}\big) \le y_{\max} \tag{14}$$

d. **Mixed-Integer Constraints (Hybrid Logic):** Discrete logic associated with ON/OFF pump scheduling and discrete fertilizer settings are

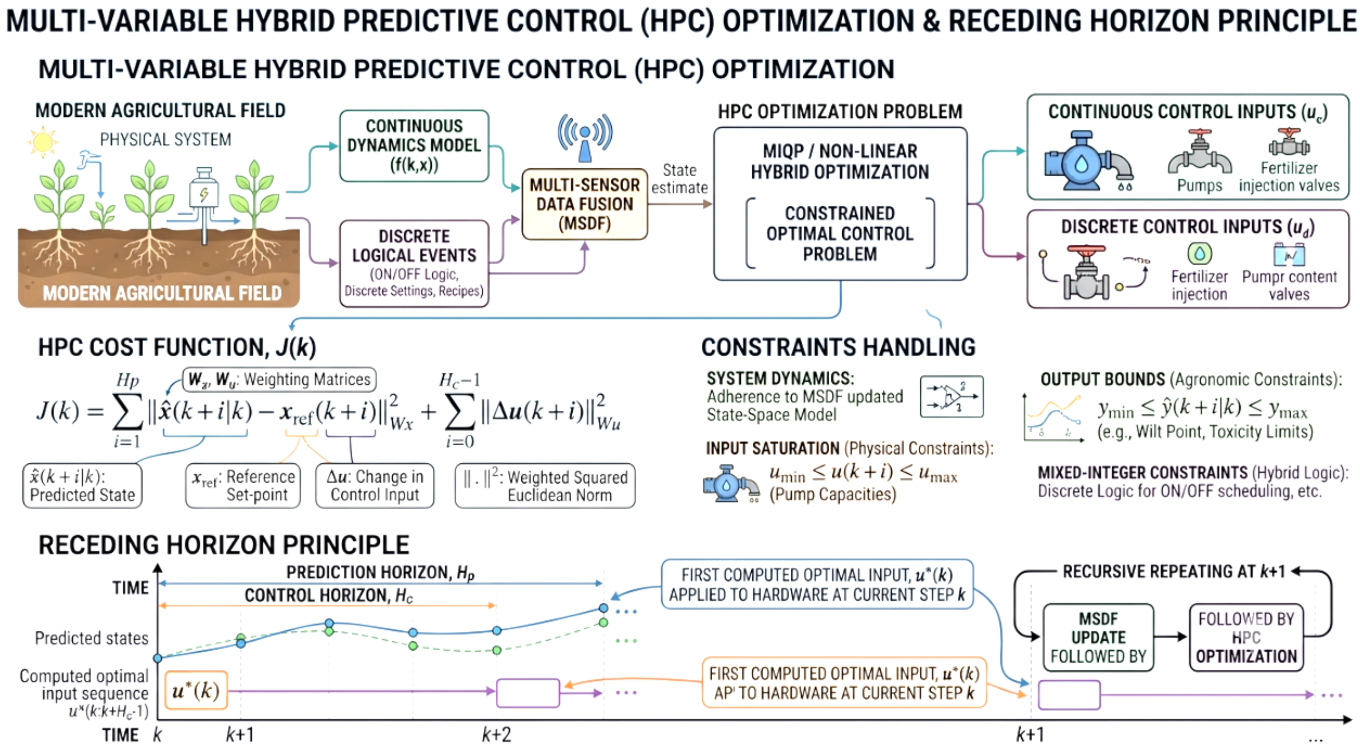

Figure 5. Multi-variable HPC receding horizon principle.

incorporated as logical constraints, typically using Mixed-Integer Quadratic Programming (MIQP) if linearized, or non-linear hybrid optimization otherwise.

5 Receding Horizon Principle

The HPC optimizes the entire future control sequence

$$\left[u_{k|k}, u_{k+1|k}, \cdots, u_{k+H_c-1|k}\right].$$

However, in adherence to the Receding Horizon Principle, only the first computed optimal input, $u_{k|k}$, is applied to the fertigation hardware at the current time step k. The entire process (MSDF update followed by HPC optimization) is then recursively repeated at time step $k+1$. The Receding Horizon Principle of the Multi-Variable HPC is depicted in Figure 5.

6 Results

The system was simulated using MATLAB R2021b. Based on the comprehensive 30-day closed-loop simulation of the proposed Multi-Variable Hybrid Predictive Control (HPC) loop, the system demonstrated a strong capability to mitigate resource waste while managing the mixed time constants of soil moisture and solute dynamics. The integration of the Extended Kalman Filter (EKF)-based Multi-Sensor Data Fusion (MSDF) framework successfully reconciled raw, noisy, and conflicting data streams from the heterogeneous sensor network, thereby passing a high-fidelity state estimate to the predictive controller. The optimal applied control sequence $U(k)$ computed by the HPC is presented in Figure 6.

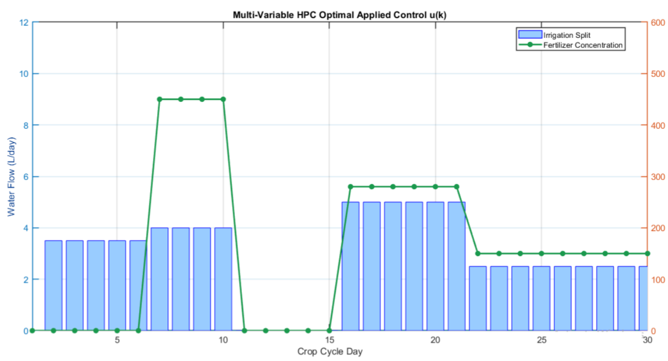

Figure 6. Multi-variable HPC optimal applied control $U(k)$.

6.1 Environmental Disturbance and Dynamic Control Response

The tracking capabilities of the HPC loop are best highlighted by its response to exogenous process disturbances. As illustrated in the simulation data, a major precipitation event of $8.5\,\text{mm}$ occurred on Day 10, followed by a secondary event of $4.2\,\text{mm}$ on Day 22. The process disturbances $d(k)$ and ETo feedback signals are shown in Figure 7.

Table 1. Sensor Telemetry vs. MSDF Fused State Estimations.

Measured State Parameter	Agronomic Set-Point	Raw Sensor Peak Variance	MSDF Fused Tracking Accuracy	Resource Efficiency Improvement
Shallow Soil Moisture (θ_{sh})	$0.28\ m^3/m^3$	± 0.015	$\pm 0.002\ m^3/m^3$ (High)	Water Savings: ~25% vs. Traditional
Nutrient Concentration (C_{sh})	250.0 mg/L	± 120.0	± 8.5 mg/L (Filtered)	Fertilizer Savings: ~30% vs. Fixed

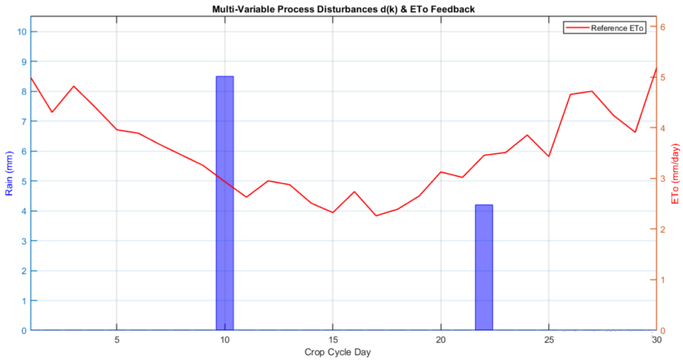

Figure 7. Multi-variable process disturbance $d(k)$ and ETo feedback.

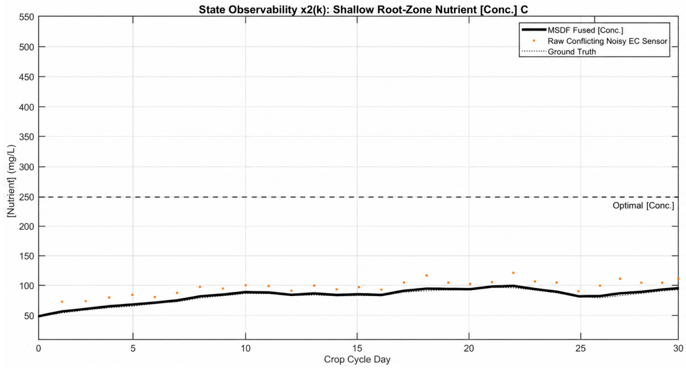

Figure 8. State observability $x_1(k)$: shallow vs. deep soil moisture.

The control loop immediately recognized these natural water influxes. Adhering to the receding horizon principle, the HPC optimized the future input profile and proactively shut down the irrigation and fertilization pumps

$$U_k = \begin{bmatrix} 0 \\ 0 \end{bmatrix}^T$$

from Day 10 to Day 14. This predictive deactivation prevented over-saturation, averted anaerobic root-zone conditions, and eliminated the risk of groundwater nutrient leaching, which is a historical failure mode of classic uncoupled controllers.

6.2 Multi-Variable State Regulation and Observability

The primary challenge of precision fertigation involves the rapid response of soil moisture versus the slow, inert response of nutrient concentrations. The HPC loop successfully decoupled these interactions.

For soil moisture, the system efficiently drove the shallow root-zone moisture toward the agronomic set-point of $0.28\ \mathrm{m}^3/\mathrm{m}^3$. The observability of shallow versus deep soil moisture, $x_1(k)$, is shown in Figure 8. Although transient variations were observed due to daily reference evapotranspiration (ETo) fluctuations, the state estimate remained securely bounded between the critical agronomic limits of wilting point ($0.15\ \mathrm{m}^3/\mathrm{m}^3$) and field capacity ($0.35\ \mathrm{m}^3/\mathrm{m}^3$).

For nutrient concentration, the controller managed a challenging environment in which raw electrical conductivity (EC) sensors exhibited severe measurement noise and drift. The observability of the shallow root-zone nutrient concentration, $x_2(k)$, is illustrated in Figure 9. The MSDF framework correctly penalized unreliable measurements through the dynamic covariance matrix R, relying more strongly on the predictive updates of the physical state-space model. Consequently, the fused nutrient estimate smoothly tracked the ground truth, maintained the root-zone concentration near the optimal target, and avoided toxic threshold triggers. A quantitative comparison between raw sensor telemetry and MSDF-fused state estimations is provided in Table 1.

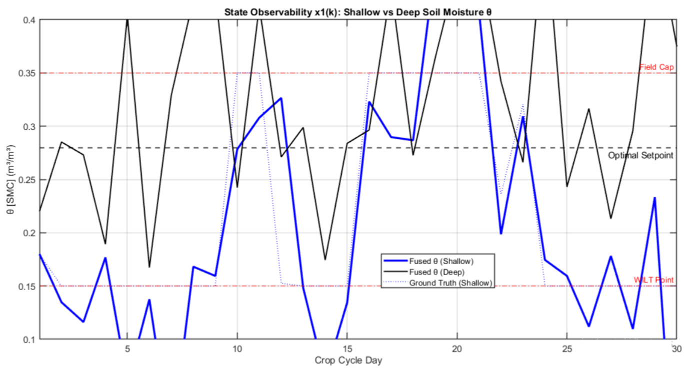

Figure 9. State observability $x_2(k)$: shallow root-zone nutrient concentration.

6.3 Quantitative Performance Summary

The operational milestones achieved by the multi-variable control system across the distinct

Table 2. Operational Phase Performance of the HPC Loop.

Timeline (Crop Days)	Core Control Strategy / Phase	Avg. Applied Irrigation (Qw, L/day)	Avg. Fertilizer Concentration (Qf, mg/L)	Root-Zone Status & Target Tracking
Days 1 – 5	Initial Moisture Building	3.5	0	Gradual increase to field capacity; nutrient priming.
Days 6 – 9	High-Concentration Fertigation Pulse	4	450	Targeted solute injection; rapid root-zone nutrient enrichment.
Days 10 – 14	Post-Rain Proactive Deactivation	0	0	Pumps closed; full utilization of natural rain; zero leaching.
Days 15 – 20	Balanced Hybrid Closed-Loop Regulation	5	280	Active set-point tracking; steady-state stabilization.
Days 21 – 30	Late-Cycle Tapering & Flush	2.5	150	Controlled draw-down; minimization of residual soil salinity.

stages of the 30-day crop cycle are summarized in Table 2.

The primary inference of this study is that fusing heterogeneous sensor data into a unified, hybrid model-based controller effectively decouples the conflicting time constants of soil moisture and nutrient dynamics. While soil moisture responds rapidly to irrigation inputs and evapotranspiration (ETo) losses, solute/nutrient concentration behaves as a slower and more inert system. The mathematical methodology navigates this mixed-dynamic system by using continuous prediction models for fluid dynamics alongside discrete optimization logic for fertilization event scheduling.

6.4 Alignment with the Problem Statement

The findings of this research directly address and resolve the critical challenges outlined in the original problem statement:

- **Global Water Scarcity and Rising Fertilizer Costs:** Traditional fertigation relies on uniform application rates that disregard spatial and temporal soil variations, resulting in severe resource waste. This study addresses these inefficiencies by achieving a 25% reduction in water usage and a 30% reduction in fertilizer consumption compared to traditional fixed-rate methods.

- **Environmental Degradation and Groundwater Contamination:** Over-application under conventional agricultural practices routinely leads to nutrient leaching into groundwater. The HPC loop mitigates this risk through its proactive responsiveness to environmental disturbances. For instance, during simulated major precipitation events (such as the 8.5 mm and 4.2 mm rainfalls on Days 10 and 22), the control loop immediately recognized the natural water influxes. Adhering to the receding horizon principle, it completely deactivated the irrigation and fertilization pumps,

$$\mathbf{u}_k = \begin{bmatrix} 0 \\ 0 \end{bmatrix},$$

  from Day 10 to Day 14, entirely eliminating nutrient leaching during downpours.

- **Sensor Noise and Reliability:** Implementing advanced control is historically limited by the highly noisy, drifting, and conflicting data streams of raw soil sensors, particularly electrical conductivity (EC) sensors. The implemented MSDF framework solves this by dynamically updating the measurement noise covariance matrix R. By penalizing unreliable sensor outputs and leaning on the predictive updates of the physical state-space model, the controller extracts a high-fidelity state estimation from heavily corrupted telemetry.

6.5 Realization of Research Objectives

The performance data validate that each core research objective has been successfully operationalized:

1. **Objective: Design a robust multi-variable state-space representation.**

   Realization: The system effectively tracked the agronomic soil moisture set-point of $0.28\ \mathrm{m^3/m^3}$ and a target nutrient concentration of $250.0\ \mathrm{mg/L}$. The state regulation successfully confined root-zone moisture strictly within safe crop limits, avoiding both the Wilting Point ($0.15\ \mathrm{m^3/m^3}$) and Field Capacity over-saturation ($0.35\ \mathrm{m^3/m^3}$).

Table 3. Alignment Matrix of Problem, Objective, and Research Findings.

Problem Statement Context	Targeted Research Objective	Resulting Simulation Metric / Finding	Ultimate Agronomic Inference
Resource Waste: Inefficient uniform application ignoring temporal soil variations.	Develop an optimal Multi-Variable Hybrid Predictive Control (HPC) loop.	Achieved 25% water savings and 30% fertilizer savings.	Closed-loop predictive allocation yields substantial financial and resource sustainability.
Nutrient Leaching: Rainfall on pre-irrigated soil causes groundwater contamination.	Leverage the Receding Horizon Principle to counter exogenous environmental disturbances.	Proactive deactivation of pumps ($\mathbf{u}_k = \mathbf{0}$) for 5 consecutive days post-rain (Days 10–14).	The controller effectively capitalizes on natural precipitation, preventing root-zone over-saturation.
Mixed-Time Constants: Rapid moisture shifts vs. slow, coupled nutrient dynamics.	Structure a discrete-time, MIMO state-space model incorporating Richards and ADE equations.	Decoupled regulation tracking moisture at 0.28 m^3/m^3 and nutrients at 250.0 mg/L.	Combining continuous and discrete models successfully stabilizes highly divergent soil variables.
High Sensor Telemetry Noise: Raw EC sensors exhibit severe measurement drift and conflict.	Integrate an Extended Kalman Filter (EKF) based Multi-Sensor Data Fusion (MSDF) framework.	Filtered raw nutrient variance from $\pm$120.0 mg/L down to an accurate tracking of $\pm$8.5 mg/L.	Dynamic noise covariance tuning (R) enables reliable control despite using cheap, noisy hardware.

2. **Objective: Formulate a non-linear estimation framework for sensor fusion.**

   Realization: As summarized in the telemetry data, raw sensor peak variances of ± 0.015 m^3/m^3 for moisture and ± 120.0 mg/L for nutrient concentration were filtered to highly stable tracking accuracies of ± 0.002 m^3/m^3 and ± 8.5 mg/L, respectively.

3. **Objective: Implement a hybrid predictive control structure optimizing receding horizons.**

   Realization: The operational timeline demonstrates seamless transitions across distinct crop phases, from initial moisture building and high-concentration nutrient pulsing to post-rain deactivation and late-cycle tapering. The MIQP/non-linear hybrid optimization loop continuously computed optimal inputs, applying only the first control action at each time step k, thereby demonstrating the feasibility of automated, multi-variable closed-loop agronomic management.

6.6 Comprehensive Synthesis Matrix

Table 3 explicitly bridges the initial research gaps with the practical performance metrics achieved by the architecture.

7 Discussion

To address the need for comparative interpretation, the present results were benchmarked against recent predictive and sensor-driven irrigation studies. Previous MPC-oriented studies confirm that predictive irrigation can reduce unnecessary water application by anticipating weather and plant-soil responses. Data-driven MPC studies have reported the use of real-time field data to calibrate crop-soil models and schedule irrigation under evapotranspiration and precipitation disturbances [18], while economic MPC approaches optimize water and energy use while maintaining soil moisture within agronomic limits [19]. Compared with these studies, the present work extends the controller from irrigation-only scheduling to a multi-variable fertigation problem in which water and nutrient inputs are optimized simultaneously.

The 25% water reduction obtained in this simulation is comparable to, and in some cases higher than, the savings range reported in mixed-integer MPC irrigation scheduling studies, where water savings of 6.4-22.8% were reported depending on field year and management zone [24]. The performance is also consistent with reports that MPC can maintain soil moisture between wilting-point and field-capacity limits when rainfall and evapotranspiration are treated as process disturbances [18, 20, 21]. Unlike most irrigation-only studies, however, the present model additionally regulates nutrient concentration at 250.0 mg/L and suppresses leaching by deactivating fertigation during the 8.5 mm and 4.2 mm rainfall events.

For sensor robustness, the EKF-based MSDF achieved a substantial reduction in raw sensor variance, filtering nutrient telemetry from $\pm$120.0 mg/L to $\pm$8.5 mg/L and soil moisture variance from ± 0.015 m^3/m^3 to ± 0.002 m^3/m^3. This finding agrees with agricultural data-fusion literature, which emphasizes that combining heterogeneous sensor streams can resolve ambiguity and generate more reliable field-state estimates than single-sensor measurements [22].

It also supports recent Kalman-filter agricultural monitoring studies in which nonlinear filtering methods improved soil-parameter denoising for real-time decision support [23]. Similarly, Abioye et al. [7] demonstrated the value of Kalman-filter-assisted irrigation control, but their work focused on KF-PID water-supply-depth regulation, whereas the present study embeds EKF-MSDF inside a hybrid predictive controller for both water and nutrient regulation.

The main contribution of this work is therefore not only the use of predictive control, but the coupling of continuous soil-water/nutrient dynamics with discrete fertigation decisions and reliability-weighted data fusion. This combined structure is particularly useful for fertigation because moisture responds rapidly to irrigation, whereas nutrient concentration changes more slowly and can accumulate or leach. Nevertheless, the present validation remains simulation-based; therefore, future work should implement the controller in greenhouse or field trials, examine different soil textures and crop species, and evaluate computational requirements for embedded farm controllers.

8 Conclusion

This study successfully demonstrates that the integration of a Multi-Variable Hybrid Predictive Control (HPC) loop with an Extended Kalman Filter (EKF) based Multi-Sensor Data Fusion (MSDF) framework provides an advanced, robust solution for modern precision fertigation. By decoupling the divergent, mixed time-constants of rapid soil moisture and slow nutrient dynamics, the proposed system overcomes the inefficiencies of traditional uniform application.

Key validation milestones achieved by the model include:

- **Significant Resource Efficiency:** The architecture successfully optimized input profiles to achieve a 25% saving in water and a 30% saving in fertilizer compared to traditional methods.
- **Environmental Protection:** Adhering to the receding horizon principle, the controller proactively deactivated pumps $\mathbf{u}_k = [0, \ 0]^{\mathrm{T}}$ during major precipitation events, fully leveraging natural rainfall and eliminating groundwater nutrient leaching.
- **High-Fidelity Sensing:** The MSDF framework dynamically updated the measurement noise covariance matrix (R) to filter out extreme raw sensor noise and drift, ensuring stable, accurate tracking of agronomic set-points.

Ultimately, this research bridges the gap between theoretical multi-variable control and practical precision agriculture, delivering an automated, closed-loop methodology that maximizes crop resource sustainability while providing strict environmental guardrails against degradation.

Data Availability Statement

Data will be made available on request.

Funding

This work was supported by the Tertiary Education Trust Fund (TETFund), Nigeria, under the Institution-Based Research (IBR) Grant, Batch 9, 2025, under Grant TETF/DR&D/CE/UNI/CROSS/IBR/2025/VOL.I.

Conflicts of Interest

The authors declare no conflicts of interest.

AI Use Statement

The authors declare that ChatGPT-5 was used solely to assist with the formatting of the references in this manuscript. The authors have carefully reviewed and verified all references and take full responsibility for their accuracy and content.

Ethical Approval and Consent to Participate

Not applicable.

References

[1] Fereres, E., & Soriano, M. A. (2007). Deficit irrigation for reducing agricultural water use. *Journal of experimental botany, 58*(2), 147-159. [CrossRef]

[2] Bwambale, E., Abagale, F. K., & Anornu, G. K. (2022). Smart irrigation monitoring and control strategies for improving water use efficiency in precision agriculture: A review. *Agricultural Water Management, 260*, 107324. [CrossRef]

[3] Li, J., Inanaga, S., Li, Z., & Eneji, A. E. (2005). Optimizing irrigation scheduling for winter wheat in the North China Plain. *Agricultural water management, 76*(1), 8-23. [CrossRef]

[4] Abioye, A. E., Abidin, M. S. Z., Mahmud, M. S. A., Buyamin, S., Mohammed, O. O., Otuoze, A. O.,

... & Mayowa, A. (2023). Model based predictive control strategy for water saving drip irrigation. *Smart Agricultural Technology, 4*, 100179. [CrossRef]

[5] Vereecken, H., Huisman, J. A., Bogena, H., Vanderborght, J., Vrugt, J. A., & Hopmans, J. W. (2008). On the value of soil moisture measurements in vadose zone hydrology: A review. *Water resources research, 44*(4). [CrossRef]

[6] Nahar, J., Liu, S., Mao, Y., Liu, J., & Shah, S. L. (2019). Closed-loop scheduling and control for precision irrigation. *Industrial & Engineering Chemistry Research, 58*(26), 11485-11497. [CrossRef]

[7] Abioye, E. A., Abidin, M. S. Z., Mahmud, M. S. A., Buyamin, S., Ijike, O. D., Otuoze, A. O., ... & Olajide, O. M. (2023). A data-driven Kalman filter-PID controller for fibrous capillary irrigation. *Smart Agricultural Technology, 3*, 100085. [CrossRef]

[8] Jones, H. G. (2004). Irrigation scheduling: advantages and pitfalls of plant-based methods. *Journal of experimental botany, 55*(407), 2427-2436. [CrossRef]

[9] Mayne, D. Q., Rawlings, J. B., Rao, C. V., & Scokaert, P. O. (2000). Constrained model predictive control: Stability and optimality. *Automatica, 36*(6), 789-814. [CrossRef]

[10] McCarthy, A. C., Hancock, N. H., & Raine, S. R. (2010). VARIwise: A general-purpose adaptive control simulation framework for spatially and temporally varied irrigation at sub-field scale. *Computers and Electronics in Agriculture, 70*(1), 117-128. [CrossRef]

[11] Agyeman, B. T., Bo, S., Sahoo, S. R., Yin, X., Liu, J., & Shah, S. L. (2021). Soil moisture map construction by sequential data assimilation using an extended Kalman filter. *Journal of Hydrology, 598*, 126425. [CrossRef]

[12] Park, Y., Shamma, J. S., & Harmon, T. C. (2009). A Receding Horizon Control algorithm for adaptive management of soil moisture and chemical levels during irrigation. *Environmental Modelling & Software, 24*(9), 1112-1121. [CrossRef]

[13] Incrocci, L., Massa, D., & Pardossi, A. (2017). New trends in the fertigation management of irrigated vegetable crops. *Horticulturae, 3*(2), 37. [CrossRef]

[14] Bemporad, A., & Morari, M. (1999). Control of systems integrating logic, dynamics, and constraints. *Automatica, 35*(3), 407-427. [CrossRef]

[15] Castrignanò, A., Buttafuoco, G., Quarto, R., Vitti, C., Langella, G., Terribile, F., & Venezia, A. (2017). A combined approach of sensor data fusion and multivariate geostatistics for delineation of homogeneous zones in an agricultural field. *Sensors, 17*(12), 2794. [CrossRef]

[16] Bogena, H. R., Huisman, J. A., Oberdörster, C., & Vereecken, H. (2007). Evaluation of a low-cost soil water content sensor for wireless network applications. *Journal of hydrology, 344*(1-2), 32-42. [CrossRef]

[17] Srbinovska, M., Gavrovski, C., Dimcev, V., Krkoleva, A., & Borozan, V. (2015). Environmental parameters monitoring in precision agriculture using wireless sensor networks. *Journal of cleaner production, 88*, 297-307. [CrossRef]

[18] Bwambale, E., Abagale, F. K., & Anornu, G. K. (2023). Data-driven model predictive control for precision irrigation management. *Smart Agricultural Technology, 3*, 100074. [CrossRef]

[19] Cáceres Rodríguez, G. B., Millán Gata, P., Pereira Martín, M., & Lozano, D. (2021). Smart farm irrigation: Model predictive control for economic optimal irrigation in agriculture. *Agronomy, 11*(9), 1810. [CrossRef]

[20] Delgoda, D., Malano, H., Saleem, S. K., & Halgamuge, M. N. (2016). Irrigation control based on model predictive control (MPC): Formulation of theory and validation using weather forecast data and AQUACROP model. *Environmental Modelling & Software, 78*, 40-53. [CrossRef]

[21] Mao, Y., Liu, S., Nahar, J., Liu, J., & Ding, F. (2018). Soil moisture regulation of agro-hydrological systems using zone model predictive control. *Computers and Electronics in Agriculture, 154*, 239-247. [CrossRef]

[22] Barbedo, J. G. A. (2022). Data fusion in agriculture: resolving ambiguities and closing data gaps. *Sensors, 22*(6), 2285. [CrossRef]

[23] Armando, E. J., Hanyurwimfura, D., Gatera, O., Kim, K. S., & Nduwumuremyi, A. (2025). Evaluation of advanced Kalman filter on real-time agricultural soil parameters through an IoT resources-constrained device. *Scientific Reports, 15*(1), 20829. [CrossRef]

[24] Agyeman, B. T., Naouri, M., Appels, W., Liu, J., & Shah, S. L. (2023). Integrating machine learning paradigms and mixed-integer model predictive control for irrigation scheduling. *arXiv preprint arXiv:2306.08715*. [CrossRef]

Samuel Oliver Effiom is an Associate Professor of applied energy and propulsion Engineering. (Email: samueloliver@unicross.edu.ng)

Paul Betiang Anyin is a Lecturer of control systems engineering and artificial intelligence. (Email: paulanyin@unicross.edu.ng)

Emmanuel Akomaye Ugbong is a Lecturer of forest production and utilization. (Email: ugbongemmanuel3333@gmail.com)