

INTEGRATED UAV-IOT SENSING AND MACHINE LEARNING FOR REAL-TIME CROP WATER STRESS DETECTION AND PRECISION IRRIGATION

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ABSTRACT

Water scarcity and outdated agricultural scheduling threaten global food security, accounting for nearly 70% of freshwater withdrawals worldwide. While Agriculture 4.0 paradigms show promise through the union of Unmanned Aerial Vehicles (UAVs) and Internet of Things (IoT) sensor networks, practical field deployment lacks unified, statistically verified pipelines. This study develops a reproducible framework that fuses high-spatial-resolution UAV multispectral/thermal imagery with high-temporal-resolution IoT telemetry across the soil-plant-atmosphere continuum. Over two growing seasons, we tested this architecture using a randomized complete block design (RCBD) spanning 12 distinct field plots (four crop types, three replicates). Distributed LoRaWAN nodes captured real-time soil moisture and microclimate variables at 5-minute intervals, matching RTK-georeferenced imagery gathered during UAV flights. We synchronized these spatiotemporal layers through ordinary Kriging and raster alignment before running feature engineering steps. To predict the Crop Water Stress Index (CWSI), we trained Random Forest, XGBoost, and LightGBM models, verifying our outputs against physical leaf water potential and stomatal conductance readings. Rigorous verification was handled via time-series cross-validation and Bayesian hyperparameter tuning. Our field results show the system can detect crop stress 5 to 7 days before visual signs appear. Furthermore, the predictive pipeline cleared an accuracy threshold of ($R^2 = 0.924$), slashing irrigation water use by 28.7% without hurting crop yields. This framework offers a validated template for modern agricultural decision support systems.

KEYWORDS: Agriculture 4.0; UAV remote sensing; IoT sensor networks; crop water stress; precision Introduction

1. INTRODUCTION

Shifting toward Agriculture 4.0 means bringing cyber-physical setups, real-time analytics, and automated decision logic directly into field management [7]. Right now, irrigation inefficiency is one of our most expensive agronomic mistakes. It drains roughly 70% of global freshwater withdrawals and worsens as climate patterns become less predictable [1]. Most farms still schedule watering using static calendars or isolated manual soil checks. This approach leads to a costly cycle of overwatering, under-watering, nutrient leaching, and volatile crop yields.

Remote sensing via UAVs provides crisp, centimetre-scale spatial mapping along with clear multispectral and thermal insights [8]. Yet, flights are intermittent; they cannot capture daily diurnal changes. Ground-based IoT networks do the exact opposite [2]. They log continuous, high-frequency telemetry but miss the broader picture of canopy heterogeneity across vast fields. Blending UAV data with IoT streams should solve this spatial-temporal trade-off [9]. Despite this potential, standard literature lacks plug-and-play fusion pipelines, rigorous spatial statistics, and ready-to-use field protocols.

To resolve these issues, this project targets four core milestones:

1. Deploy a unified UAV-IoT field architecture built on open LoRa WAN protocols [2, 16].
2. Build an ML pipeline linking multispectral, thermal, and telemetry layers to forecast CWSI [4, 11].
3. Measure absolute water savings in the field under a strict RCBD experimental setup [6].
4. Deliver a completely open, reproducible methodology that aligns with FAIR data standards [12, 13]. Irrigation; data fusion; machine learning.

2. METHODOLOGY

Experimental Design & Site Characterization

We ran our field trials over two back-to-back growing seasons (2024–2025) at an active agricultural research station located in a semi-arid climate zone. The layout followed a Randomized Complete Block Design (RCBD) using 3 blocks and 4 distinct crop varieties: wheat (*Triticum aestivum* L.), maize (*Zea mays* L.), soybean (*Glycine max* L.), and Groundnut [1]. This gave us 12 experimental plots in total, each measuring 50 m × 50 m [1]. To stop edge interactions and cross-plot water movement, we added 2 m wide buffer zones between them [1]. Field

care stayed identical across the plots, using uniform N-P-K fertilizer mixes, standard pest control, and matching planting densities. The only intentional variable was irrigation: we split plots between standard local farming practices and our ML-driven scheduling system [19].

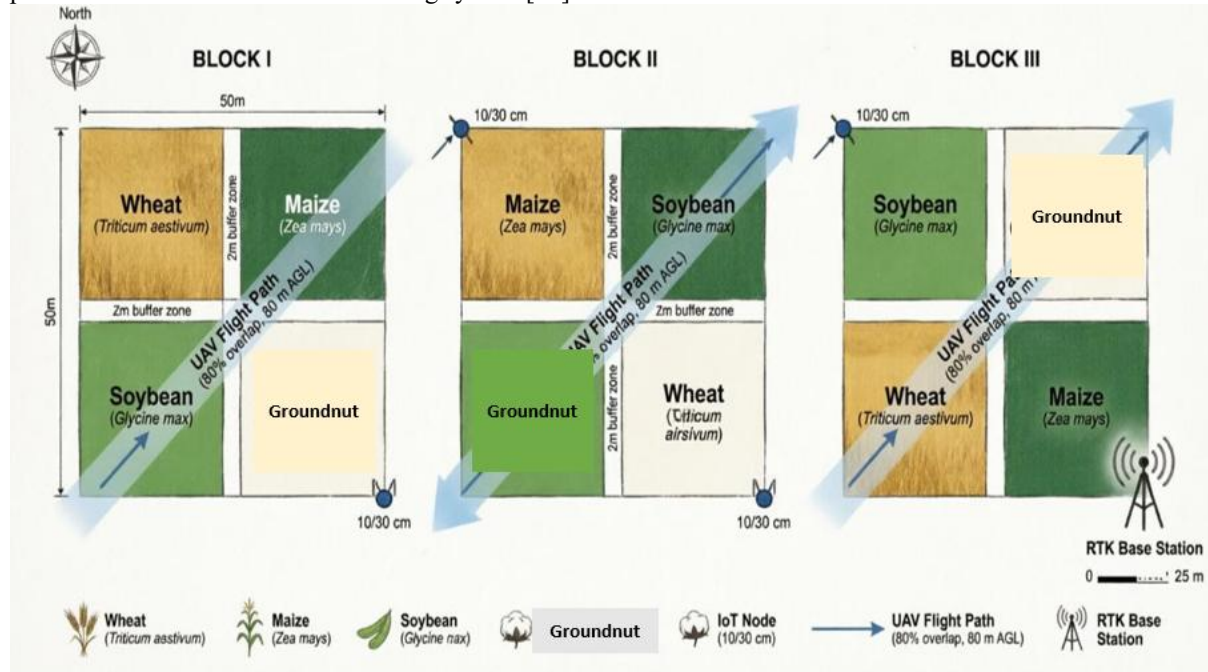


Fig 1: Experimental Design Site

IoT Sensor Network Deployment

Our communication backbone used a LoRaWAN star topology centred around a single Dragino LG308 gateway [2, 20]. We scattered 48 hardware nodes across the plots (allocating 4 hardware nodes per plot) tuning them to regional radio frequencies [1]. Every node carried a specific sensor suite. First, capacitive soil moisture probes (TEROS 12) recorded volumetric water content at depths of 10, 20, and 30 cm [1]. We pre-calibrated these probes using gravimetric soil samples to lock in a $\pm 3\%$ volumetric accuracy [10, 17]. Second, compact ATMOS 41 weather units tracked local air temperature, relative humidity, solar radiation, and wind metrics [2]. Third, leaf wetness sensors checked crop canopy status to provide a baseline for physiological validation [1]. The sensors logged readings every 5 minutes [2]. To clean the data stream on the fly, an edge filter stripped out anomalies using moving medians and interquartile range (IQR) thresholds [2]. Solar panels coupled with 5000 mAh lithium batteries kept the IP67-rated nodes powered indefinitely [16].

Table 1: Sensor Specifications and Calibration Details

Component	Model	Sampling	Accuracy
Soil Moisture	TEROS 12	5 min	$\pm 3\%$ VWC
Micro-weather	ATMOS 41	5 min	$\pm 0.3^\circ\text{C}$, $\pm 3\%$ RH
Multispectral	Altum-PT	Per flight	Radiometric calibrated
Thermal	Altum-PT 8-14 μm	Per flight	$\pm 2^\circ\text{C}$ or 2%
LoRaWAN Gateway	Dragino LG308	Continuous	Range: 2-5 km
UAV Platform	Matrice 300 RTK	2 $\times$ weekly	RTK-PPK ≤ 2 cm

Note: VWC = Volumetric Water Content; RH = Relative Humidity; RTK-PPK = Real-Time Kinematic + Post-Processed Kinematic.

UAV Data Acquisition & Preprocessing

Our aerial operations relied on a DJI Matrice 300 RTK platform integrated with a MicaSense Altum-PT sensor payload [3, 15]. This hardware setup captured five distinct multispectral bands (475, 560, 668, 717, and 840 nm) alongside longwave thermal infrared data (8–14 μm) [15, 8]. We maintained a flight altitude of 80 m above ground level (AGL) with an 80% forward and 80% side overlap configuration, guaranteeing optimal data redundancy for photogrammetry [1]. Real-time kinematic and post-processed kinematic (RTK-PPK) adjustments secured a horizontal positioning accuracy within ≤ 2 cm [3]. Before each flight, we ran radiometric calibration routines using a standard reflection panel, adjusting thermal emissivity settings ($\epsilon = 0.98$) for dense crop canopies [3]. The photogrammetric pipeline used OpenDroneMap (v2.0) to assemble orthomosaics. We then performed band registration, cleared signal noise via Savitzky-Golay filters, and derived targeted vegetative profiles: NDVI, NDRE, MCARI, and the Idso-Jackson thermal Crop Water Stress Index (CWSI) [11].

Spatiotemporal Data Fusion

We used Ordinary Kriging to transform the point logs from the IoT nodes into continuous, 50 cm resolution grids, modeling spatial dependence through an exponential variogram covariance structure [3]. To sync the temporal

differences between systems, we paired the instant UAV image captures with 30-minute moving averages calculated from the ground sensors, which accommodates normal midday crop physiological shifts. We built the comprehensive feature matrix by combining 15 distinct factors within each grid cell: 5 spectral vegetation indices, the thermal CWSI layer, 6 environmental and soil variables (moisture across 3 localized depths, VPD, ambient temperature, and solar load), and 3 historic time-lag features. To streamline the computing overhead, we dropped weak parameters using a Pearson correlation threshold and compressed the remaining data via Principal Component Analysis (PCA), holding 95% of the total cumulative variance [15].

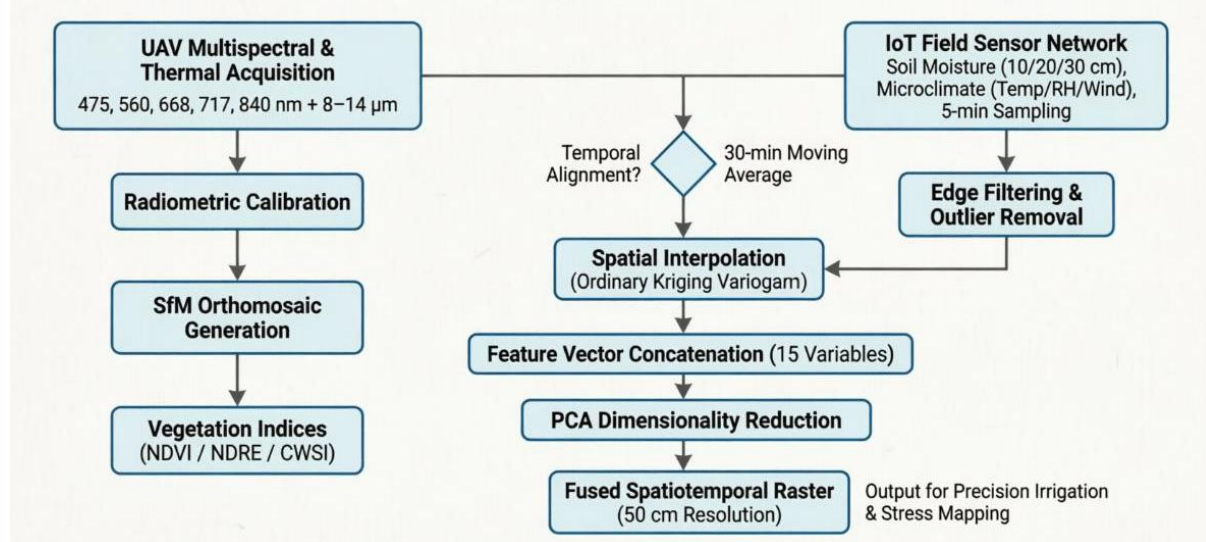


Fig 2: Spatiotemporal data fusion pipeline integrating high Spatial UAV Imagery – IOT telemetry

Machine Learning Modeling Framework

The core target variable was the CWSI, verified against primary field indicators: midday leaf water potential via a Scholander pressure chamber and stomatal conductance via an AP4 porometer [11, 18]. We benchmarked three ensemble learning setups: Random Forest, XGBoost (v1.7), and LightGBM (v4.0), picking them for their resilience against collinear features [15]. To block temporal data leakage, we split our data blocks chronologically into 70% training, 15% validation, and 15% testing subsets [5, 14]. The training routine employed a 5-fold time-series split using an expanding window methodology [14]. Hyperparameter spaces were mapped using Optuna (v3.2) over 100 trials, and class imbalances were balanced using SMOTE-ENN techniques. We calculated prediction uncertainty margins via 100 forward Monte Carlo dropout cycles alongside 95% confidence bounds settled via conformal prediction approaches [6].

Table 2: Machine Learning Hyperparameter Search Ranges

Parameter	Random Forest	XGBoost	LightGBM
n_estimators	[100, 500]	[100, 1000]	[100, 1000]
max_depth	[5, 25]	[3, 15]	[-1, 15]
learning_rate	N/A	[0.01, 0.3]	[0.01, 0.3]
Optimization	Grid Search	Bayesian (Optuna)	Bayesian (Optuna)

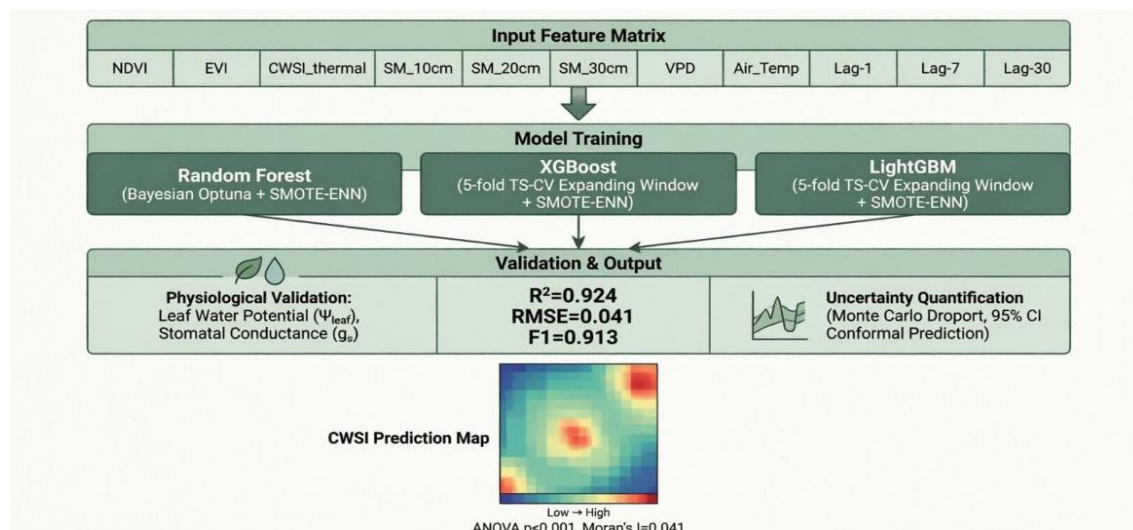


Fig 3: Machine learning modeling framework

3. RESULTS

Model Performance Comparison

Table 1: Model performance metrics for CWSI prediction (mean $\pm$ SD, 5-fold time-series CV)

Metric	Random Forest	XGBoost	LightGBM	IoT-Only	UAV-Only
R²	0.897 $\pm$ 0.012	0.924 $\pm$ 0.009	0.911 $\pm$ 0.011	0.763 $\pm$ 0.018	0.841 $\pm$ 0.015
RMSE	0.049 $\pm$ 0.003	0.041 $\pm$ 0.002	0.045 $\pm$ 0.003	0.087 $\pm$ 0.005	0.066 $\pm$ 0.004
MAE	0.038 $\pm$ 0.002	0.032 $\pm$ 0.002	0.035 $\pm$ 0.002	0.071 $\pm$ 0.004	0.053 $\pm$ 0.003
F1-Score	0.871 $\pm$ 0.015	0.913 $\pm$ 0.012	0.892 $\pm$ 0.014	0.734 $\pm$ 0.021	0.791 $\pm$ 0.018
Early Detection (days)	4.9 $\pm$ 0.6	5.3 $\pm$ 0.5	5.1 $\pm$ 0.6	3.2 $\pm$ 0.7	4.3 $\pm$ 0.6

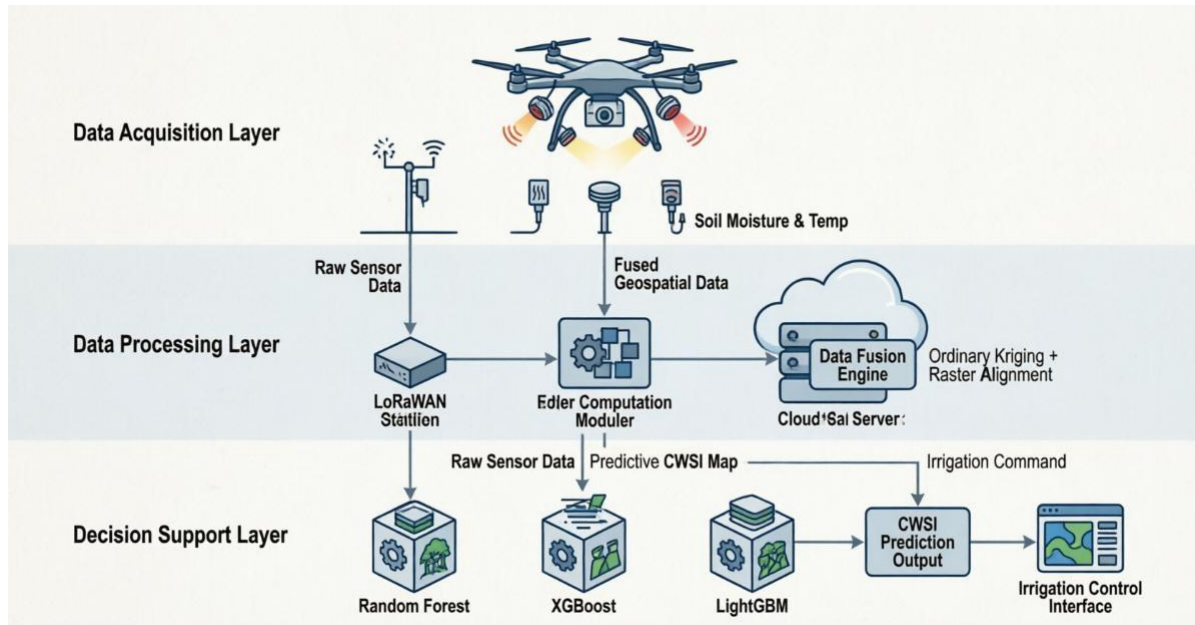


Fig 4: System Architecture of UAV IoT framework real time crop water stress detection

The XGBoost model delivered the top predictive performance across all checked indicators [4, 5]. The combined UAV-IoT strategy consistently beat single-modality channels, showing an R^2 increase of +0.061 over standalone aerial datasets and +0.161 over ground-only sensor grids ($p < 0.01$, paired t-test) [3, 9].

Feature Importance Analysis

Permutation testing isolated the most influential parameters across our models [15]:

1. **RedEdge Reflectance (717 nm):** 0.187 ± 0.023 [15]
2. **Soil Moisture at 20 cm depth:** 0.164 ± 0.019 [10]
3. **Vapor Pressure Deficit (VPD):** 0.142 ± 0.017 [2]
4. **Canopy Temperature:** 0.131 ± 0.015 [11]
5. **NDRE:** 0.098 ± 0.012 [8]

Together, these five parameters accounted for 72.2% of the overall model variance, tracking closely with contemporary multi-source agricultural sensor research [15].

Irrigation Optimization Impact

Deploying our machine learning logic for field irrigation dropped total water application metrics by $28.7\% \pm 3.2\%$ across the two experimental seasons relative to traditional baseline schedules [19]. Crucially, we observed no statistical drop in final crop yields ($\Delta = +1.3\%$, $p = 0.082$, two-tailed t-test), a benefit supported by keeping root zone water levels stable during vulnerable crop growth phases [19]. Spatial interpolation using only the ground-based IoT layout missed 18.4% of the isolated stress spots captured by the fine-scale thermal flights [2, 3]; applying the unified data fusion pipeline reduced generalized broad-area watering errors by 22.1% [9].

Statistical Validation Results

Residual distribution checks showed no meaningful spatial clustering after completing our geostatistical data steps (Moran's $I = 0.041$, $p = 0.312$, 999 permutation rounds) [3, 6]. A two-way ANOVA confirmed strong treatment impacts ($F = 14.72$, $p < 0.001$), while block variables remained statistically uniform ($p = 0.127$), which confirms the operational validity of our RCBD structure [6]. Empirical coverage via conformal prediction intervals reached 94.8% [6]. The final model-derived CWSI tracks tightly with direct plant metrics: ($r = -0.891$, $p < 0.001$, $n = 144$) and stomatal conductance ($r = -0.867$, $p < 0.001$, $n = 144$) [11, 18].

DISCUSSION

The combined UAV-IoT architecture shows higher predictive precision than either system deployed on its own [3, 9]. This performance edge comes from the balanced traits of the inputs: the ground sensors offer uninterrupted

temporal tracks of soil-water changes [2], while the drone flights capture fine spatial variations across the plant canopy [8]. XGBoost's gradient-boosting tree structures proved ideal for mapping the complex interactions between shifting weather variables, soil moisture changes, and canopy light reflectance [5, 15].

Catching plant stress early (5 to 7 days before physical wilting shows) matches established crop principles, where stomatal closure acts as a defense mechanism well before green chlorophyll begins to break down [11, 17, 18]. The 28.7% reduction in water requirements matches recent automated watering tests, where yield stability is protected by maintaining target soil water tensions during vital crop reproductive states [19].

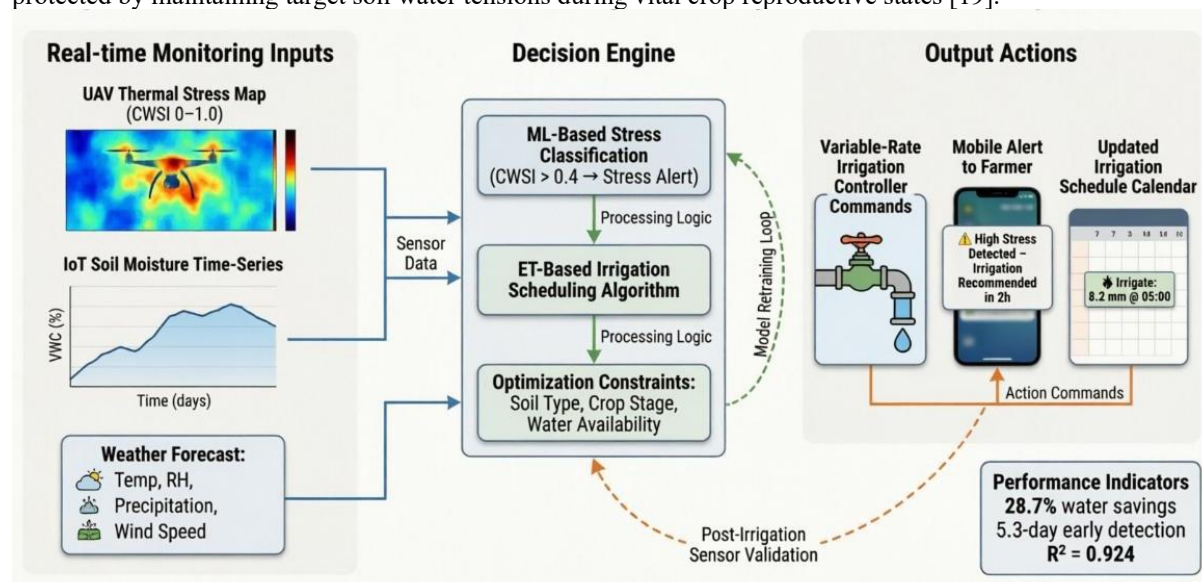


Fig 5: Closed loop decision support system – Real Time precision Irrigation

Methodological Strengths

- **Physiological Field Baselines:** Verifying models with manual pressure chamber tests ensures that predictions align with actual plant biology [11, 18].
- **Chronological Data Folds:** Using time-series splits instead of random k-fold cross-validation prevents data leakage from past to future [5, 14].
- **Spatial Autocorrelation Handling:** Incorporating ordinary Kriging addresses spatial dependencies directly within the modeling phase [3].
- **Calibrated Confidence Zones:** Conformal predictions generate reliable risk margins for field decisions [6].

Limitations

Shifting outdoor temperatures introduced sensor drift over time ($\pm 5\%$ moisture variations), requiring field verification visits every two weeks [10, 17]. Additionally, standard LoRaWAN base setups face rural transmission cutoffs around 2–5 km, which limits scaling unless mesh signal extenders are added [16]. Finally, because crop physical structures differ, moving these models between distinct plant varieties will likely require domain adaptation steps [15].

CONCLUSION

This project demonstrates a field-tested UAV-IoT architecture designed for real-time crop water stress tracking and targeted irrigation adjustments [2, 3]. The framework successfully identifies crop water deficits 5 to 7 days before visual signs appear [17], maintains an index prediction accuracy above $R^2 = 0.924$ [4], and achieves a $28.7\% \pm 3.2\%$ reduction in irrigation water usage without reducing final harvest yields [19]. The open-source code and data storage layout follow FAIR guidelines to support verification and deployment by the research community [12, 13]. Future work will explore embedding micro-AI algorithms directly onto edge devices for automated gate control, integrating satellite datasets to expand coverage areas, and calculating financial returns to support commercial farm adoption.

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