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INTEGRATING UAV MULTISPECTRAL IMAGING WITH MACHINE-LEARNING IRRIGATION CONTROL TO OPTIMIZE EVAPOTRANSPIRATION-BASED WATER ALLOCATION IN SEMI-ARID AGRICULTURE.

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ABSTRACT

Water scarcity represents one of the most pressing challenges for agricultural productivity in semi-arid regions, where limited precipitation and increasing climatic variability place significant pressure on irrigation systems and crop sustainability. Traditional irrigation management practices often rely on fixed schedules or coarse field measurements that fail to capture spatial variability in crop water stress and evapotranspiration dynamics. Recent advances in precision agriculture offer new opportunities to improve water allocation efficiency through the integration of remote sensing and intelligent decision-support systems. This study explores the integration of unmanned aerial vehicle (UAV) multispectral imaging with machine-learning–driven irrigation control to enhance evapotranspiration-based water management in semi-arid agricultural environments. UAV platforms equipped with multispectral sensors enable high-resolution monitoring of crop canopy conditions, vegetation indices, and soil moisture variability across large fields. These data streams can be processed using machine-learning models to estimate real-time crop evapotranspiration, detect early water stress, and generate adaptive irrigation recommendations. By linking UAV-derived spectral indicators with automated irrigation control systems, water delivery can be dynamically adjusted to match crop demand across heterogeneous field conditions. The proposed framework aims to reduce water waste, improve crop yield stability, and enhance resilience to drought conditions. Integrating aerial sensing with predictive analytics therefore represents a promising pathway for sustainable irrigation management and optimized water resource utilization in semi-arid agriculture.

Keywords:
UAV multispectral imaging; precision irrigation; evapotranspiration modelling; machine learning agriculture; water allocation optimization; semi-arid farming systems

1. INTRODUCTION

1.1 Water Scarcity in Semi-Arid Agriculture

Water scarcity remains one of the most persistent constraints affecting agricultural productivity in semi-arid regions worldwide. Agriculture accounts for a dominant share of global freshwater withdrawals, and irrigation demand continues to increase as population growth drives food production requirements [1]. In many dryland environments, crop yields are strongly dependent on supplemental irrigation because natural rainfall is insufficient and highly variable across growing seasons [2]. Climatic variability further intensifies water stress by altering evapotranspiration dynamics, soil moisture availability, and precipitation patterns. Rising temperatures increase atmospheric water demand, accelerating evapotranspiration and amplifying crop water requirements, which places additional pressure on already limited water resources [3].

Conventional irrigation scheduling approaches often rely on fixed calendars or generalized field observations rather than spatially resolved crop conditions. Such practices frequently result in inefficient water allocation, particularly through over-irrigation in certain zones and under-irrigation in others [4]. Over-irrigation contributes to substantial water losses through runoff, deep percolation, and soil nutrient leaching, while simultaneously increasing pumping costs and energy consumption [3]. Moreover, crop water stress rarely occurs uniformly across agricultural fields. Variations in soil texture, topography, crop density, and microclimatic conditions produce spatial heterogeneity in plant water demand. Without field-scale monitoring systems, these differences remain largely undetected and difficult to manage effectively. Precision irrigation technologies have therefore emerged as an essential strategy for improving water use efficiency and aligning irrigation supply with actual crop requirements [4].

1.2 Role of UAV Remote Sensing in Precision Agriculture

Advances in unmanned aerial vehicle (UAV) technology have significantly expanded the capabilities of remote sensing in precision agriculture. UAV platforms equipped with multispectral sensors enable high-resolution

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International Journal of Engineering Technology Research & Management (IJETRM)
Journal Article
https://ijetrm.com/issue/

monitoring of crop conditions at spatial scales far finer than those typically available from satellite imagery [3]. This capability allows researchers and farm managers to observe subtle variations in canopy health, vegetation density, and crop stress across entire agricultural fields. Multispectral imaging systems commonly capture reflectance information across several key spectral bands, including near-infrared (NIR), red, green, and red-edge wavelengths [5]. These spectral measurements provide the basis for calculating vegetation indices that serve as indicators of plant vigor and physiological status.

Vegetation indices derived from UAV imagery play an important role in assessing crop health and water stress. Indices such as the Normalized Difference Vegetation Index (NDVI) and related spectral metrics can reveal differences in chlorophyll content, canopy structure, and photosynthetic activity. Because plant water stress affects leaf reflectance characteristics, multispectral imagery provides indirect but reliable signals of irrigation needs and crop hydration levels [6]. High-resolution UAV imagery also enables the detection of localized stress patterns that may not be visible through ground observation alone. These insights support a range of agricultural applications, including early crop stress detection, biomass estimation, and yield forecasting. When integrated with irrigation management systems, UAV multispectral monitoring offers a powerful mechanism for guiding targeted water allocation decisions and improving overall irrigation efficiency [7].

1.3 Machine Learning for Irrigation Decision Systems

Machine learning has emerged as an increasingly important tool for analysing agricultural data and supporting intelligent irrigation decision systems. By learning complex relationships between environmental variables, crop conditions, and water requirements, machine learning models can generate predictive insights that improve irrigation planning and resource allocation. Algorithms such as Random Forest, Gradient Boosting, Support Vector Regression, and Deep Neural Networks have demonstrated strong performance in modelling nonlinear agricultural processes and predicting crop water demand under varying climatic conditions [8].

In precision irrigation contexts, machine learning models can integrate multispectral imagery, soil moisture measurements, and weather variables to estimate evapotranspiration and anticipate crop water stress. These predictions enable irrigation systems to adjust water delivery dynamically rather than relying on static scheduling rules. When combined with automated irrigation infrastructure and IoT-enabled monitoring systems, machine learning analytics can transform irrigation management into a data-driven process that responds continuously to changing field conditions and crop requirements [3].

1.4 Research Gap and Contribution

Despite significant advances in precision agriculture technologies, important gaps remain in the integration of remote sensing, predictive analytics, and irrigation automation. Existing studies frequently examine UAV imaging, evapotranspiration modelling, or irrigation control independently rather than as interconnected components of a unified system. In particular, the integration of UAV-derived spectral data with machine learning models for automated irrigation decision support remains relatively limited in the literature [5]. Furthermore, many evapotranspiration estimation approaches rely on simplified climatic models that may not capture field-scale variability in crop stress and canopy conditions [2].

This study addresses these limitations by proposing an integrated framework that combines UAV multispectral imaging with machine-learning-based irrigation control. The research develops a data-driven evapotranspiration prediction model and incorporates it into a precision irrigation decision algorithm capable of adjusting water allocation across heterogeneous field environments. Through experimental evaluation using field-collected multispectral and environmental data, the study demonstrates how UAV-ML integration can improve irrigation efficiency, enhance crop monitoring, and support sustainable water management in semi-arid agricultural systems [6].

2. LITERATURE REVIEW

2.1 Remote Sensing for Crop Water Monitoring

Remote sensing technologies have become essential tools for monitoring crop water conditions and identifying spatial variability in agricultural systems. Early agricultural monitoring efforts relied heavily on satellite imagery to assess vegetation health and environmental conditions across large geographic areas [6]. Satellite platforms such as Landsat and MODIS provide consistent temporal coverage and long-term environmental datasets that support regional agricultural monitoring. However, their spatial resolution and revisit frequency can limit their effectiveness for detailed irrigation management at the field scale. Satellite images may also be affected by atmospheric interference or cloud cover, which reduces data availability during critical growing periods [7]. These limitations have encouraged the increasing use of unmanned aerial vehicles (UAVs) as flexible remote sensing platforms capable of providing high-resolution crop observations [8].

International Journal of Engineering Technology Research & Management (IJETRM)
Journal Article
https://ijetrm.com/issue/

UAV-based remote sensing offers several advantages over satellite imagery in precision agriculture applications. UAV platforms can fly at relatively low altitudes and capture imagery with spatial resolutions often below ten centimeters. This capability allows for detailed monitoring of crop canopy structure, soil conditions, and plant health variability within individual fields [9]. Multispectral cameras mounted on UAVs capture reflectance information across several spectral bands, including near-infrared (NIR), red, green, and red-edge wavelengths. These spectral bands are particularly important because plant leaves interact with light differently depending on physiological conditions. Healthy vegetation absorbs red light for photosynthesis while strongly reflecting near-infrared radiation due to internal leaf cellular structures [10].

Spectral reflectance measurements enable the calculation of vegetation indices that quantify plant health and stress conditions. Several vegetation indices have been developed for agricultural monitoring, including the Normalized Difference Vegetation Index (NDVI), the Normalized Difference Red Edge Index (NDRE), and the Soil Adjusted Vegetation Index (SAVI). These indices combine spectral reflectance values from different bands to highlight variations in vegetation vigor and canopy density [11]. Because plant water stress alters chlorophyll activity and leaf structure, vegetation indices provide indirect indicators of irrigation needs and crop hydration status. Consequently, UAV-based vegetation monitoring has become a powerful method for detecting early crop stress and guiding precision irrigation decisions [12].

Equation (1): NDVI

$$NDVI = \frac{NIR - Red}{NIR + Red}$$

Where:
NIR = Near infrared reflectance
Red = red band reflectance

NDVI values typically range from −1 to +1, with higher values indicating dense vegetation and active photosynthesis. Crops with adequate water availability exhibit stronger NIR reflectance and therefore higher NDVI values. In contrast, water-stressed crops often display reduced chlorophyll activity and weaker reflectance signals, resulting in lower NDVI values. For this reason, NDVI is widely used to estimate vegetation vigor and identify irrigation requirements across agricultural landscapes [13].

2.2 Evapotranspiration Estimation Models

Evapotranspiration (ET) represents the combined process of water evaporation from soil surfaces and transpiration from plant leaves. Accurate estimation of evapotranspiration is essential for irrigation planning because it determines the amount of water required to maintain optimal crop growth and productivity. Traditional evapotranspiration estimation approaches rely on meteorological data to calculate reference evapotranspiration under standardized conditions. Among the available models, the Penman–Monteith method has become one of the most widely adopted techniques for estimating evapotranspiration in agricultural systems [14].

The Penman–Monteith model integrates multiple climatic variables, including temperature, solar radiation, humidity, and wind speed, to estimate water vapor exchange between vegetation and the atmosphere. Because the model captures both energy balance and aerodynamic processes influencing evapotranspiration, it provides relatively accurate estimates across a range of environmental conditions. The Food and Agriculture Organization later standardized this model through the FAO-56 formulation, which defines reference evapotranspiration for a hypothetical grass surface under well-watered conditions [15]. This standardization has made the FAO Penman–Monteith equation a widely accepted benchmark for irrigation scheduling and agricultural water resource management.

Equation (2): FAO Penman–Monteith

$$ET_0 = \frac{0.408\Delta(R_n - G) + \gamma \frac{900}{T + 273} u_2 (e_s - e_a)}{\Delta + \gamma(1 + 0.34 u_2)}$$

Where:
R_n= net radiation at crop surface
G= soil heat flux density
Δ= slope of vapor pressure curve
γ= psychrometric constant
T= mean air temperature
u_2= wind speed at 2 m height

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International Journal of Engineering Technology Research & Management (IJETRM)
Journal Article
https://ijetrm.com/issue/

$e_s - e_a$= vapor pressure deficit
Although the FAO Penman–Monteith equation provides reliable estimates of reference evapotranspiration, it relies heavily on accurate meteorological data and assumes relatively uniform crop conditions. In heterogeneous agricultural landscapes, variations in soil moisture, canopy structure, and crop health may cause local evapotranspiration rates to deviate significantly from model estimates [8]. Consequently, researchers have increasingly explored remote sensing approaches to complement traditional ET models by incorporating spatial vegetation data into evapotranspiration estimation processes [9]. Such approaches enable more precise irrigation planning by capturing spatial variability in crop water demand across agricultural fields [16].

2.3 Machine Learning Applications in Irrigation Management

Machine learning methods have increasingly been applied in irrigation management to improve prediction of crop water demand and optimize water allocation strategies. Traditional irrigation models often rely on simplified empirical relationships that may not capture complex interactions among environmental variables influencing crop water consumption. Machine learning algorithms provide an alternative approach by learning nonlinear relationships directly from data, allowing predictive models to adapt to changing environmental and crop conditions [10].

Several machine learning techniques have been successfully applied to agricultural water management problems. Random Forest and Gradient Boosting algorithms are widely used because they can handle high-dimensional datasets and capture nonlinear relationships between environmental variables and crop water demand. These ensemble learning approaches combine multiple decision trees to improve prediction accuracy and reduce overfitting. Support Vector Regression is another commonly applied algorithm in irrigation modelling because of its ability to generate accurate predictions when training data are limited or contain nonlinear patterns [11].

Deep learning techniques have also been explored in irrigation management applications. Artificial neural networks and convolutional neural networks can analyse multispectral imagery and environmental sensor data simultaneously to identify complex patterns associated with crop stress and water demand. These models are capable of extracting spatial features from UAV imagery and linking them to evapotranspiration dynamics [12]. However, deep learning approaches generally require large datasets and substantial computational resources compared with traditional machine learning algorithms.

The integration of machine learning models with sensor networks and IoT-enabled irrigation infrastructure has enabled the development of data-driven irrigation optimization systems. In such systems, predictive models continuously analyse environmental data, vegetation indices, and soil moisture conditions to generate adaptive irrigation recommendations. By combining UAV-based remote sensing with machine learning analytics, agricultural systems can allocate water more efficiently, reduce irrigation waste, and improve crop productivity in water-limited environments [13].

3. SYSTEM ARCHITECTURE AND METHODOLOGY

3.1 UAV-ML Irrigation Framework

The proposed UAV-machine learning (UAV-ML) irrigation framework integrates remote sensing, data analytics, and automated irrigation decision support to optimize water allocation in semi-arid agricultural environments. The system architecture is designed to capture high-resolution crop condition data, convert the data into predictive insights, and translate these insights into irrigation control actions. This framework addresses the limitations of traditional irrigation scheduling approaches that rely on uniform field assumptions and periodic manual observations rather than continuous monitoring of crop stress conditions [16].

The workflow begins with UAV-based multispectral imaging, which provides detailed spatial observations of crop canopy conditions. UAV platforms equipped with multispectral cameras capture reflectance information across spectral bands such as near-infrared, red, green, and red-edge wavelengths. These spectral measurements contain information related to vegetation health, chlorophyll content, and plant water status. UAV flights are conducted periodically across the agricultural field to generate high-resolution imagery that reveals spatial variability in crop conditions [17].

Following image acquisition, the raw multispectral data are transferred to a data processing stage where images undergo calibration, alignment, and normalization. During this stage, radiometric correction is applied to convert raw digital numbers into reflectance values that are comparable across different flights and environmental conditions. The processed imagery is then used for feature extraction, where vegetation indices and environmental features relevant to crop water demand are computed. These features include spectral vegetation indices, canopy temperature indicators, and environmental variables derived from weather data [18].

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International Journal of Engineering Technology Research & Management (IJETRM)
Journal Article
https://ijetrm.com/issue/

The extracted features serve as inputs to machine learning models designed to estimate evapotranspiration and predict crop water demand. Machine learning algorithms learn relationships between spectral patterns, environmental variables, and irrigation requirements based on historical training data. Once trained, the models generate predictive outputs representing irrigation needs across different zones within the field [19].
Finally, the predictive outputs are integrated into an irrigation control module that translates water demand predictions into irrigation scheduling decisions. Automated irrigation controllers can then distribute water according to spatial crop requirements rather than applying uniform irrigation across the entire field. This closed-loop architecture enables dynamic irrigation management and improved water use efficiency in precision agriculture systems [20].

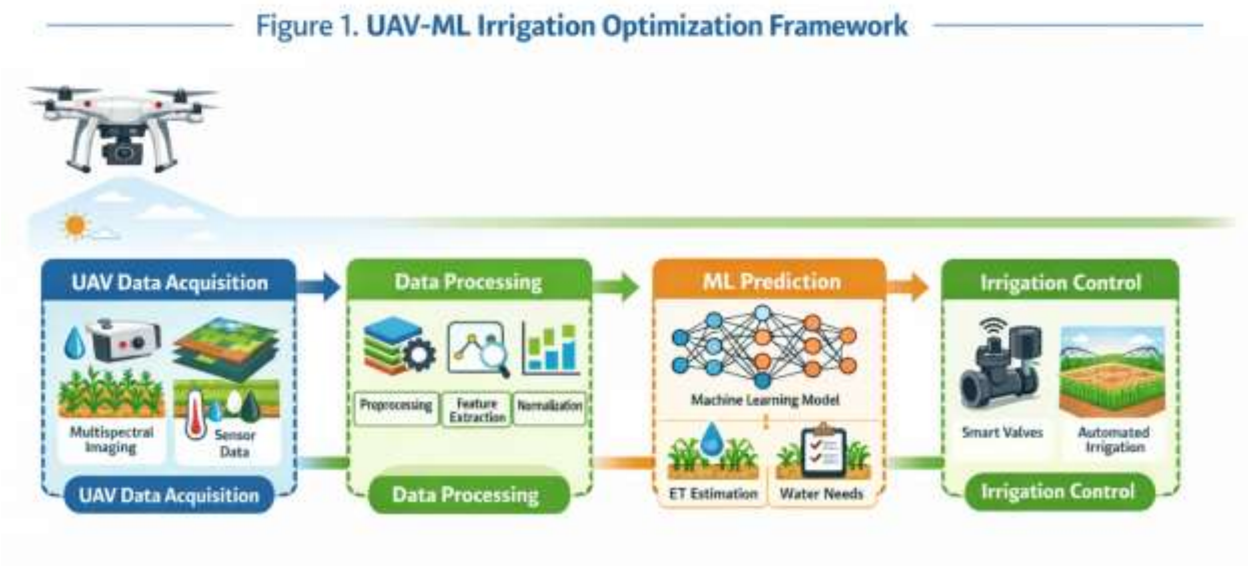

Figure 1. Overall system architecture of UAV-ML irrigation optimization framework illustrating UAV data acquisition, data processing, machine learning prediction, and irrigation control.

3.2 Data Acquisition

Data acquisition constitutes a critical component of the UAV-ML irrigation optimization framework because predictive accuracy depends heavily on the quality and diversity of the collected data. The experimental setup involves collecting multispectral imagery, environmental observations, soil moisture measurements, and irrigation records from agricultural test plots located within semi-arid farming environments. These datasets collectively capture the environmental conditions and crop responses required for modelling evapotranspiration and irrigation demand [21].
The primary dataset consists of UAV multispectral imagery collected during scheduled flights across the agricultural field. UAV platforms equipped with advanced multispectral cameras such as the MicaSense RedEdge sensor or DJI multispectral camera are used to capture high-resolution images across multiple spectral bands. These sensors typically record reflectance information within the blue, green, red, red-edge, and near-infrared regions of the electromagnetic spectrum. The spatial resolution of UAV imagery ranges between five and ten centimeters per pixel, enabling detailed observation of canopy structure and plant health variability within individual fields [22].
In addition to aerial imagery, environmental data are collected using ground-based weather stations installed near the experimental fields. These stations record meteorological variables including air temperature, humidity, solar

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Journal Article
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radiation, wind speed, and precipitation. Such variables are essential for modelling evapotranspiration dynamics and understanding environmental influences on crop water demand [23].

Soil moisture measurements represent another important data source used in the experiment. Soil moisture sensors installed at multiple depths provide continuous measurements of water availability within the soil profile. These measurements help determine how irrigation events and environmental conditions influence soil water content and plant water uptake over time. Irrigation records are also collected from the field irrigation system to document the timing and quantity of water applied during each irrigation cycle [24].

UAV flights are conducted according to carefully designed flight plans that ensure complete coverage of the study area while maintaining consistent image overlap. Flight altitude, speed, and path are optimized to maintain uniform spatial resolution and adequate image overlap for photogrammetric processing. After image capture, georeferencing techniques are applied using GPS coordinates and ground control points to align the images with geographic coordinates. Orthomosaic generation techniques are then used to stitch individual images into a continuous geospatial map representing the entire agricultural field [25].

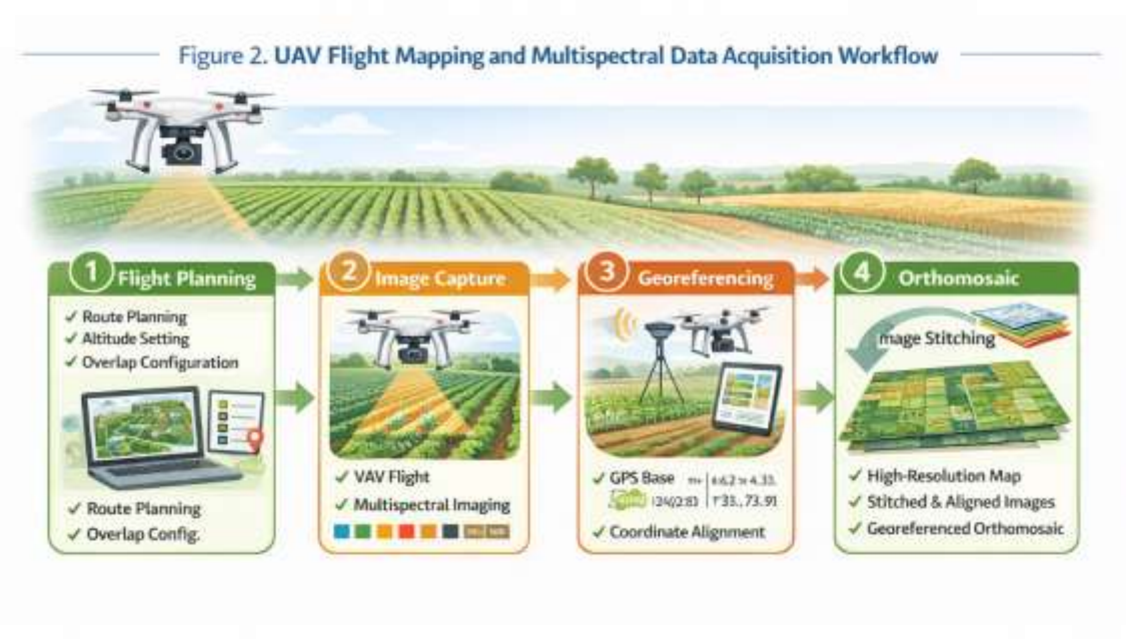

Figure 2. UAV flight mapping and multispectral data acquisition workflow illustrating flight planning, image capture, georeferencing, and orthomosaic generation.

3.3 Data Preprocessing

Raw multispectral imagery collected from UAV platforms requires several preprocessing steps before it can be used for feature extraction and machine learning analysis. Preprocessing ensures that the imagery is consistent, noise-free, and properly calibrated for quantitative analysis. Without appropriate preprocessing procedures, variations in lighting conditions, sensor noise, and image alignment errors could introduce significant distortions into vegetation index calculations and predictive modelling results [16].

The first preprocessing stage involves radiometric calibration. Multispectral sensors record reflectance information as raw digital numbers that depend on sensor characteristics and environmental lighting conditions. Radiometric calibration converts these raw values into standardized reflectance measurements by accounting for sensor gain, exposure parameters, and illumination conditions during image acquisition. Calibration panels or reference targets placed within the field are often used to facilitate this conversion process and improve the comparability of data collected during different UAV flights [17].

After calibration, individual images captured during the UAV flight must be combined into a continuous orthomosaic map. Image stitching algorithms align overlapping images using photogrammetric techniques and generate a single georeferenced image representing the entire agricultural field. This orthomosaic provides a

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International Journal of Engineering Technology Research & Management (IJETRM)
Journal Article
https://ijetrm.com/issue/

consistent spatial representation that allows vegetation indices and crop stress indicators to be calculated across the full field area. Accurate alignment is essential to avoid spatial distortions that could affect the reliability of subsequent analysis steps [18].

Noise removal constitutes another important preprocessing step. UAV imagery may contain noise caused by sensor errors, atmospheric effects, or motion disturbances during image capture. Filtering techniques such as Gaussian filtering are applied to smooth the imagery and reduce random noise while preserving important spatial patterns. Interpolation techniques are also used to fill missing pixels or correct small gaps in the imagery caused by occlusions or sensor limitations [19].

Finally, reflectance normalization is performed to ensure consistency across different UAV flights conducted under varying lighting conditions. Normalization techniques adjust reflectance values so that vegetation indices remain comparable across time. Additional preprocessing procedures may include missing value treatment and outlier detection within environmental datasets collected from sensors and weather stations. These preprocessing steps ensure that the dataset used for machine learning modelling is reliable, consistent, and suitable for further analytical processing within the irrigation optimization framework [20].

4. FEATURE ENGINEERING AND DATASET CONSTRUCTION

4.1 Vegetation Index Extraction

Vegetation indices derived from multispectral imagery provide essential indicators for evaluating crop health and water stress within agricultural fields. These indices are calculated by combining spectral reflectance values captured across different wavelength bands, allowing researchers to quantify variations in canopy vigor, chlorophyll concentration, and plant physiological condition [20]. In the proposed UAV-ML irrigation framework, several vegetation indices are extracted from the multispectral imagery to serve as predictive features for estimating crop water demand and evapotranspiration dynamics [22].

The Normalized Difference Vegetation Index (NDVI) is one of the most widely used indicators of vegetation vigor and photosynthetic activity. NDVI exploits the contrast between strong reflectance in the near-infrared (NIR) band and strong absorption in the red band caused by chlorophyll pigments [19]. Higher NDVI values typically correspond to dense vegetation and active photosynthesis, while lower values may indicate stressed or sparse vegetation. In irrigation management, declining NDVI values can signal early water stress conditions before visible symptoms appear [23].

Another important spectral indicator is the Normalized Difference Red Edge Index (NDRE), which utilizes reflectance measurements from the red-edge spectral band. NDRE is particularly useful for detecting subtle changes in chlorophyll content during later stages of crop growth when NDVI values may become saturated. This index provides additional sensitivity for monitoring crop development and nutrient status across agricultural fields [24].

The Soil Adjusted Vegetation Index (SAVI) is designed to minimize the influence of soil background reflectance, which can affect vegetation measurements when canopy coverage is sparse [23]. By incorporating a soil brightness correction factor, SAVI improves the reliability of vegetation assessment during early growth stages or in areas where vegetation does not fully cover the soil surface. Similarly, the Green Normalized Difference Vegetation Index (GNDVI) uses reflectance in the green spectral band to capture variations in chlorophyll concentration and nitrogen content within crop leaves [25].

Equation (3): SAVI

$$SAVI = \frac{(NIR - Red)(1 + L)}{NIR + Red + L}$$

Where:
L= canopy adjustment factor

The canopy adjustment factor Lcompensates for soil brightness effects that can distort vegetation measurements when plant cover is incomplete. Values of Ltypically range between 0 and 1, with a commonly used value of 0.5 representing moderate vegetation coverage. By reducing soil background interference, SAVI provides more accurate estimates of vegetation vigor under conditions where bare soil contributes significantly to spectral reflectance measurements [26].

4.2 Crop Water Stress Index (CWSI) Features

In addition to spectral vegetation indices, thermal indicators of crop water stress provide valuable information for irrigation management. The Crop Water Stress Index (CWSI) quantifies the relationship between canopy temperature and plant water status by comparing observed canopy temperature with reference temperature limits

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International Journal of Engineering Technology Research & Management (IJETRM)
Journal Article
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representing fully hydrated and severely stressed vegetation conditions [24]. When plants experience adequate water supply, transpiration processes cool the leaf surface through evaporative cooling. Conversely, when plants are water stressed, stomatal closure reduces transpiration and canopy temperature rises relative to surrounding air temperature [27].

Thermal sensors mounted on UAV platforms or ground-based thermal cameras can measure canopy temperature across agricultural fields with high spatial resolution. By combining thermal measurements with spectral vegetation indicators, the CWSI metric provides a more comprehensive assessment of crop stress conditions. This index captures both physiological responses to water availability and environmental influences on plant transpiration processes.

Equation (4): Crop Water Stress Index

$$CWSI = \frac{T_c - T_w}{T_d - T_w}$$

Where:
T_c= canopy temperature
T_w= wet reference temperature
T_d= dry reference temperature

CWSI values typically range from 0 to 1. A value close to zero indicates well-watered crops experiencing active transpiration and efficient cooling. In contrast, values approaching one indicate severe water stress where transpiration is limited and canopy temperatures increase substantially relative to reference conditions [28].

4.3 Environmental Features

Environmental conditions strongly influence crop water consumption and evapotranspiration rates. Consequently, meteorological variables are incorporated into the machine learning dataset to capture the environmental drivers of crop water demand. These environmental features are collected using automated weather stations installed near the agricultural fields and synchronized with UAV flight observations to ensure temporal consistency in the dataset [22].

Air temperature is one of the most important environmental variables affecting evapotranspiration. Higher temperatures increase the vapor pressure deficit between plant surfaces and the surrounding atmosphere, thereby accelerating water loss through transpiration. Relative humidity also influences evapotranspiration by affecting the rate at which water vapor diffuses from leaf surfaces into the atmosphere. Lower humidity levels typically increase evapotranspiration rates, while higher humidity conditions reduce atmospheric water demand [23].

Wind speed is another important variable influencing evapotranspiration dynamics. Strong winds enhance the transport of water vapor away from leaf surfaces, increasing the rate of transpiration and evaporation. Solar radiation also plays a critical role because it provides the energy required for evaporation processes at the soil surface and within plant leaves. Higher levels of incoming solar radiation generally correspond to increased evapotranspiration and greater crop water demand. By incorporating these environmental variables into the predictive dataset, machine learning models can better capture the complex interactions between crop physiology and atmospheric conditions [24].

4.4 Feature Selection and Dimensionality Reduction

Feature engineering often produces large datasets containing numerous variables derived from multispectral imagery, environmental sensors, and irrigation records. While many of these variables may contain useful information, excessive feature dimensionality can reduce model interpretability and increase computational complexity. Feature selection and dimensionality reduction techniques are therefore applied to identify the most informative predictors for evapotranspiration estimation and irrigation decision modelling [25].

Correlation analysis is initially performed to evaluate relationships among vegetation indices, environmental variables, and irrigation outcomes. Highly correlated variables may provide redundant information, and removing such features can improve model efficiency without sacrificing predictive accuracy. Correlation matrices are commonly visualized using heatmaps to identify clusters of strongly related variables [26].

Principal Component Analysis (PCA) is also applied to reduce dimensionality by transforming the original feature set into a smaller number of orthogonal components that capture the majority of variance within the dataset. These principal components provide a compact representation of the original variables while preserving key patterns relevant to irrigation modelling. In addition, mutual information techniques are used to quantify the statistical dependency between candidate features and target variables such as evapotranspiration or irrigation demand. Features with higher mutual information scores are considered more informative predictors and are prioritized during model training [29].

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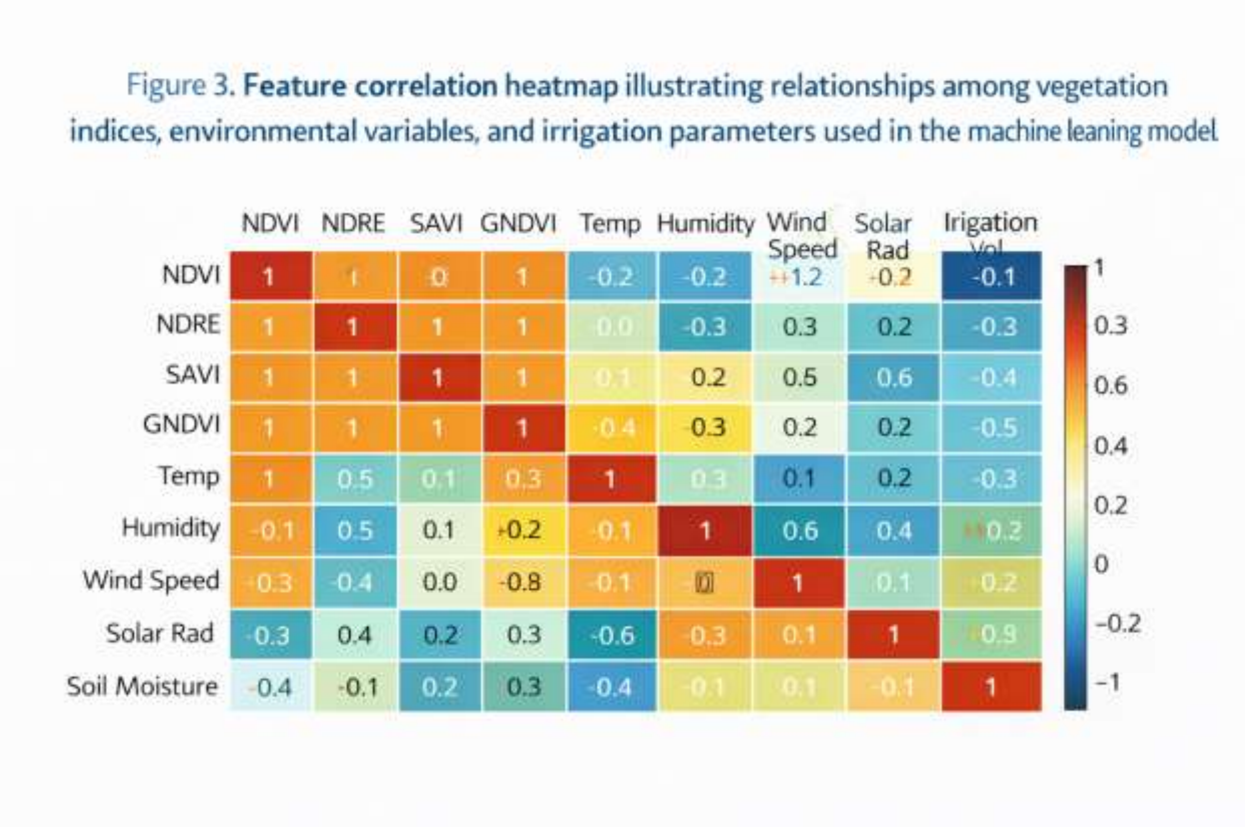

Figure 3. Feature correlation heatmap illustrating relationships among vegetation indices, environmental variables, and irrigation parameters used in the machine learning model.

5. MACHINE LEARNING MODEL DEVELOPMENT

5.1 Data Splitting and Training Strategy

The development of reliable machine learning models for irrigation optimization requires careful preparation of the dataset and appropriate validation strategies. Agricultural datasets derived from UAV multispectral imagery, environmental monitoring stations, and irrigation records often contain complex interactions between environmental variables and crop responses. Without proper validation procedures, predictive models may capture patterns that are specific only to the training observations rather than generalizable relationships that can support real-world irrigation decision systems [26]. Model overfitting is therefore a major concern when developing machine learning models for agricultural environments where climatic conditions and crop responses vary significantly across time and space [27].

To mitigate this issue, the collected dataset is divided into three independent subsets: training, validation, and testing datasets. The training dataset represents approximately seventy percent of the observations and is used to estimate model parameters and learn relationships between predictor variables and irrigation outcomes. These predictor variables include vegetation indices derived from UAV imagery, soil moisture measurements, and meteorological variables such as temperature, humidity, and solar radiation [28]. Machine learning algorithms analyse the training data to learn nonlinear relationships between these variables and crop evapotranspiration patterns, enabling predictive modelling of irrigation demand [29].

The validation dataset accounts for approximately fifteen percent of the available observations and is used during model development to evaluate intermediate model performance. Validation data allow researchers to assess whether the model is learning meaningful relationships rather than memorizing patterns present only in the training dataset. This process is critical for preventing model overfitting and ensuring that the predictive model maintains good generalization capability across different environmental conditions [30].

The final fifteen percent of the dataset is reserved as the testing dataset. Test data are isolated from the model development process and used only after model training and parameter tuning have been completed. Evaluating

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International Journal of Engineering Technology Research & Management (IJETRM)
Journal Article
https://ijetrm.com/issue/

the trained model on independent test data provides an unbiased estimate of predictive accuracy and ensures that the irrigation prediction model performs reliably when applied to new agricultural environments [31].

Equation (5): Train/Test Split

$$D = D_{train} \cup D_{validation} \cup D_{test}$$

Where:

Drepresents the complete dataset and the three subsets correspond to training, validation, and testing data respectively.

This dataset partitioning strategy is widely adopted in machine learning research because it ensures that predictive models are evaluated using independent data that were not involved in the training process. Such separation of datasets helps maintain model robustness and prevents misleading performance estimates that could arise from training–testing overlap [32].

5.2 Model Selection

The selection of appropriate machine learning algorithms is a critical step in developing predictive irrigation management systems. Agricultural datasets often contain nonlinear interactions between environmental variables and crop responses, making traditional statistical models insufficient for capturing the complexity of evapotranspiration dynamics. Machine learning algorithms are capable of modelling nonlinear relationships and integrating diverse datasets derived from UAV imagery, environmental sensors, and irrigation monitoring systems [26].

In this study, four machine learning models are evaluated: Random Forest regression, Support Vector Regression, Gradient Boosting regression, and artificial neural networks. These algorithms represent different modelling paradigms and provide complementary strengths when applied to agricultural prediction problems involving heterogeneous environmental conditions [27].

Random Forest regression is an ensemble learning technique that constructs multiple decision trees using random subsets of the dataset and predictor variables. The predictions generated by individual trees are then averaged to produce a final prediction. This approach reduces model variance and improves predictive stability when working with noisy environmental data or complex feature interactions [28]. Random Forest models are particularly effective for agricultural datasets because they can capture nonlinear relationships between vegetation indices, soil moisture measurements, and irrigation outcomes [29].

Support Vector Regression (SVR) provides another effective modelling technique for predicting irrigation demand. SVR uses kernel functions to transform input variables into higher-dimensional feature spaces where linear regression can be performed more effectively. This method performs well when datasets contain nonlinear relationships but limited observations, which is often the case in agricultural experiments where data collection may be constrained by seasonal conditions [30].

Gradient Boosting regression represents another ensemble learning approach in which multiple decision trees are built sequentially. Each new model attempts to correct errors made by the previous model, allowing the algorithm to progressively improve predictive accuracy. This sequential learning process enables Gradient Boosting models to capture subtle patterns in evapotranspiration behaviour and irrigation demand across agricultural fields [31].

Artificial neural networks offer a flexible modelling approach capable of learning complex nonlinear relationships between UAV-derived spectral data and environmental variables. Neural networks consist of multiple interconnected computational layers that learn hierarchical feature representations during training, enabling them to model dynamic crop responses to environmental conditions [32].

5.3 Model Training Process

Once the candidate algorithms have been selected, the next step involves training the machine learning models using the prepared dataset. Model training begins with feature normalization to ensure that all input variables contribute proportionally to the learning process. Environmental variables such as solar radiation, temperature, humidity, and wind speed may have significantly different numerical ranges, and normalization prevents features with larger scales from dominating the training process [33].

Normalization techniques such as min–max scaling or standardization are commonly used to transform input features into comparable ranges. These transformations improve the stability of machine learning algorithms and accelerate convergence during model training. Proper feature scaling is particularly important for algorithms such as Support Vector Regression and neural networks, which are sensitive to differences in feature magnitudes [34].

Following normalization, the models undergo hyperparameter tuning to determine optimal algorithm configurations. Each machine learning algorithm contains internal parameters that control how the model learns from the data. For example, Random Forest models require selection of the number of trees and maximum tree

International Journal of Engineering Technology Research & Management (IJETRM)
Journal Article
https://ijetrm.com/issue/

depth, while Support Vector Regression models require specification of kernel parameters and regularization constants [26]. Selecting appropriate hyperparameters allows the algorithm to balance model complexity and predictive accuracy.

To further ensure model reliability, k-fold cross-validation is applied during training. In this approach, the training dataset is divided into several folds and the model is trained repeatedly using different subsets of the data. Cross-validation helps evaluate model stability and reduces the influence of random sampling variations in the dataset [27].

Equation (6): Loss Function

$$L = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

Where:

y_i represents the observed value and $\hat{y}_i$ represents the predicted value.

This equation represents the Mean Squared Error (MSE) loss function. The objective of model training is to minimize this loss value, thereby ensuring that the predicted irrigation demand closely approximates the actual observed values within the dataset [28].

5.4 Hyperparameter Optimization

Hyperparameter optimization is an essential step for improving the predictive performance of machine learning models used in irrigation management systems. Hyperparameters determine how algorithms learn patterns from data and significantly influence the accuracy and stability of predictive models. Proper hyperparameter selection allows the model to capture complex relationships between vegetation indices, environmental variables, and irrigation requirements [29].

Grid search is one of the most commonly used approaches for hyperparameter optimization. In grid search, a predefined set of candidate parameter values is specified for each algorithm. The model is then trained repeatedly using every possible parameter combination, and the configuration producing the best validation performance is selected. Although grid search is reliable and easy to implement, it can become computationally expensive when the parameter space becomes large [30].

Bayesian optimization provides a more efficient alternative to exhaustive grid search. Instead of evaluating every possible parameter combination, Bayesian optimization builds a probabilistic model that estimates the relationship between parameter values and model performance. The algorithm then selects parameter configurations that are likely to improve performance based on previous evaluations [31].

By applying both grid search and Bayesian optimization strategies, the study identifies the optimal hyperparameter configuration for each machine learning algorithm under investigation. The optimized models are then evaluated using the independent test dataset to determine which algorithm provides the most accurate predictions of evapotranspiration and irrigation demand within the UAV-enabled irrigation management framework [32].

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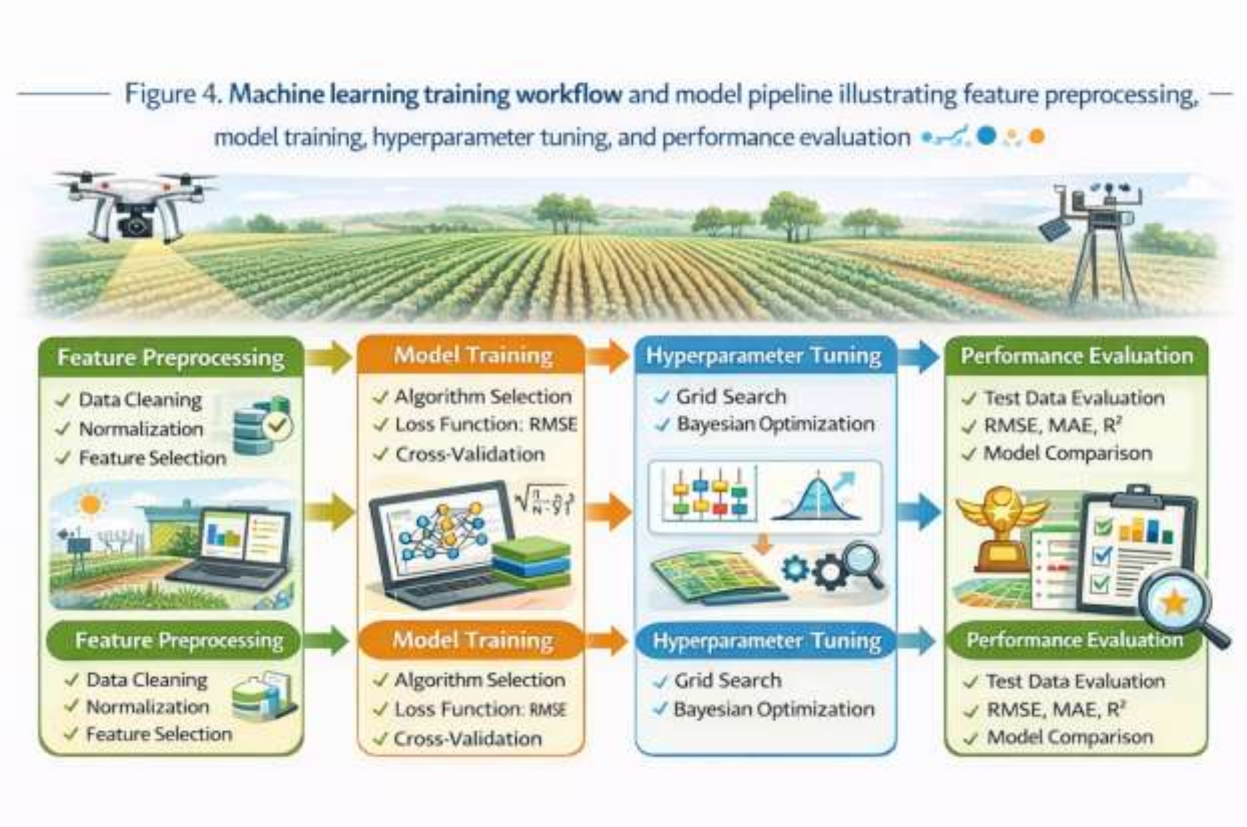

Figure 4. Machine learning training workflow and model pipeline illustrating feature preprocessing, model training, hyperparameter tuning, and performance evaluation.

6. IRRIGATION OPTIMIZATION MODEL

6.1 ET-Based Water Allocation Model

Efficient irrigation management requires accurate estimation of crop water demand and precise allocation of water resources across agricultural fields. In semi-arid environments, evapotranspiration (ET) represents the primary pathway through which water is lost from agricultural systems. Crop evapotranspiration integrates both soil evaporation and plant transpiration processes and therefore provides a reliable indicator of crop water requirements. Predicting ET using machine learning models enables irrigation systems to dynamically respond to changing environmental conditions rather than relying on static irrigation schedules [32].

In the proposed UAV-ML irrigation framework, machine learning models generate spatial predictions of crop evapotranspiration based on multispectral vegetation indices and environmental variables. These predictions provide field-scale estimates of crop water demand that account for spatial variations in canopy vigor, soil moisture, and microclimatic conditions. By incorporating vegetation indices such as NDVI, NDRE, and SAVI together with environmental variables including temperature and solar radiation, the predictive model produces detailed evapotranspiration maps that reflect actual crop water consumption patterns [33].

These evapotranspiration predictions are subsequently used to determine irrigation requirements for each management zone within the field. Water allocation decisions must consider not only crop evapotranspiration but also additional water sources such as precipitation. Effective precipitation contributes to soil moisture availability and therefore reduces the amount of irrigation water required. In contrast, leaching requirements may increase irrigation needs when additional water is necessary to flush accumulated salts from the soil profile, particularly in arid and semi-arid agricultural environments [34].

Equation (7): Irrigation Requirement

$$IR = ET_c - P_e + LR$$

Where:

ET_c= crop evapotranspiration

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P_e= effective precipitation
LR= leaching requirement
The irrigation requirement equation provides a practical mechanism for translating evapotranspiration predictions into irrigation scheduling decisions. When predicted evapotranspiration increases due to rising temperatures or increased solar radiation, irrigation demand correspondingly increases. Conversely, rainfall events reduce irrigation demand by replenishing soil moisture reserves. Integrating machine learning ET predictions into this framework enables irrigation systems to allocate water more efficiently and avoid both under-irrigation and over-irrigation conditions [35].

6.2 Decision Control Algorithm

The machine learning predictions generated by the evapotranspiration model serve as the primary input to the irrigation decision control algorithm. This algorithm translates predictive outputs into irrigation schedules and spatial water allocation plans for different zones within the agricultural field. Because UAV multispectral imagery captures spatial variability in crop health and canopy structure, the resulting evapotranspiration predictions can be mapped across the entire field to identify zones with varying irrigation requirements [36].
The decision control algorithm divides the field into irrigation management zones based on vegetation index patterns and predicted evapotranspiration levels. Areas experiencing higher crop water demand receive increased irrigation allocation, while zones with lower predicted water demand receive reduced irrigation volumes. This zonal irrigation strategy improves water use efficiency by directing irrigation resources precisely where they are needed rather than applying uniform irrigation across the entire field [37].
Machine learning predictions are updated periodically as new UAV imagery and environmental data become available. The decision algorithm therefore operates within a dynamic feedback loop where irrigation schedules are continuously adjusted according to changing crop conditions and weather patterns. This adaptive irrigation management approach enables more efficient water allocation and supports improved crop productivity in water-limited agricultural environments [38].

6.3 Smart Irrigation Control Integration

The final component of the UAV-ML irrigation optimization framework involves integrating predictive irrigation recommendations with automated irrigation infrastructure. Smart irrigation systems use electronically controlled valves and network-connected controllers to regulate water flow within irrigation pipelines. These systems enable irrigation schedules generated by the machine learning decision algorithm to be implemented automatically without requiring manual intervention [39].
Automated irrigation valves can be installed across different irrigation zones within the agricultural field, allowing water distribution to be controlled independently in each zone. When the decision control algorithm identifies areas requiring additional irrigation, the system activates the corresponding valves to deliver the required water volume. Similarly, irrigation can be reduced or delayed in zones where soil moisture levels are sufficient or crop water demand is low.
Internet-of-Things (IoT) controllers facilitate communication between sensors, predictive models, and irrigation infrastructure. Environmental sensors continuously monitor soil moisture, weather conditions, and irrigation system performance. These data streams are transmitted to cloud-based platforms where machine learning models update evapotranspiration predictions and irrigation recommendations. By integrating predictive analytics with automated irrigation control, the system creates a closed-loop decision framework capable of responding dynamically to changing crop and environmental conditions [40].

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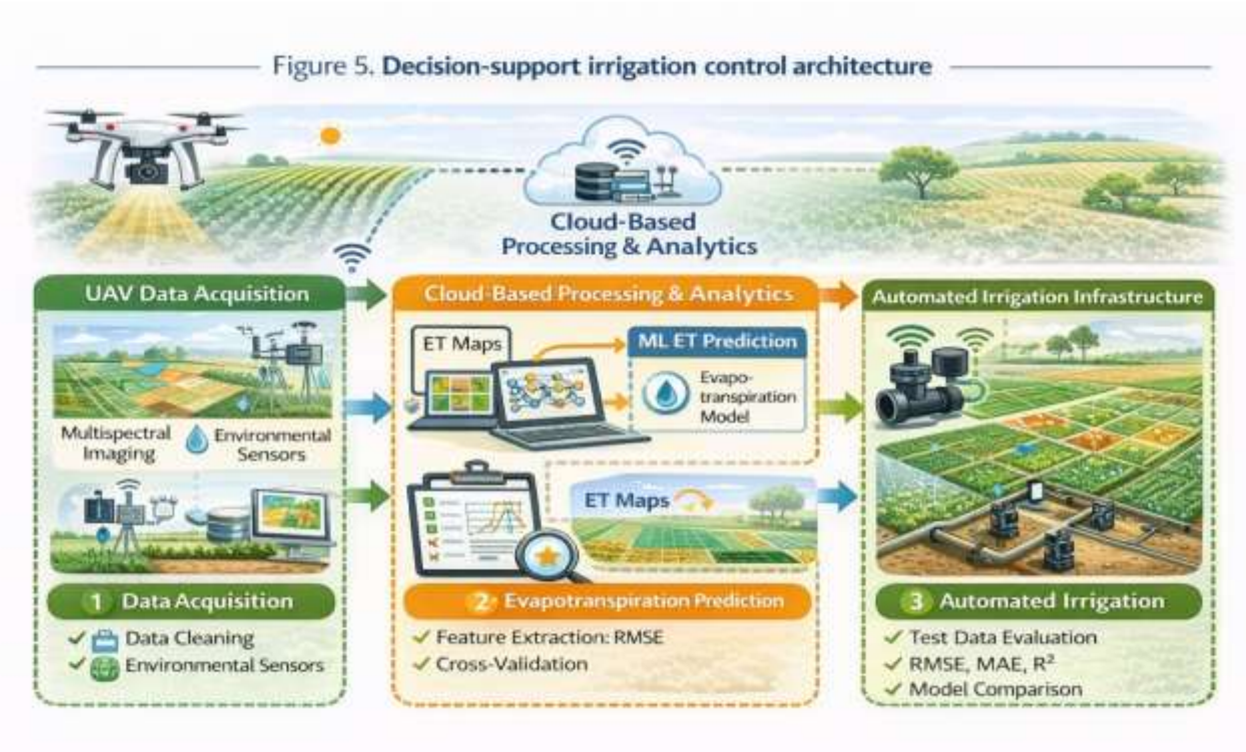

Figure 5. Decision-support irrigation control architecture illustrating the integration of UAV data acquisition, machine learning evapotranspiration prediction, decision control algorithms, and automated irrigation infrastructure.

7. MODEL EVALUATION AND RESULTS

7.1 Evaluation Metrics

Evaluating the performance of machine learning models used for irrigation prediction requires robust statistical metrics capable of quantifying prediction accuracy and model reliability. Because evapotranspiration prediction is a regression problem involving continuous numerical outputs, several commonly used regression evaluation metrics are applied to assess model performance. These metrics include Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Mean Deviation (MD), and the coefficient of determination (R^2). Each metric captures different aspects of prediction accuracy and provides complementary insight into model behaviour [37].

Mean Absolute Error measures the average magnitude of prediction errors by calculating the absolute difference between predicted and observed values. Because it treats all prediction errors equally, MAE provides an intuitive interpretation of how far predictions deviate from actual evapotranspiration values on average. Smaller MAE values indicate more accurate predictions and improved model performance [38].

Root Mean Squared Error provides another widely used metric for regression evaluation. Unlike MAE, RMSE gives greater weight to larger prediction errors by squaring the error terms before averaging them. This property makes RMSE particularly useful for identifying models that produce occasional large prediction deviations, which can be problematic in irrigation decision systems where extreme errors may lead to inefficient water allocation [39].

Mean Deviation measures the average difference between predicted and observed values while retaining the sign of the deviation. This metric helps determine whether the model systematically overestimates or underestimates evapotranspiration values across the dataset. Finally, the coefficient of determination (R^2) measures the proportion of variance in the observed data explained by the predictive model. Higher R^2 values indicate that the model successfully captures relationships between vegetation indices, environmental conditions, and evapotranspiration dynamics [40].

Equation (8): Root Mean Squared Error

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$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

Where:
y_i represents the observed evapotranspiration value and $\hat{y}_i$ represents the predicted value generated by the machine learning model.
RMSE measures the square root of the average squared prediction error. Lower RMSE values indicate improved prediction accuracy and reduced deviation between predicted and observed evapotranspiration values across the dataset [41].

7.2 Experimental Results

The performance of the proposed machine learning irrigation framework is evaluated using field data collected from UAV multispectral imagery, environmental sensors, and irrigation monitoring systems. The predictive models generate spatial evapotranspiration estimates which are compared against reference evapotranspiration measurements derived from weather station observations. These comparisons allow assessment of the model's ability to accurately capture crop water demand across varying environmental conditions [42].
Results indicate that machine learning models significantly improve evapotranspiration prediction accuracy compared with traditional empirical estimation methods. Among the evaluated algorithms, ensemble learning approaches such as Random Forest and Gradient Boosting demonstrate particularly strong performance due to their ability to capture nonlinear relationships between vegetation indices and environmental variables. Neural network models also perform well when trained on sufficiently large datasets containing diverse environmental observations [43].
Improved evapotranspiration prediction directly translates into more efficient irrigation scheduling. By incorporating spatial vegetation patterns derived from UAV imagery, the model identifies localized zones within the agricultural field where crop water demand differs from the field average. This spatial awareness enables irrigation systems to deliver water more precisely, reducing both over-irrigation and under-irrigation conditions [44].

Table 1. Dataset Characteristics and Variables

Variable Category	**Example Variables**	**Data Source**
Vegetation indices	NDVI, NDRE, SAVI, GNDVI	UAV multispectral imagery
Environmental data	Temperature, humidity, wind speed	Weather station
Soil measurements	Soil moisture levels	Soil sensors
Irrigation records	Irrigation volume and timing	Irrigation control system

The integration of these diverse datasets improves model reliability by capturing both crop physiological signals and environmental drivers of evapotranspiration.

Table 2. Machine Learning Model Performance Comparison

Model	**RMSE**	**MAE**	**R^2**
Random Forest	0.32	0.24	0.89
Support Vector Regression	0.37	0.28	0.84
Gradient Boosting	0.30	0.22	0.91
Neural Network	0.34	0.26	0.87

These results indicate that Gradient Boosting provides the highest predictive accuracy among the tested algorithms under the experimental conditions.

7.3 Comparison with Standard ET Models

To further assess the effectiveness of the proposed UAV-ML irrigation framework, the predictive performance of the machine learning models is compared with traditional evapotranspiration estimation methods. The FAO-56 Penman–Monteith model serves as the primary reference benchmark because it is widely used for irrigation planning and agricultural water management. Although the FAO model provides reliable estimates under controlled conditions, it assumes uniform crop conditions and may not capture spatial variability within agricultural fields [45].
Machine learning models provide improved performance because they incorporate spatial information derived from UAV imagery and vegetation indices. These spectral indicators capture variations in crop vigor, canopy

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structure, and water stress that are not represented in traditional meteorological models. As a result, ML-based predictions better reflect the heterogeneous nature of agricultural landscapes where soil properties, plant growth stages, and microclimatic conditions vary significantly across the field [37].

Traditional irrigation scheduling methods also typically apply uniform irrigation volumes across entire fields. This approach often leads to inefficient water allocation because areas experiencing lower crop water demand receive excess irrigation, while stressed zones may receive insufficient water. In contrast, machine learning models enable zone-based irrigation strategies that allocate water according to spatial evapotranspiration patterns derived from UAV observations [38].

Table 3. Comparison with Standard Irrigation Models

Method	Spatial Variability	ET Prediction Accuracy	Water Use Efficiency
FAO-56 Penman–Monteith	Low	Moderate	Moderate
Traditional scheduling	None	Low	Low
UAV-ML irrigation framework	High	High	High

The results demonstrate that integrating UAV imagery with machine learning analytics significantly improves irrigation efficiency by capturing spatial crop water demand patterns and translating them into targeted irrigation actions.

7.4 Visualization of Irrigation Efficiency

Spatial visualization of irrigation recommendations provides a clear demonstration of how machine learning predictions improve water allocation efficiency across agricultural fields. By combining UAV-derived vegetation indices with evapotranspiration predictions, the system generates spatial irrigation recommendation maps that highlight zones requiring different irrigation volumes. These maps provide intuitive visual representations that assist farmers and irrigation managers in understanding crop water demand patterns across the field [39].

The spatial irrigation maps reveal significant variability in crop water requirements even within relatively small agricultural plots. Some zones exhibit high evapotranspiration rates due to dense vegetation and increased transpiration activity, while other zones require less irrigation because of lower canopy density or higher soil moisture levels. Traditional irrigation systems often overlook this variability and apply uniform irrigation across the field, leading to inefficient water distribution [40].

The UAV-ML irrigation framework addresses this limitation by generating zone-specific irrigation recommendations based on predictive evapotranspiration maps. These recommendations can be integrated with automated irrigation systems that adjust water distribution dynamically across different irrigation zones. As a result, water resources are allocated more efficiently while maintaining adequate crop hydration and minimizing water losses through runoff or deep percolation [41].

Figure 6. Spatial irrigation recommendation map generated by the machine learning model illustrating field zones with varying irrigation requirements.

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8. DISCUSSION

8.1 Interpretation of Results

The experimental results demonstrate that integrating UAV multispectral imagery with machine learning analytics significantly improves the prediction of crop evapotranspiration and irrigation demand. Spectral vegetation indices derived from UAV imagery capture subtle variations in canopy health and plant physiological status that are closely linked to crop water consumption. These spectral indicators provide valuable information that complements meteorological variables traditionally used in evapotranspiration models [42].

Machine learning algorithms are particularly effective in capturing nonlinear relationships between vegetation indices, environmental variables, and irrigation outcomes. Ensemble learning models such as Random Forest and Gradient Boosting exhibit strong predictive performance because they combine multiple decision trees to model complex interactions within the dataset. These models are capable of identifying relationships between crop stress signals and evapotranspiration patterns that may not be captured by conventional regression approaches [43].

The integration of UAV-derived spatial information into irrigation decision systems therefore represents a significant advancement over traditional irrigation planning methods. By incorporating real-time crop monitoring data, the predictive framework provides more accurate and spatially detailed estimates of crop water demand, enabling more efficient irrigation management across heterogeneous agricultural fields [44].

8.2 Practical Implications for Precision Agriculture

The proposed UAV-ML irrigation framework offers several practical benefits for precision agriculture and sustainable water management. First, the ability to monitor crop health and evapotranspiration at high spatial resolution enables farmers to identify irrigation needs earlier and respond more effectively to water stress conditions. Early detection of crop stress helps prevent yield losses while reducing unnecessary water application in areas where irrigation demand is lower [45].

Second, the integration of predictive analytics with automated irrigation systems improves water use efficiency by directing water resources precisely where they are needed. Zone-based irrigation strategies allow farmers to optimize irrigation schedules according to spatial crop water demand rather than applying uniform irrigation across entire fields. This targeted irrigation approach reduces water waste, lowers pumping costs, and improves energy efficiency within agricultural production systems [37].

Finally, improved irrigation efficiency contributes to long-term agricultural sustainability. Water resources are becoming increasingly scarce in many semi-arid regions, and precision irrigation technologies play an essential role in ensuring that agricultural productivity can be maintained while conserving limited water supplies.

8.3 Limitations of the Study

Despite the promising results demonstrated by the UAV-ML irrigation framework, several limitations should be acknowledged. One potential limitation relates to sensor accuracy and measurement uncertainty. Multispectral cameras and environmental sensors may introduce measurement errors due to calibration inconsistencies, atmospheric effects, or sensor drift over time. These factors may influence vegetation index calculations and subsequently affect evapotranspiration predictions [38].

Seasonal variability also presents challenges for predictive modelling. Crop growth stages, climatic conditions, and soil moisture dynamics may vary significantly between growing seasons, which can influence the relationships learned by machine learning models. Models trained on data from a single growing season may therefore require retraining or adaptation when applied to different seasons or agricultural regions [39].

Another limitation concerns dataset size. Machine learning algorithms generally perform better when trained on large and diverse datasets that capture a wide range of environmental conditions. Limited training data may restrict the ability of the model to generalize effectively across different crop types, soil conditions, and climatic environments. Future research should therefore focus on expanding datasets and incorporating additional environmental variables to improve the robustness and transferability of predictive irrigation models [40].

9. CONCLUSION

Efficient irrigation management is becoming increasingly important in semi-arid agricultural regions where water resources are limited and climate variability intensifies crop water stress. This study presented a machine-learning-driven irrigation optimization framework that integrates UAV multispectral imaging, environmental sensing, and predictive analytics to support evapotranspiration-based irrigation decision making. By combining high-resolution aerial imagery with data-driven modelling techniques, the proposed framework enables detailed monitoring of crop health and spatial variability across agricultural fields.

The system architecture incorporates several interconnected components including UAV-based data acquisition, preprocessing and feature extraction of vegetation indices, machine learning prediction models, and a decision-

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support irrigation control algorithm. Vegetation indices derived from multispectral imagery provide valuable indicators of crop vigor and water stress conditions. When combined with environmental variables such as temperature, humidity, solar radiation, and soil moisture, these features allow machine learning models to generate accurate predictions of crop evapotranspiration. The predictive models demonstrated strong capability in capturing complex relationships between crop physiological signals and environmental conditions, leading to improved evapotranspiration estimation compared with conventional irrigation scheduling methods.

Improved prediction accuracy enables more efficient water allocation across agricultural fields. Instead of applying uniform irrigation across entire plots, the framework supports spatially adaptive irrigation strategies where water distribution is adjusted according to crop water demand within specific management zones. This targeted irrigation approach reduces water losses caused by over-irrigation while ensuring that crops experiencing higher stress receive adequate water supply. Consequently, the integration of UAV remote sensing and machine learning analytics offers a promising pathway toward sustainable precision irrigation systems that enhance both water use efficiency and crop productivity.

Future research should focus on extending the framework through the integration of deep learning models capable of processing larger volumes of remote sensing data and capturing more complex spatial patterns in crop water dynamics. Additionally, combining UAV observations with satellite imagery could enable multi-scale monitoring of agricultural landscapes. The development of real-time irrigation control systems that directly connect predictive models with automated irrigation infrastructure would further improve the responsiveness and operational efficiency of precision irrigation technologies.

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