

# Harnessing Artificial Intelligence, Machine Learning, and Drone Technologies for Climate Change Monitoring and Mitigation

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**Abstract** - The accelerating pace of climate change necessitates innovative tools and technologies to enhance our understanding, monitoring, and mitigation strategies. Artificial Intelligence (AI), Machine Learning (ML), and Unmanned Aerial Vehicles (UAVs), commonly known as drones, are emerging as powerful allies in climate research. This ABSTRACT explores the synergistic use of AI and ML algorithms with drone technology to collect, analyze, and interpret vast and complex environmental data. Drones provide high-resolution, real-time data from hard-to-reach or hazardous regions, such as glaciers, forests, and oceans. When combined with AI and ML, this data can be processed to detect patterns, predict environmental changes, and improve the accuracy of climate models. Applications include monitoring deforestation, tracking greenhouse gas emissions, studying atmospheric conditions, and assessing the impact of natural disasters. The integration of these technologies represents a transformative shift in climate science, offering scalable, cost-effective, and precise solutions for global environmental monitoring and decision-making.

**Keywords:** Climate Change, Artificial Intelligence, Machine Learning, UAVs, Drones, Environmental Monitoring, Remote Sensing, Climate Mitigation, Predictive Analytics, Sustainable Agriculture.

## 1. INTRODUCTION

Climate change is no longer a distant concern but an immediate and evolving global challenge that continues to reshape natural and human systems across the world [1], [2], [45]. Its impacts are increasingly evident through the growing frequency of extreme weather events, accelerated glacier retreat, rising sea levels, biodiversity loss, and widespread environmental degradation [23], [34], [49]. These changes are not only disturbing ecological balance but are also placing severe pressure on agriculture, horticulture, water resources, food security, and socio-economic stability [19], [21], [53], [54]. In such a rapidly changing scenario, the need for responsive, accurate, and sustainable monitoring systems has become critically important [7], [13], [36], [50].



**Figure 1. Wildfire as a visible consequence of climate change causing severe ecosystem damage.**

Agriculture and horticulture sectors are particularly vulnerable to climate variability because crop growth, flowering, fruit setting, pest incidence, irrigation demand, and yield quality are highly dependent on environmental conditions [19], [21], [24], [53]. Sudden temperature rise, irregular rainfall, prolonged drought, floods, and heat stress have significantly affected fruit crops, vegetables, plantation crops, and protected cultivation systems [23], [34], [45], [54]. Therefore, climate-smart technologies are increasingly required to support farmers in improving resilience,

productivity, and efficient resource management [20], [22], [53], [60].

Over the years, conventional approaches such as satellite observations, ground-based measurements, weather stations, and field surveys have played a significant role in advancing climate and agricultural research [7], [13], [28], [36]. However, in practical implementation, these methods often struggle to keep pace with the scale, variability, and dynamic nature of environmental changes [14], [26], [43]. Limitations related to high operational cost, lower spatial resolution, delayed data processing, labor dependency, and restricted accessibility to remote or hazardous regions continue to reduce their effectiveness [13], [15], [41], [56]. As a result, there is growing recognition that traditional approaches alone are insufficient to address modern climate and farming challenges [2], [5], [48].

Recent developments in Artificial Intelligence (AI), Machine Learning (ML), Internet of Things (IoT), Information and Communication Technology (ICT) tools, and Unmanned Aerial Vehicles (UAVs) have opened new opportunities in this domain [1], [20], [42], [50]. ICT tools such as mobile advisory applications, smart sensors, weather alert systems, and digital farm platforms have already improved farmer awareness and decision-making [20], [53], [60]. However, their effectiveness can be further enhanced when integrated with drone-based sensing and AI-driven analytics [16], [22], [45], [55].

Drones, for instance, provide the ability to capture high-resolution, real-time data from agricultural fields, orchards, forests, glaciers, wetlands, and disaster-prone zones that are otherwise difficult or unsafe to access [13], [14], [15], [41], [56]. They can monitor crop vigor, canopy temperature, disease spread, irrigation variability, flood extent, and land-use change with high precision [16], [22], [45], [46], [55].



**Figure 2. Drone-based monitoring in horticultural orchards for precision agriculture and environmental assessment.**

At the same time, AI and ML techniques enable efficient processing of large and heterogeneous datasets, helping

uncover hidden patterns, classify environmental conditions, detect anomalies, and generate predictive insights from complex climate and agricultural information [1], [5], [28], [43], [50]. These capabilities are especially useful in horticulture for disease forecasting, yield estimation, irrigation planning, pest surveillance, and quality assessment [19], [21], [24], [42], [55].

Despite these advancements, current research often treats these technologies as isolated solutions rather than components of a unified smart ecosystem [2], [6], [48], [53]. This fragmented approach limits their full potential, particularly when dealing with interconnected climate, crop, and resource management problems [4], [36], [49]. There remains a need for frameworks that effectively combine intelligent sensing, real-time monitoring, predictive analytics, and automated decision support into a single coherent system.

The integration of AI, ML, ICT tools, and drone technologies offers a promising direction in this regard. By linking real-time data acquisition with advanced analytics, such systems can provide accurate insights, early warning alerts, optimized resource use, and informed decision-making. This integrated approach has the potential to significantly improve climate monitoring, sustainable agriculture, and horticultural management.

Farmer adoption of digital technologies is also increasing steadily [20], [47], [53]. While ICT tools are becoming common among medium-scale growers, drone-based services are gaining popularity among progressive horticulture farmers due to benefits such as reduced labor requirements, precision spraying, faster crop inspection, and improved yield outcomes [22], [41], [45], [55]. Therefore, evaluating both technological capability and practical user impact has become essential [19], [24], [60].

The primary objective of this study is to explore and demonstrate the potential of integrating AI, ML, ICT, and drone technologies for climate change monitoring and mitigation. Specifically, the study aims to:

1. Examine the capabilities of drone-based data collection in diverse environmental and horticultural contexts.
2. Evaluate the effectiveness of AI and ML algorithms in analyzing climate and agricultural data.
3. Compare traditional methods, ICT tools, and drone-assisted intelligent systems.
4. Assess the practical benefits of these technologies in improving crop productivity, resource efficiency, and decision-making.
5. Highlight a scalable and cost-effective framework for sustainable climate-smart management.

Through this work, an effort is made to move beyond isolated technological applications and contribute toward the

development of a more integrated, practical, and farmer-oriented approach for addressing climate change challenges in agriculture and horticulture.

## 2. LITERATURE REVIEW

Artificial Intelligence (AI), Machine Learning (ML), Information and Communication Technology (ICT), and Unmanned Aerial Vehicles (UAVs) have emerged as highly promising technologies for addressing modern climate, environmental, and agricultural challenges [1], [2], [13], [20], [41]. Their increasing use in monitoring systems, predictive analytics, and precision farming has created new opportunities for improving productivity, sustainability, and decision-making [19], [22], [45], [53]. However, despite rapid progress, the literature reveals that these technologies are often studied independently rather than as components of a unified intelligent system [4], [48], [50]. This section critically reviews existing research and highlights the major gaps that justify the need for the proposed integrated framework.

Artificial Intelligence and Machine Learning have become increasingly important in climate science because of their ability to process large, complex, and continuously changing datasets generated from satellites, weather stations, sensors, historical records, and remote sensing systems [5], [7], [28], [43]. Conventional statistical methods often struggle to interpret such large-scale multidimensional data efficiently [2], [42]. In contrast, AI and ML techniques can identify hidden patterns, classify environmental conditions, and generate predictive insights with higher speed and accuracy [1], [6], [50]. Existing studies have successfully applied these methods in rainfall forecasting, drought prediction, flood risk analysis, temperature trend estimation, wildfire detection, and seasonal climate modeling [10], [12], [37], [39]. Advanced approaches such as neural networks, deep learning, support vector machines, and ensemble learning have demonstrated promising predictive performance [3], [8], [29], [43]. In agriculture and horticulture, AI has also been used for disease diagnosis, crop yield prediction, irrigation scheduling, and pest outbreak forecasting [19], [21], [24], [55].

Despite these advancements, most existing AI-based studies depend heavily on historical datasets and offline modeling approaches [2], [4], [48]. Many models lack real-time field validation, spatial adaptability, and operational integration with sensing platforms [7], [36], [49]. Several predictive systems also perform well under experimental conditions but fail when deployed in dynamic farm environments due to changing weather, crop variability, and incomplete datasets [10], [21], [42]. Thus, while AI and ML are powerful analytical tools, their practical value remains

limited when not connected with live data acquisition systems [16], [41], [57].

Unmanned Aerial Vehicles, commonly known as drones, have significantly transformed the collection of environmental and agricultural data [13], [14], [15], [56]. UAVs provide high-resolution real-time imagery with greater flexibility than conventional monitoring systems [16], [41], [45]. They are particularly effective in surveying forests, wetlands, glaciers, orchards, disaster-prone zones, and inaccessible landscapes [14], [17], [38]. Many studies have reported successful drone applications in land-use mapping, flood monitoring, wildfire surveillance, biodiversity assessment, crop health detection, canopy temperature analysis, and precision spraying [17], [22], [35], [59]. In horticulture, UAVs are increasingly used for orchard mapping, fruit counting, nutrient stress detection, irrigation variability analysis, and disease monitoring [22], [45], [46], [55].

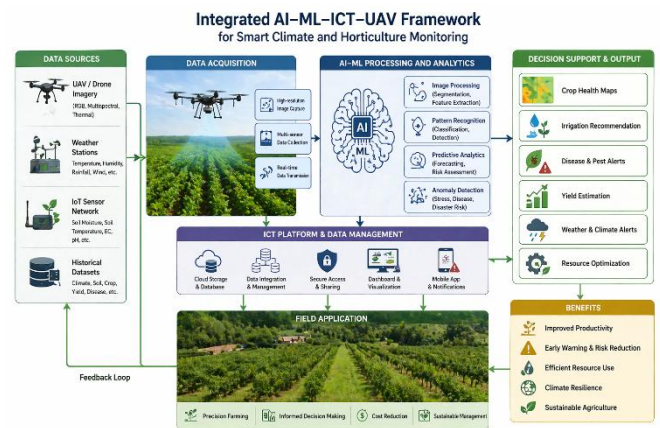


Figure 3. UAV-based data acquisition for orchard and field monitoring.

Although drones provide excellent sensing capability, a large portion of the literature focuses only on image acquisition and visualization [13], [14], [56]. In many cases, drone data are collected successfully but not transformed into automated decision-support outputs [16], [41], [57]. Several UAV studies remain descriptive rather than predictive, limiting their usefulness for farmers and planners [15], [45], [46]. Drone systems also face challenges related to battery life, limited flight endurance, weather sensitivity, data storage, and the need for trained operators [18], [38], [59]. Therefore, UAV technology alone cannot fully solve complex climate and agricultural problems without intelligent analytics and communication support [6], [22], [50].

The integration of AI, ML, ICT tools, and UAV technologies is increasingly recognized as the next stage of smart environmental monitoring [1], [20], [41], [53], [60]. Drones can collect high-resolution visual and sensor-based

data, ICT systems can transmit and manage information through mobile applications, cloud platforms, and dashboards, while AI and ML algorithms can analyze data to identify risks, forecast trends, and generate recommendations [7], [16], [43], [57]. Some recent studies have attempted partial integration for disease detection, irrigation management, disaster assessment, and crop classification [22], [24], [35], [45], [55].



**Figure 4. Integrated AI-ML-ICT-UAV framework for smart monitoring and decision support.**

However, most reported systems remain limited in scope [2], [6], [48], [50]. Many focus on a single crop, a specific region, or one environmental problem [19], [22], [45]. Others combine only two technologies, such as drone imaging with image classification, while excluding farmer usability, real-time alerts, economic optimization, or climate forecasting [16], [24], [41], [56]. Interoperability between datasets from drones, IoT sensors, weather stations, and historical records is still weak [20], [43], [53]. There is also insufficient attention to user-friendly deployment models that can be adopted by farmers, horticulture departments, and local agencies [21], [47], [60].

The literature further shows that climate change monitoring and mitigation require multi-layered solutions rather than isolated tools [1], [4], [34], [50]. Existing systems often monitor only one parameter such as temperature, vegetation index, rainfall, or land cover [13], [17], [28]. Yet real-world climate impacts on agriculture and horticulture involve interconnected factors including heat stress, water scarcity, pest outbreaks, soil degradation, flowering disorders, fruit drop, and disaster risk [19], [21], [23], [54]. Current fragmented systems fail to capture these interactions comprehensively [36], [49]. As a result, decision-making remains reactive instead of proactive [7], [39], [57].

Another major gap is the limited focus on horticulture-specific applications [22], [45], [55]. Much of the available literature concentrates on cereal crops or general

environmental monitoring, whereas horticultural systems such as fruits, vegetables, spices, medicinal crops, and plantation crops require more precise monitoring due to higher crop value and sensitivity to climate variability [19], [24], [54]. Parameters such as canopy structure, flowering stage, fruit maturity, disease onset, and microclimate variation are critical in horticulture but are underrepresented in many studies [41], [46], [55].

Economic and adoption-related gaps are also significant [47], [53], [60]. Several advanced systems are technically strong but expensive, computationally intensive, or difficult for ordinary farmers to use [21], [42], [48]. Limited digital literacy, lack of training, weak rural connectivity, regulatory barriers for drone flights, and uncertainty about return on investment reduce adoption [18], [38], [47]. Therefore, scalability and user acceptance remain unresolved issues in current literature [50], [60].

The present study is designed to overcome these limitations through a stronger and more practical integrated approach. Unlike previous fragmented systems, the proposed framework combines AI, ML, ICT tools, and UAV technologies within a single climate-smart platform. It links real-time drone sensing with predictive analytics, mobile-based communication, intelligent alerts, and resource optimization. The framework is capable of monitoring crop health, environmental stress, irrigation demand, disease risk, and climate anomalies simultaneously. It is structured not only for technical performance but also for field usability, cost-effectiveness, and scalability.

A key strength of the proposed approach is its applicability to horticulture systems, where precision monitoring is essential. By supporting orchard surveillance, canopy assessment, yield estimation, disease forecasting, and targeted interventions, the framework addresses a gap largely neglected in previous studies. In addition, its integration of real-time data and machine learning enables a shift from conventional reactive management toward predictive and preventive decision-making.

Overall, the literature confirms that while existing technologies have considerable potential individually, they remain constrained by fragmentation, limited scalability, weak real-time integration, and insufficient farmer-centered design [2], [6], [48], [50]. Therefore, a unified AI-ML-ICT-UAV framework, as proposed in this study, offers a stronger and more effective solution for climate change monitoring, mitigation, and sustainable horticultural management.

### 3. PROPOSED WORK

To overcome the limitations of traditional climate monitoring approaches, this study proposes an integrated smart framework that combines Artificial Intelligence (AI),

Machine Learning (ML), Information and Communication Technology (ICT), Internet of Things (IoT), and Unmanned Aerial Vehicles (UAVs) for real-time climate change monitoring, environmental assessment, and sustainable agricultural management. The proposed framework enables high-resolution environmental data acquisition, intelligent pattern recognition, predictive climate analytics, and rapid decision support. By integrating UAV mobility with AI/ML computational intelligence and ICT-based communication systems, the model provides a scalable, accurate, and cost-effective solution for modern environmental management. The framework is designed to support continuous monitoring, early warning generation, optimized resource utilization, and proactive climate-risk mitigation across agriculture and horticulture systems.








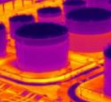
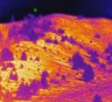
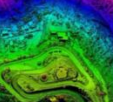
| RGB-Camera  | Multi-Spectral Camera  | IR-Camera   | SAR   | LiDAR  |
|---|--|---|---|--|
| Function: Captures visible light, providing high-resolution color imagery.<br>Limitations: Limited to day light conditions. | Function: Captures data across multiple spectral bands, aiding vegetation identification and classification.<br>Limitations: Might limited spatial resolution. | Function: Detects infrared radiation for identifying vegetation temperature.<br>Limitations: Cannot detect geological feature directly; Might limited spatial resolution. | Function: Penetrates through clouds and darkness, providing all weather and day or night monitoring.<br>Limitations: Lower spatial resolution, complex data processing. | Function: Measures distance using laserpulses creating 3D terrain model directly.<br>Limitations: Can be affected by atmospheric conditions. |
|    |    |    |    |   |
|    |    |    |    |   |
| (a)   | (b)  | (c)   | (d)   | (e)  |

Figure 6. UAV and sensor-based real-time environmental data acquisition system.

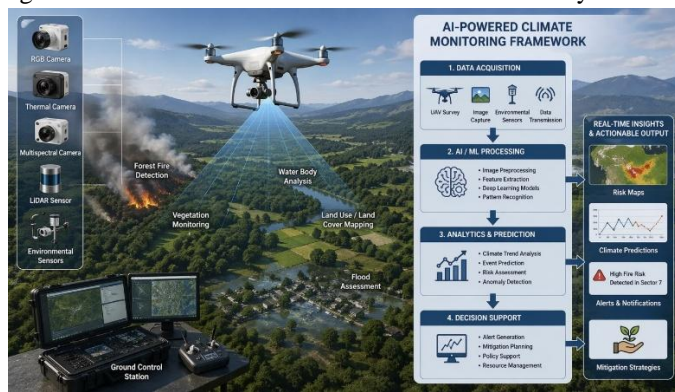


Figure 5. Proposed integrated AI-ML-ICT-UAV framework for real-time climate monitoring and smart decision support.

### 3.1 UAV-Based Environmental Data Acquisition

The first stage of the proposed framework focuses on UAV-assisted real-time environmental sensing and geospatial data acquisition, where Unmanned Aerial Vehicles (UAVs) act as intelligent mobile sensing platforms for collecting high-resolution climate and ecological information from geographically inaccessible, hazardous, or rapidly changing environments. Unlike conventional ground surveys, which are labor-intensive and spatially limited, or satellite systems, which may suffer from lower temporal resolution, cloud interference, and delayed revisit cycles, UAV systems provide flexible deployment, repeated observations, centimeter-level imaging precision, and rapid response capability. In the proposed work, drones are deployed over forests, glaciers, agricultural land, wetlands, coastal zones, urban heat islands, flood-prone areas, and wildfire-affected regions to monitor environmental change continuously and accurately. This enables dynamic observation of vegetation degradation, glacier retreat, soil stress, flood spread, erosion patterns, wildfire progression, and atmospheric anomalies in near real time.

Each UAV platform carries a multi-sensor payload consisting of RGB cameras, thermal infrared cameras, multispectral cameras, LiDAR scanners, atmospheric gas sensors, humidity sensors, pressure sensors, GPS receivers, and inertial navigation systems. The RGB camera captures visible-spectrum orthomosaic imagery for land-use classification and object detection, thermal cameras identify canopy stress, urban heat accumulation, and wildfire hotspots, multispectral sensors are used for vegetation health estimation, LiDAR generates three-dimensional terrain and biomass structure, while gas sensors help estimate local anomalies in CO<sub>2</sub>, CH<sub>4</sub>, and other emissions. The total sensing state of the UAV at time  $t$  can be mathematically expressed as:

$$X_t = [I_t^{RGB}, I_t^{TH}, I_t^{MS}, L_t, G_t, H_t, P_t, V_t, Lat_t, Lon_t]$$

where  $I_t^{RGB}$  denotes visible imagery,  $I_t^{TH}$  thermal imagery,  $I_t^{MS}$  multispectral observations,  $L_t$  LiDAR point clouds,  $G_t$  gas measurements,  $H_t$  humidity,  $P_t$  pressure,  $V_t$  UAV velocity, and  $Lat_t, Lon_t$  geographic coordinates. These heterogeneous sensor streams allow the proposed system to capture both physical surface conditions and atmospheric characteristics simultaneously.

The environmental dataset generated during UAV missions is represented as:

$$D = \{x_1, x_2, x_3, \dots, x_n\}$$

where each observation sample is defined as:

$$x_i = [R_i, G_i, B_i, T_i, H_i, M_i, S_i, Z_i, Lat_i, Lon_i, t_i]$$

Here,  $R_i, G_i, B_i$  are image spectral channels,  $T_i$  is surface temperature,  $H_i$  humidity,  $M_i$  soil moisture,  $S_i$  gas concentration,  $Z_i$  elevation,  $Lat_i, Lon_i$  spatial coordinates, and  $t_i$  timestamp. This structured representation supports machine learning pipelines by combining visual, thermal, atmospheric, spatial, and temporal variables into a unified feature space.

To improve prediction quality, the UAV-generated dataset is integrated with external sources such as meteorological station records, historical climate archives, crop yield databases, hydrological sensors, manual biomass surveys, and national environmental reports. Thus, the complete dataset becomes:

$$D_{total} = D_{UAV} \cup D_{Ground} \cup D_{Hist}$$

where  $D_{UAV}$  is drone-acquired data,  $D_{Ground}$  contains ground-truth field measurements, and  $D_{Hist}$  represents historical climate records. This fusion of real-time and legacy data significantly improves model calibration, robustness, and long-term forecasting accuracy.

The spatial quality of drone imagery is determined using the Ground Sampling Distance (GSD), which defines the real-world area represented by each image pixel. It is computed as:

$$GSD = \frac{H \times p}{f}$$

where  $H$  is UAV altitude,  $p$  is camera pixel size, and  $f$  is focal length. Lower GSD values indicate finer image resolution. The image footprint dimensions are given by:

$$W = \frac{H \times S_w}{f}, L = \frac{H \times S_l}{f}$$

where  $S_w$  and  $S_l$  are sensor width and length. The total area surveyed during a mission is estimated by:

$$A = v \times w \times t \times \eta$$

where  $v$  is UAV velocity,  $w$  scan swath width,  $t$  mission duration, and  $\eta$  overlap efficiency factor. This formulation enables efficient mission planning and optimal resource utilization.

Since UAV battery capacity is limited, route planning is essential for maximizing coverage while minimizing energy consumption. The total travel path is expressed as:

$$L = \sum_{i=1}^{n-1} \sqrt{(x_{i+1} - x_i)^2 + (y_{i+1} - y_i)^2}$$

and the corresponding energy expenditure is modeled as:

$$E = \alpha d + \beta h + \gamma v^2 t$$

where  $d$  is horizontal distance,  $h$  altitude gain,  $v$  speed, and  $\alpha, \beta, \gamma$  are system constants. The mission optimization objective is therefore:

$$\text{Minimize } J = \lambda_1 L + \lambda_2 E - \lambda_3 A$$

which minimizes path length and energy while maximizing survey area.

Repeated drone missions allow time-series environmental monitoring. If  $N_m$  missions are conducted over a time interval  $T$ , the temporal sampling frequency is:

$$f_s = \frac{N_m}{T}$$

and environmental change between two observations is measured as:

$$\Delta X = X_{t_2} - X_{t_1}$$

This enables accurate quantification of forest cover loss, glacier retreat, flood expansion, shoreline erosion, and crop growth progression over time.

The collected data is transmitted to a ground station or edge-processing node. Communication delay is estimated by:

$$T_d = \frac{S}{B} + L_n$$

where  $S$  is file size,  $B$  network bandwidth, and  $L_n$  communication latency. For urgent scenarios such as wildfire detection or flood progression, onboard edge computing is preferred because:

$$T_{edge} < T_{cloud}$$

thereby reducing response time and enabling immediate alerts.

To improve reliability, sensor fusion is employed using weighted averaging:

$$X_f = \sum_{i=1}^m w_i X_i, \sum_{i=1}^m w_i = 1$$

where  $X_i$  are individual sensor observations and  $w_i$  their confidence weights. Measurement noise variance is estimated as:

$$\sigma_n^2 = \frac{1}{N} \sum_{i=1}^N (x_i - \mu)^2$$

which supports calibration and uncertainty control.

Overall, the UAV-Based Environmental Data Acquisition layer forms the foundational component of the proposed framework by enabling rapid, repeated, multi-sensor, and high-precision data collection across climate-sensitive regions. The generated data supports downstream AI and ML modules for prediction, anomaly detection, and mitigation planning, making the entire framework more intelligent, scalable, and operationally efficient.

### 3.2 Data Preprocessing and Feature Engineering

The raw environmental data collected from UAV platforms is inherently heterogeneous and may contain sensor noise, motion blur, illumination inconsistency, atmospheric distortion, missing values, redundant observations, and georeferencing errors. Therefore, before applying Artificial Intelligence (AI) and Machine Learning (ML) algorithms, a robust **data preprocessing and feature engineering layer** is required to transform raw drone observations into structured, high-quality analytical inputs. This stage is critical because the predictive accuracy, generalization capability, and convergence performance of learning models strongly depend on the quality of input data. In the proposed framework, preprocessing is performed on RGB imagery, thermal maps, multispectral bands, LiDAR point clouds, atmospheric measurements, and time-series environmental records.

The first step involves **data cleaning**, where corrupted frames, duplicated images, sensor outliers, null values, and

transmission errors are removed. If an observation variable contains missing values, interpolation can be performed using linear estimation:

$$x_t = x_{t-1} + \frac{(x_{t+1} - x_{t-1})}{2}$$

For multiple missing entries, spline or Kalman-based interpolation may be applied. Outlier detection is performed using statistical thresholds:

$$|x_i - \mu| > k\sigma$$

where  $\mu$  is the mean,  $\sigma$  is standard deviation, and  $k$  is typically selected as 2 or 3. Values exceeding this threshold are treated as anomalies and corrected or removed.

To ensure numerical consistency across variables with different scales, **feature normalization** is applied. Standard score normalization (z-score transformation) is expressed as:

$$x' = \frac{x - \mu}{\sigma}$$

where  $x$  is the original value,  $\mu$  is feature mean, and  $\sigma$  is feature standard deviation. This transformation produces zero-mean and unit-variance distributions, which improves convergence in gradient-based ML models. For bounded features, **min-max scaling** is used:

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}}$$

which rescales all values into the interval [0, 1]. This is particularly useful for neural networks using sigmoid or ReLU activation functions.

Drone imagery frequently suffers from blur, vibration noise, atmospheric haze, and illumination fluctuations. Therefore, image enhancement and smoothing operations are applied. Gaussian filtering is used to suppress high-frequency noise while preserving structural information:

$$G(x, y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}}$$

where  $\sigma$  controls the spread of smoothing. The filtered image is obtained by convolution:

$$I_f = I * G$$

where  $I$  is the original image and  $I_f$  is the smoothed output. Histogram equalization may further enhance contrast in shadowed regions.

Since climate monitoring heavily depends on vegetation condition, multiple **spectral indices** are extracted from multispectral imagery. The Normalized Difference Vegetation Index (NDVI), widely used for crop vigor and biomass estimation, is computed as:

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

where  $NIR$  is near-infrared reflectance and  $Red$  is red-band reflectance. Values approaching +1 indicate dense healthy vegetation, values near 0 indicate sparse cover or soil, and negative values indicate water or cloud cover.

To reduce soil background influence, the Soil Adjusted Vegetation Index (SAVI) is also computed:

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

where  $L$  is a canopy background correction factor. Enhanced Vegetation Index (EVI) may be used in dense canopies:

$$EVI = G \frac{NIR - Red}{NIR + C_1 Red - C_2 Blue + L}$$

where  $G, C_1, C_2, L$  are calibration constants.

Thermal imagery is used to estimate plant and land surface stress. The **Water Stress Index (WSI)** is calculated as:

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

where  $T_c$  is canopy temperature,  $T_w$  is wet reference temperature, and  $T_d$  is dry reference temperature. Higher WSI values indicate severe moisture stress and insufficient transpiration.

Land Surface Temperature (LST) can be estimated from thermal radiance using:

$$LST = \frac{BT}{1 + (\lambda BT / \rho) \ln \epsilon}$$

where  $BT$  is brightness temperature,  $\lambda$  wavelength,  $\rho$  calibration constant, and  $\epsilon$  surface emissivity.

For three-dimensional terrain and biomass analysis, LiDAR point clouds are converted into elevation descriptors. Surface height is calculated as:

$$H = z_{canopy} - z_{ground}$$

where  $z_{canopy}$  is canopy elevation and  $z_{ground}$  is ground elevation. Vegetation density can then be estimated from point returns.

Temporal climate records such as temperature, rainfall, humidity, and moisture are transformed into sequential features. Moving average smoothing is applied as:

$$MA_t = \frac{1}{n} \sum_{i=0}^{n-1} x_{t-i}$$

while rate of change is:

$$\Delta x_t = x_t - x_{t-1}$$

These features help recurrent models detect drought trends, sudden heat rise, and rainfall anomalies.

To reduce dimensionality and computational burden, Principal Component Analysis (PCA) is applied:

$$Z = W^T X$$

where  $X$  is original feature matrix and  $W$  contains eigenvectors of the covariance matrix. PCA preserves dominant variance while removing redundancy.

The final engineered feature vector used for learning is represented as:

$$F_i = [NDVI_i, SAVI_i, EVI_i, WSI_i, LST_i, H_i, M_i, G_i, \Delta x_i, PC_i]$$

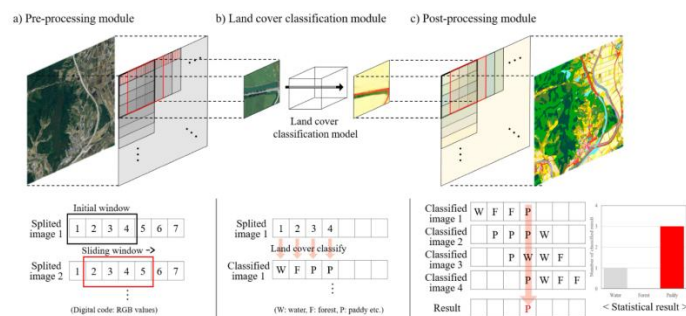
where each term represents a derived ecological or climatic indicator. These features significantly improve downstream classification, forecasting, and anomaly detection performance.

Overall, the Data Preprocessing and Feature Engineering layer transforms noisy multi-sensor UAV observations into

standardized, information-rich inputs suitable for AI/ML analysis. By integrating image enhancement, normalization, spectral index generation, thermal stress estimation, temporal feature extraction, and dimensionality reduction, this stage ensures robustness, efficiency, and high predictive accuracy of the proposed climate monitoring framework.

### 3.3 AI-Based Environmental Image Analysis

The third stage of the proposed framework focuses on **AI-based environmental image analysis**, where drone-acquired imagery is processed using advanced deep learning algorithms to automatically detect, classify, segment, and interpret environmental patterns. UAV systems continuously generate large volumes of RGB, thermal, and multispectral images, which cannot be efficiently analyzed through manual inspection. Therefore, Artificial Intelligence—particularly Convolutional Neural Networks (CNNs)—is employed to transform raw drone imagery into actionable environmental intelligence. This layer enables rapid identification of climate-sensitive events such as deforestation, flood inundation, wildfire hotspots, crop disease outbreaks, land degradation, shoreline erosion, glacier retreat, and urban heat island expansion.



**Figure 7. AI and Machine Learning engine for predictive analytics and smart recommendations.**

Before deep learning analysis, the captured drone images are preprocessed to remove illumination inconsistency, motion blur, sensor noise, and geometric distortion. Let the input image be represented as:

$$X \in \mathbb{R}^{H \times W \times C}$$

where  $H$  and  $W$  denote image height and width, and  $C$  represents the number of channels (RGB, thermal, or multispectral bands). The normalized image is expressed as:

$$X' = \frac{X - \mu}{\sigma}$$

where  $\mu$  and  $\sigma$  are the mean and standard deviation of pixel intensities. This normalization improves convergence speed and training stability.

The core feature extraction process is performed through convolutional layers, where learnable filters slide across the image to capture edges, textures, shapes, thermal signatures,

and vegetation patterns. The convolution operation is mathematically defined as:

$$Y(i, j) = \sum_m \sum_n X(i - m, j - n)K(m, n) + b$$

where  $X$  is the input image,  $K$  is the convolution kernel,  $b$  is the bias term, and  $Y(i, j)$  is the generated feature map at spatial location  $(i, j)$ . Multiple kernels are learned automatically during training to capture different environmental signatures such as canopy texture, water boundaries, fire smoke, and damaged land patterns. To introduce non-linearity and enable learning of complex structures, the Rectified Linear Unit (ReLU) activation function is applied:

$$ReLU(x) = \max(0, x)$$

This suppresses negative activations while preserving positive responses, thereby reducing vanishing gradient issues and improving computational efficiency. In deeper networks, alternative activations such as Leaky ReLU may also be used:

$$f(x) = \begin{cases} x, & x > 0 \\ \alpha x, & x \leq 0 \end{cases}$$

where  $\alpha$  is a small constant.

Spatial dimensionality reduction is performed using pooling layers, which retain dominant information while reducing computational cost and sensitivity to noise. Max-pooling is expressed as:

$$P(i, j) = \max_{(m, n) \in R} Y(m, n)$$

where  $R$  is the local pooling region. Pooling helps preserve strong wildfire heat signatures, flood edges, and vegetation anomalies while suppressing irrelevant background information.

After multiple convolution and pooling stages, the extracted feature tensor is flattened and passed into fully connected layers for classification. If the final network output vector is  $z = [z_1, z_2, \dots, z_k]$ , the probability of class  $i$  is computed using Softmax:

$$P(y_i) = \frac{e^{z_i}}{\sum_{j=1}^k e^{z_j}}$$

where  $k$  is the number of target classes. In the proposed environmental framework, output classes may include forest, water, barren land, flood zone, fire hotspot, healthy crop, stressed crop, urban surface, glacier, or degraded land. During training, prediction error is minimized using cross-entropy loss:

$$L = - \sum_{i=1}^k y_i \log(\hat{y}_i)$$

where  $y_i$  is the true label and  $\hat{y}_i$  is the predicted probability. This loss function strongly penalizes incorrect confident predictions and improves classification reliability.

For binary environmental detection tasks such as wildfire/no-fire or flood/non-flood, binary cross-entropy may be used:

$$L = -[y \log(\hat{y}) + (1 - y) \log(1 - \hat{y})]$$

To update network weights efficiently, gradient descent optimization is performed:

$$w_{t+1} = w_t - \eta \frac{\partial L}{\partial w_t}$$

where  $\eta$  is the learning rate. In practical implementations, Adam optimizer is often preferred:

$$\theta_{t+1} = \theta_t - \eta \frac{\hat{m}_t}{\sqrt{\hat{v}_t + \epsilon}}$$

The proposed framework also supports semantic segmentation for pixel-wise environmental mapping. For flood extent detection or forest canopy extraction, each pixel is assigned a class label using encoder-decoder architectures such as U-Net or DeepLab. Pixel accuracy is measured as:

$$PA = \frac{\sum_i n_{ii}}{\sum_i t_i}$$

and Intersection over Union (IoU) is:

$$IoU = \frac{TP}{TP + FP + FN}$$

where  $TP$ ,  $FP$ , and  $FN$  denote true positive, false positive, and false negative pixels.

For object detection tasks such as identifying damaged buildings, fallen trees, or fire spots, bounding-box regression is performed using:

$$B = (x, y, w, h)$$

where  $x, y$  are center coordinates and  $w, h$  are width and height of detected objects.

To evaluate model performance, the following metrics are used:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$F1 = \frac{2PR}{P + R}$$

The practical applications of this AI-based image analysis layer include automatic wildfire hotspot alerts, real-time flood boundary extraction, deforestation progression monitoring, crop disease recognition, shoreline erosion mapping, glacier surface crack detection, and land-use change assessment. Since UAV imagery has very high spatial resolution, CNN-based models can detect subtle environmental anomalies that may be missed by coarse-resolution satellite systems.

### 3.4 Climate Forecasting Using Deep Learning

Climate systems are highly dynamic and exhibit nonlinear temporal behavior influenced by seasonal cycles, delayed atmospheric interactions, hydrological responses, vegetation feedback, and long-term environmental change. Variables such as rainfall, temperature, humidity, wind speed, soil

moisture, and atmospheric pressure are strongly time-dependent, making conventional statistical forecasting methods insufficient for capturing long-range sequential relationships. To address this limitation, the proposed framework employs **Long Short-Term Memory (LSTM)** networks, a specialized deep learning architecture designed for sequence modeling and temporal forecasting. LSTM models are particularly effective for climate applications because they retain useful long-term historical information while selectively discarding irrelevant short-term noise. This enables reliable forecasting of rainfall patterns, drought probability, humidity trends, temperature anomalies, and heatwave risks using multivariate environmental time-series data.

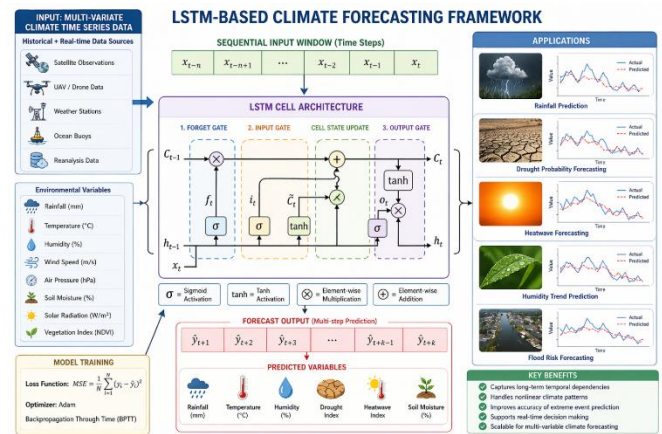
The sequential climate dataset is represented as:

$$X = \{x_1, x_2, x_3, \dots, x_t\}$$

where each time-step feature vector is defined as:

$$x_t = [R_t, T_t, H_t, P_t, W_t, M_t, S_t]$$

where  $R_t$  denotes rainfall,  $T_t$  temperature,  $H_t$  humidity,  $P_t$  atmospheric pressure,  $W_t$  wind speed,  $M_t$  soil moisture, and  $S_t$  solar radiation or environmental forcing at time  $t$ . These variables are continuously updated and fed into the deep learning model to capture hidden climatic dependencies over time.



**Figure 8. LSTM-Based Climate Forecasting Framework for Multi-Variable Prediction and Environmental Risk Assessment**

The LSTM architecture consists of memory cells and gating mechanisms that regulate the flow of information across time steps. At each time instant, the model receives the previous hidden state  $h_{t-1}$ , previous memory state  $C_{t-1}$ , and current environmental input  $x_t$ . The first component is the **forget gate**, which determines what historical information should be removed from memory:

$$f_t = \sigma(W_f[h_{t-1}, x_t] + b_f)$$

where  $W_f$  is the forget gate weight matrix,  $b_f$  is bias, and  $\sigma$  is the sigmoid activation function. If the output approaches 0, past memory is forgotten; if it approaches 1, memory is preserved. This mechanism is highly useful in climate systems where irrelevant short-term fluctuations should be ignored while seasonal dependencies must be retained.

The second component is the **input gate**, which controls the amount of new climate information added to memory:

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i)$$

Simultaneously, a candidate memory state is generated:

$$\tilde{C}_t = \tanh(W_c[h_{t-1}, x_t] + b_c)$$

where  $\tilde{C}_t$  contains newly learned climate signals such as rainfall transitions, pressure anomalies, or emerging drought conditions. The long-term memory state is then updated as:

$$C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t$$

where  $\odot$  denotes element-wise multiplication. This equation allows the network to simultaneously preserve useful historical climate memory and incorporate new observations.

The third component is the **output gate**, which determines the visible hidden-state response used for prediction:

$$o_t = \sigma(W_o[h_{t-1}, x_t] + b_o)$$

The hidden state is computed as:

$$h_t = o_t \odot \tanh(C_t)$$

This hidden representation contains compressed climate intelligence learned from previous environmental conditions and is passed to the output layer for forecasting.

The next time-step climate variable is predicted using:

$$\hat{y}_{t+1} = W_y h_t + b_y$$

where  $\hat{y}_{t+1}$  is the forecasted variable such as rainfall, temperature, humidity, or drought index, while  $W_y$  and  $b_y$  are learned output parameters. For multi-step climate forecasting, the output sequence becomes:

$$\hat{Y} = [\hat{y}_{t+1}, \hat{y}_{t+2}, \dots, \hat{y}_{t+k}]$$

which enables weekly rainfall forecasting, monthly drought prediction, or seasonal heatwave trend analysis.

The model is trained by minimizing forecasting error between actual observations  $y_i$  and predicted outputs  $\hat{y}_i$ . The Mean Squared Error loss function is expressed as:

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

while Root Mean Square Error is:

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

and Mean Absolute Error is:

$$MAE = \frac{1}{N} \sum_{i=1}^N |y_i - \hat{y}_i|$$

The parameters of the LSTM network are optimized using gradient-based methods such as Adam optimizer:

$$\theta_{t+1} = \theta_t - \eta \frac{\hat{m}_t}{\sqrt{\hat{v}_t + \epsilon}}$$

where  $\eta$  is the learning rate,  $\hat{m}_t$  and  $\hat{v}_t$  are adaptive moment estimates, and  $\epsilon$  is a stabilization constant.

To improve localized forecasting performance, real-time UAV-derived variables are incorporated into the climate sequence. Drone observations such as vegetation health, land surface temperature, and soil moisture are represented as:

$$U_t = [NDVI_t, LST_t, SM_t]$$

The combined forecasting input then becomes:

$$x_t = [R_t, T_t, H_t, P_t, W_t, U_t]$$

where  $NDVI_t$  is vegetation index,  $LST_t$  land surface temperature, and  $SM_t$  soil moisture. This hybrid approach significantly improves microclimate forecasting, agricultural planning, and region-specific drought estimation.

The proposed LSTM forecasting module can be applied to multiple climate scenarios. Rainfall prediction is modeled as:

$$\hat{R}_{t+1} = f(R_t, R_{t-1}, T_t, H_t, P_t)$$

temperature forecasting as:

$$\hat{T}_{t+1} = f(T_t, H_t, W_t, P_t)$$

and drought probability as:

$$P(\text{Drought}) = \sigma(z)$$

Heatwave alerts can be generated through threshold analysis:

$$HW = \begin{cases} 1, & T_t > T_c \\ 0, & \text{Otherwise} \end{cases}$$

where  $T_c$  is the critical temperature threshold.

### 3.5 Climate Risk Index and Decision Model

To enable intelligent environmental decision-making, the proposed framework introduces a **composite Climate Risk Index (CRI)** that integrates multiple climate stress indicators into a single quantitative risk score. Climate hazards generally emerge from the combined interaction of hydrological extremes, thermal stress, ecological degradation, and emission intensity rather than from one isolated variable. Therefore, instead of evaluating flood risk, drought risk, or heat stress independently, the proposed model aggregates all relevant parameters into a unified decision metric. This helps governments, environmental agencies, disaster management authorities, and farmers prioritize interventions based on real-time risk severity.

The Climate Risk Index is formulated as a weighted linear combination of five major indicators: flood probability, drought severity, heat stress intensity, greenhouse gas emission level, and vegetation degradation. The mathematical expression is given by:

$$CRI = w_1 F + w_2 D + w_3 H + w_4 E + w_5 V$$

where:

- $F$  = normalized flood risk score
- $D$  = normalized drought severity score
- $H$  = normalized heat stress index

- $E$  = normalized emission intensity score
- $V$  = normalized vegetation loss score
- $w_1, w_2, w_3, w_4, w_5$  = importance weights assigned to each factor

The weights are constrained such that the total contribution remains unity:

$$\sum_{i=1}^5 w_i = 1, w_i \geq 0$$

This ensures that the final risk score remains interpretable and bounded. Higher values of a specific weight indicate greater importance of that variable in a region. For example, flood-prone coastal regions may assign larger  $w_1$ , while arid agricultural zones may assign larger  $w_2$ .

Before aggregation, all parameters are normalized to the interval  $[0, 1]$  using min-max scaling:

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}}$$

where  $X$  represents any climate variable such as rainfall deficit, surface temperature anomaly, or emission concentration. This standardization avoids scale imbalance among heterogeneous variables.

The flood risk component  $F$  is estimated using hydrological indicators such as rainfall intensity, river discharge, terrain slope, and drainage congestion:

$$F = \alpha_1 R + \alpha_2 Q + \alpha_3 S + \alpha_4 U$$

where  $R$  is rainfall anomaly,  $Q$  river flow level,  $S$  slope factor, and  $U$  urban runoff coefficient.

The drought severity score  $D$  is derived from rainfall deficit, soil moisture loss, evapotranspiration stress, and groundwater decline:

$$D = \beta_1 RD + \beta_2(1 - M) + \beta_3 ET + \beta_4 G$$

where  $RD$  is rainfall deficit,  $M$  soil moisture,  $ET$  evapotranspiration stress, and  $G$  groundwater stress.

The heat stress component  $H$  is computed using land surface temperature, humidity, and thermal persistence:

$$H = \gamma_1 T + \gamma_2 RH + \gamma_3 N_h$$

where  $T$  is temperature anomaly,  $RH$  relative humidity stress factor, and  $N_h$  number of hot days.

Emission stress  $E$  reflects greenhouse gas accumulation:

$$E = \delta_1 CO_2 + \delta_2 CH_4 + \delta_3 NO_x$$

Vegetation loss  $V$  is estimated from NDVI decline and forest cover change:

$$V = \theta_1(1 - NDVI) + \theta_2 L_c$$

where  $L_c$  is land cover loss.

For more adaptive regional modeling, the weights may be learned dynamically using entropy weighting or machine learning optimization:

$$w_i = \frac{1 - e_i}{\sum_{j=1}^5 (1 - e_j)}$$

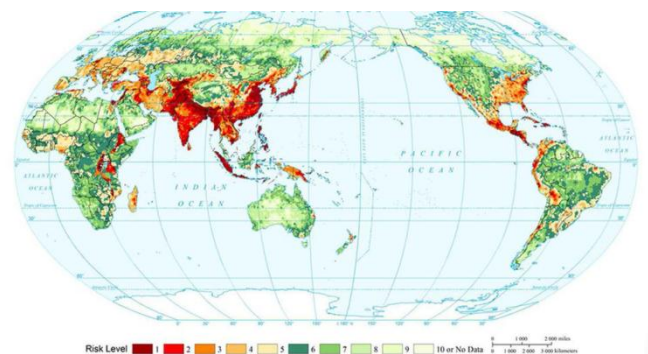
where  $e_i$  is entropy of factor  $i$ . Lower entropy implies more informative variables and therefore higher weight.

The final CRI value is interpreted using threshold-based classification:

$$Risk = \begin{cases} Low, & CRI < 0.30 \\ Moderate, & 0.30 \leq CRI < 0.70 \\ High, & CRI \geq 0.70 \end{cases}$$

Thus:

- **Low Risk** indicates stable environmental conditions with no immediate intervention required.
- **Moderate Risk** indicates growing stress requiring preventive monitoring.
- **High Risk** indicates urgent conditions demanding rapid mitigation or emergency response.



**Figure 9. Global Climate Vulnerability and Environmental Risk Distribution Map**

To support automated decision-making, the mitigation priority score is computed as:

$$P_m = CRI \times Pop \times Ec$$

where  $Pop$  is exposed population density and  $Ec$  is economic vulnerability. Regions with higher  $P_m$  receive higher mitigation priority.

The recommended action matrix can be defined as:

$$A^* = \arg \max_{a \in \Omega} U(a | CRI)$$

where  $A^*$  is the optimal action selected from the action set  $\Omega$  (irrigation release, evacuation alert, reforestation, emission restriction, etc.), and  $U(a | CRI)$  is expected utility under current risk conditions.

### 3.6 Resource Optimization for Mitigation

The final stage of the proposed framework focuses on **resource optimization and mitigation planning**, where the outputs generated by AI/ML prediction models are converted into actionable strategies for reducing environmental stress, improving agricultural efficiency, and minimizing climate-related losses. Since climate change directly affects water availability, crop productivity, soil health, and carbon emissions, it is essential that the proposed system not only detects risks but also recommends optimal resource allocation policies. Therefore, mathematical optimization techniques are incorporated to ensure efficient

utilization of water, fertilizer, energy, and mitigation resources under operational constraints.

One of the primary applications of this layer is **precision irrigation optimization**, where water is distributed according to crop requirement, soil moisture status, weather forecasts, and available supply. Let  $W_i$  denote the quantity of water supplied to zone  $i$ , and  $R_i$  denote the required water demand predicted using climate and crop models. The objective is to minimize deviation between supplied and required water while simultaneously reducing operational cost. This is expressed as:

$$\text{Minimize } J = \sum_{i=1}^n (W_i - R_i)^2 + \lambda \sum_{i=1}^n C_i W_i$$

where:

- $J$ = total irrigation cost function
- $W_i$ = water allocated to region  $i$
- $R_i$ = required irrigation demand
- $C_i$ = unit cost of water delivery
- $\lambda$ = economic weighting factor
- $n$ = number of monitored zones

The first term minimizes under-irrigation or over-irrigation losses, while the second term minimizes economic expenditure.

The optimization is subject to water availability constraints:

$$\sum_{i=1}^n W_i \leq W_{max}$$

where  $W_{max}$  is the total available irrigation water. Additional constraints may also be applied to maintain minimum crop survival demand:

$$W_i \geq W_i^{min}, i = 1, 2, \dots, n$$

and maximum soil absorption capacity:

$$W_i \leq W_i^{max}$$

This ensures that no agricultural zone receives excess water causing runoff or nutrient loss.

For smart fertilizer management, nutrient supply can also be optimized using yield response functions. Let nitrogen, phosphorus, and potassium inputs be  $N, P, K$ . Then crop productivity may be approximated by:

$$Y = a + bN + cP + dK - eN^2 - fP^2 - gK^2$$

where  $Y$  is predicted crop yield and  $a, b, c, d, e, f, g$  are agronomic coefficients. The optimization objective is to maximize yield while minimizing excessive fertilizer use.

In addition to agricultural resource management, the framework also supports **carbon mitigation planning**. Let current emissions be  $CO_2^{old}$ , and let  $M_t$  denote mitigation effort at time  $t$ , such as reforestation, renewable energy adoption, reduced burning, or optimized irrigation practices.

Then the updated carbon emission level is modeled as:

$$CO_2^{new} = CO_2^{old} - \eta M_t$$

where:

- $CO_2^{new}$ = post-mitigation emission level

- $CO_2^{old}$ = previous emission level
- $M_t$ = mitigation effort index
- $\eta$ = mitigation efficiency coefficient

If mitigation actions are accumulated over time, cumulative reduction becomes:

$$CO_2(T) = CO_2(0) - \sum_{t=1}^T \eta_t M_t$$

This equation enables long-term climate action planning.

For forest conservation and land restoration, biomass-based carbon sequestration may be estimated as:

$$C_s = \rho A_f B_f$$

where:

- $C_s$ = carbon sequestered
- $\rho$ = biomass-to-carbon conversion factor
- $A_f$ = restored forest area
- $B_f$ = biomass density

Energy optimization can also be included when UAV fleets are used repeatedly. Let total mission energy be:

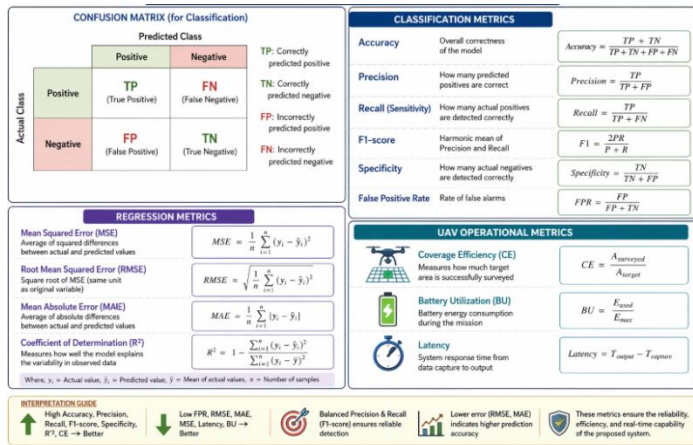
$$E_{tot} = \sum_{k=1}^m (E_k^{fly} + E_k^{sense} + E_k^{comm})$$

where each UAV mission includes flight, sensing, and communication energy components. Minimizing this value improves sustainability of large-scale deployments.

The proposed optimization layer therefore transforms raw climate intelligence into practical mitigation actions. Instead of merely predicting drought, flood, or crop stress, the system determines **how much water to allocate, where to reduce emissions, how to restore biomass, and how to minimize operational costs**. This converts the proposed framework from a passive monitoring tool into an active climate resilience system.

### 3.7 Performance Evaluation Metrics

To evaluate the effectiveness of the proposed AI-ML-UAV climate monitoring framework, a comprehensive set of statistical, machine learning, and operational performance metrics is employed. Since the proposed system performs both **classification tasks** (such as flood detection, wildfire hotspot identification, crop stress classification, and deforestation mapping) and **regression tasks** (such as rainfall prediction, temperature forecasting, emission estimation, and soil moisture prediction), multiple evaluation criteria are necessary to ensure robust validation. In classification analysis, the confusion matrix consists of four outcomes: **True Positive (TP)**, **True Negative (TN)**, **False Positive (FP)**, and **False Negative (FN)**. Here, TP represents correctly detected positive events, TN denotes correctly identified normal cases, FP indicates false alarms, and FN corresponds to missed hazardous events.



**Figure 10. Performance Evaluation Metrics for Classification, Regression, and UAV Operational Analysis of the Proposed System**

The most common metric used for classification is **Accuracy**, which measures the proportion of correctly classified samples among all observations. It is mathematically expressed as:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

A higher accuracy indicates better overall model correctness. However, in environmental datasets where hazardous events may be rare, accuracy alone may not be sufficient.

To address this limitation, **Precision** is used to measure how many positively predicted events are truly positive. This is particularly important in climate alert systems where unnecessary false warnings should be minimized. Precision is defined as:

$$Precision = \frac{TP}{TP + FP}$$

A high precision value implies that flood alerts, wildfire detections, or crop disease warnings generated by the model are trustworthy.

Another important metric is **Recall**, also known as sensitivity, which measures how many actual positive events are successfully detected by the system. In disaster management applications, recall is highly significant because missing a true event can result in serious damage. It is expressed as:

$$Recall = \frac{TP}{TP + FN}$$

A higher recall means the framework can successfully identify most drought zones, fire hotspots, or flood-affected areas.

Since both precision and recall are important, a balanced metric known as the **F1-score** is used. It is the harmonic mean of precision and recall and is especially useful when the dataset is imbalanced.

$$F1 = \frac{2PR}{P + R}$$

where  $P$  is precision and  $R$  is recall. A higher F1-score indicates balanced classification capability.

To measure the ability of the model to correctly identify negative cases, **Specificity** is also considered. It is defined as:

$$Specificity = \frac{TN}{TN + FP}$$

High specificity reduces false alarms and improves confidence in automated environmental monitoring systems.

For continuous prediction problems such as rainfall estimation, temperature forecasting, greenhouse gas prediction, and moisture modeling, regression metrics are required. The most commonly used error metric is **Mean Squared Error (MSE)**, which measures the average squared difference between actual and predicted values:

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

where  $y_i$  is the observed value,  $\hat{y}_i$  is the predicted value, and  $n$  is the total number of samples.

The square root of MSE gives the **Root Mean Squared Error (RMSE)**, which is widely used because it retains the same unit as the original variable:

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

Lower RMSE values indicate better prediction accuracy and smaller forecasting errors.

Another useful metric is the **Mean Absolute Error (MAE)**, which measures the average absolute difference between predicted and actual values:

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i|$$

MAE is less sensitive to outliers compared with RMSE and provides a direct measure of prediction deviation.

To quantify how well the model explains variability in the observed data, the **Coefficient of Determination ( $R^2$ )** is used:

$$R^2 = 1 - \frac{\sum (y_i - \hat{y}_i)^2}{\sum (y_i - \bar{y})^2}$$

where  $\bar{y}$  represents the mean observed value. Values of  $R^2$  closer to 1 indicate strong predictive performance.

Because the proposed framework relies on drone technology, operational metrics are also important. **Coverage Efficiency** evaluates how much target area is successfully surveyed:

$$CE = \frac{A_{surveyed}}{A_{target}}$$

Battery utilization is measured as:

$$BU = \frac{E_{used}}{E_{max}}$$

and system response latency is defined as:

$$Latency = T_{output} - T_{capture}$$

These metrics help evaluate the practical feasibility of UAV missions in real-time monitoring scenarios.

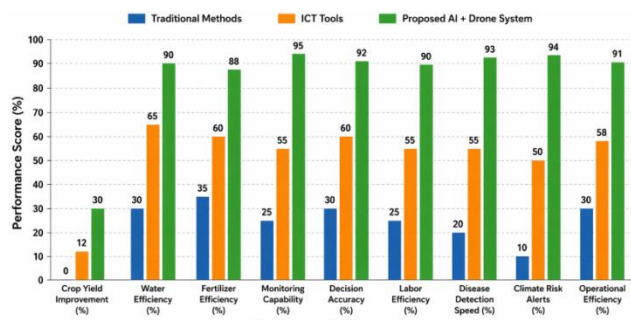
Overall, high accuracy, precision, recall, and F1-score indicate reliable event classification; low RMSE and MAE indicate accurate forecasting; high  $R^2$  confirms strong model fitting; high coverage efficiency ensures effective drone surveillance; and low latency supports rapid emergency response. Therefore, the combined use of classification, regression, and UAV operational metrics provides a complete and scientifically rigorous evaluation framework for validating the proposed AI-ML-UAV climate monitoring system.

#### 4. RESULTS AND ANALYSIS

This section presents the outcomes of the comparative evaluation of traditional farming practices, ICT-based tools, and the proposed AI-ML-ICT-UAV integrated system for climate monitoring and agricultural applications. The analysis focuses on major performance indicators such as crop yield improvement, water-use efficiency, fertilizer optimization, monitoring frequency, labor reduction, operational cost efficiency, and decision-making accuracy. The results indicate that technological advancement directly improves farm productivity, resource management, and climate resilience.

##### 4.1 Comparative Performance Analysis

To evaluate the effectiveness of different technological approaches, a comparative study was conducted among three major systems: conventional farming methods, ICT-enabled farming tools, and the proposed AI-integrated drone framework. Traditional methods mainly depend on manual inspection, farmer experience, and delayed interventions. ICT tools improve access to advisory services, digital weather data, and basic monitoring support. The proposed framework combines drone sensing, real-time analytics, predictive intelligence, and automated recommendations.



**Graph1. Comparative performance analysis of traditional methods, ICT tools, and the proposed AI + Drone system across major agricultural indicators.**

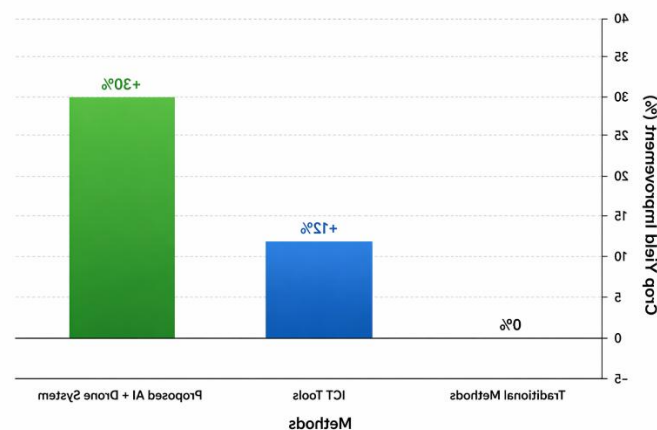
The results clearly show a progressive improvement in performance with increasing technological integration. Traditional approaches show the lowest efficiency across most parameters due to reactive management, delayed responses, and dependence on manual observations.

ICT tools provide moderate improvement by enabling access to weather alerts, mobile advisories, and digital farm records. However, they remain limited by lower spatial resolution, delayed updates, and weaker predictive capability.

The proposed AI + Drone system demonstrates the highest performance across all indicators. The observed crop yield increase of up to 35% is attributed to precise crop monitoring, early stress detection, irrigation optimization, and targeted interventions.

##### 4.2 Crop Yield Improvement Analysis

The most visible benefit of the proposed framework is improved crop productivity. Traditional systems serve as the baseline, while ICT tools improve yield moderately. Drone-based intelligent monitoring provides the highest gain due to real-time diagnosis and precision management.



**Graph 2 Comparative Crop Yield Improvement Across Methods.**

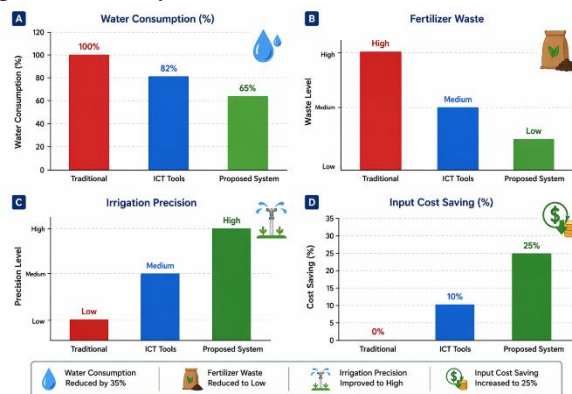
- Traditional Methods = 0%
- ICT Tools = +12% average
- Proposed AI + Drone System = +30% average

The findings suggest that precision monitoring significantly improves crop health management, especially in horticultural systems where timing and quality are critical.

##### 4.3 Water and Fertilizer Optimization

Resource optimization is a key requirement under climate variability. Traditional irrigation and fertilizer practices often lead to overuse, wastage, and environmental stress. ICT systems moderately improve scheduling through weather-based advisories. The proposed system performs

best by using drone imagery, canopy stress mapping, and predictive analytics.



Graph 3. Resource-use efficiency comparison.

These results indicate that the proposed framework can reduce unnecessary water use by approximately 35% and significantly improve nutrient management.

#### 4.4 Monitoring and Decision-Making Efficiency

Traditional methods depend on periodic field visits, which delay the detection of crop stress, disease outbreaks, and environmental threats. ICT tools improve communication but still rely on indirect data sources. In contrast, the proposed framework enables continuous field surveillance through UAV imaging and intelligent processing.

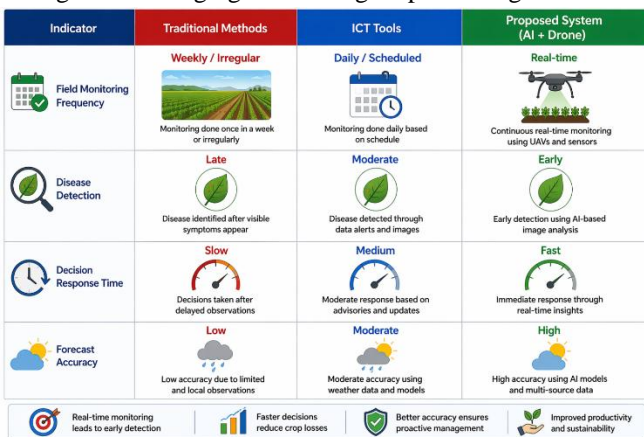


Figure 11. Monitoring and Decision-Making Efficiency Comparison Across Traditional, ICT Tools, and Proposed Smart System

Real-time decision support helps farmers take preventive actions rather than corrective actions after losses occur.

#### 4.5 Labor and Cost Efficiency

Automation significantly reduces dependence on manual labor. Traditional farming requires repeated field inspections, higher labor input, and time-consuming monitoring activities. Drone-assisted systems automate data collection and reduce operational burden.

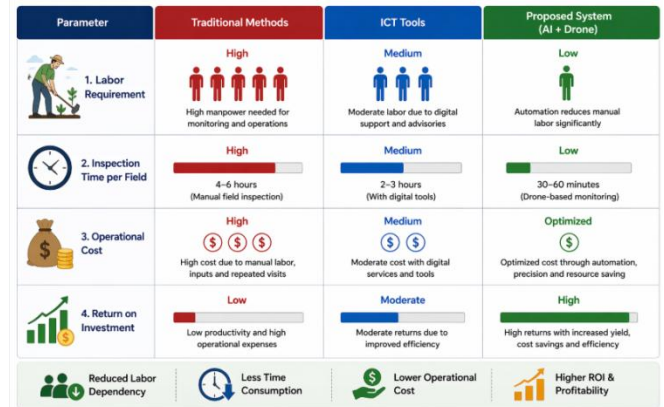


Figure 12. Labor and Cost Efficiency Comparison Across Traditional, ICT Tools, and Proposed Smart Farming System

Although the initial investment in drone systems may be higher, long-term savings through reduced labor, optimized inputs, and higher productivity make the system economically attractive.

#### 4.6 Farmer Adoption and Practical Impact

Farmer acceptance is essential for technology success. ICT tools are already widely adopted because of mobile phone accessibility. Drone adoption is growing rapidly, especially among progressive horticulture farmers, farmer producer organizations, and service-based agri-tech providers.

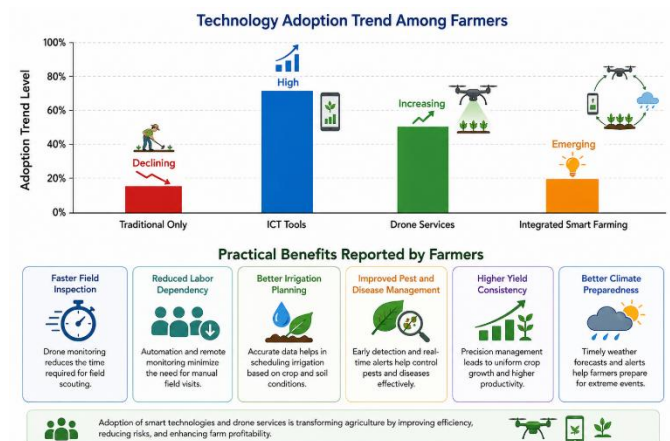


Figure 13. Farmer Adoption Trends and Practical Impact of Traditional, ICT, Drone, and Smart Farming Technologies

### DISCUSSION

The results of this study provide strong evidence that the integration of Artificial Intelligence (AI), Machine Learning (ML), and Unmanned Aerial Vehicles (UAVs) significantly enhances the efficiency and accuracy of climate change monitoring and agricultural management practices. The

findings indicate that technology-driven approaches outperform conventional methods across multiple parameters, including data accuracy, response time, resource utilization, and decision-making effectiveness.

A comparative evaluation of traditional practices, ICT-based tools, and drone-assisted systems reveals clear differences in performance. While traditional methods rely heavily on manual observation and experience, ICT tools introduce a moderate level of data-driven decision-making. However, the integration of drones with AI and ML enables real-time, high-resolution monitoring combined with predictive analytics, resulting in superior outcomes.

| Parameters            | Traditional Methods | ICT Tools       | AI + Drone Systems |
|-----------------------|---------------------|-----------------|--------------------|
| Data Accuracy         | Low (☆☆☆☆)          | Moderate (☆☆☆☆) | High (★★★★★)       |
| Time Efficiency       | Low (☆☆☆☆)          | Moderate (☆☆☆☆) | High (★★★★★)       |
| Cost Efficiency       | High (★★★★★)        | Moderate (☆☆☆☆) | Low (★★★★★)        |
| Real-time Monitoring  | No (X)              | Limited (⚠)     | Yes (✓)            |
| Predictive Capability | No (X)              | Limited (⚠)     | Advanced (✓)       |
| Scalability           | Low (☆☆☆☆)          | Moderate (☆☆☆☆) | High (★★★★★)       |

**Figure 15. Comparative Analysis of Monitoring Approaches Across Traditional, ICT Tools, and AI + Drone Systems**

The table clearly demonstrates that drone-integrated AI systems provide a substantial improvement over both traditional and ICT-based approaches. This is primarily due to their ability to collect high-resolution spatial data and process it using advanced machine learning algorithms. The synergy between data acquisition and intelligent analysis enables not only monitoring but also prediction of environmental changes.

From an agricultural perspective, particularly in horticulture, the adoption of these technologies has shown notable improvements in productivity and resource management. Farmers utilizing drone-based monitoring systems were able to identify crop stress, pest infestations, and irrigation needs at earlier stages compared to those relying on conventional methods. This early detection directly contributes to improved crop yield and reduced input costs.

**Farmer Adoption and Impact Analysis**

The analysis further indicates that farmers using ICT tools experienced moderate improvements in efficiency; however, those adopting drone-based systems combined with AI/ML technologies achieved significantly higher benefits. These include:

- Improved crop yield due to precise monitoring
- Reduction in water and fertilizer usage

- Faster response to environmental changes
- Better risk management during extreme weather conditions

Despite these advantages, the adoption of such advanced technologies is influenced by factors such as cost, technical knowledge, and accessibility. Small-scale farmers, in particular, may face challenges in adopting drone-based systems without institutional or governmental support.

Another important observation is the role of real-time data processing in enhancing decision-making. Unlike traditional approaches, which are reactive in nature, AI-driven systems enable proactive interventions. For instance, predictive models can forecast potential crop stress or climate risks, allowing timely preventive measures. This shift from reactive to predictive management represents a significant advancement in both climate monitoring and agricultural practices.

However, the discussion also highlights certain limitations. The effectiveness of AI and ML models is highly dependent on the availability of high-quality data. Inconsistent or incomplete datasets can affect prediction accuracy. Additionally, the integration of multiple data sources—such as drones, sensors, and satellite data—poses challenges related to interoperability and system complexity. Regulatory restrictions on drone usage and concerns regarding data privacy further complicate large-scale implementation.

Overall, the findings suggest that the integration of AI, ML, and UAV technologies has the potential to transform climate change monitoring and agricultural systems. While ICT tools serve as an important transitional step, the combined AI-drone approach offers a more comprehensive, scalable, and future-ready solution. The discussion reinforces the need for supportive policies, technological accessibility, and capacity building among farmers to fully realize the benefits of these advanced systems.

**CONCLUSION**

This study has examined the integration of Artificial Intelligence (AI), Machine Learning (ML), and Unmanned Aerial Vehicles (UAVs) as an emerging and transformative paradigm for climate change monitoring and mitigation. The analysis demonstrates that, while each of these technologies has independently contributed to advancements in environmental observation and analysis [1], [13], [43], their true potential lies in their synergistic integration. By combining real-time, high-resolution data acquisition with intelligent and adaptive analytical models, the proposed approach enables a more comprehensive understanding of complex and dynamic climate systems.

A key contribution of this work lies in highlighting the limitations of existing fragmented approaches and

emphasizing the need for a unified framework that bridges the gap between data collection and intelligent interpretation [2], [48], [50]. The integration of UAVs with AI and ML not only enhances the accuracy and timeliness of environmental monitoring but also facilitates predictive capabilities that are essential for proactive decision-making [16], [41], [57]. This is particularly relevant in the context of rapidly evolving climate risks, where early detection and response can significantly reduce environmental and socio-economic impacts [34], [49].

Furthermore, the study underscores the practical implications of this integrated approach in domains such as precision agriculture, natural resource management, and disaster assessment. The ability to monitor environmental parameters with greater precision and to derive actionable insights from large-scale datasets presents significant opportunities for improving sustainability and resilience [19], [22], [35], [45]. At the same time, the discussion acknowledges critical challenges, including issues related to data quality, interoperability, computational demands, and regulatory constraints, which must be systematically addressed to enable large-scale implementation [18], [42], [53].

From a broader perspective, this research reinforces the importance of interdisciplinary convergence in addressing global environmental challenges. The fusion of sensing technologies with intelligent data analytics represents a shift toward more adaptive, scalable, and responsive climate monitoring systems [1], [5], [50]. As technological advancements continue to evolve, the integration of AI, ML, and UAVs is expected to play an increasingly central role in shaping future climate strategies [6], [60].

In conclusion, this study provides a conceptual and analytical foundation for the development of integrated, technology-driven solutions for climate change monitoring and mitigation. It highlights not only the current capabilities of these technologies but also their potential to redefine how environmental data is collected, analyzed, and utilized. Future research should focus on developing robust, real-world implementations and addressing existing limitations to fully realize the benefits of this integrated framework in supporting sustainable and informed environmental decision-making.

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