

Machine Learning-Based System To Monitor, Analyze Metrics, And Reduce Disaster Risks In Crop Leaching From Rainfall

Subhakar.M¹, Dr.Muthireddy.P²

¹Research scholar, School of Computer Science and Engineering ,REVA University, Rukmini Knowledge Park, Yelahanka, Kattigenahalli, Bengaluru, Sathanur, Karnataka 560064

²Professor, School of Computer Science and Engineering, REVA University, Rukmini Knowledge Park, Yelahanka, Kattigenahalli, Bengaluru, Sathanur, Karnataka 560064

ABSTRACT

Rainfall prediction plays a crucial role in various sectors such as agriculture, water resource management, and disaster preparedness. Accurately forecasting rainfall within specific spatial constraints (such as a radius and height) is essential for making informed decisions and mitigating potential risks. Machine learning algorithms have demonstrated promising results in predicting complex meteorological phenomena, including rainfall patterns. This study analyses how machine learning (ML), meteorological data and IoT technology in a smart agriculture system to find risks from rainfall as soon as they occur. It aims to achieve three key results: first, creating a rainfall prediction system using meteorological data and advanced ML models to give localized forecasts; second, establishing a communication system using IoT and ICT that sends local alerts to farmers and authorities through SMS, voice prompts and apps; and third, deploying biodegradable thin membrane wrappers from meteorological data to save crops from water and nutrient loss. It is necessary to invest in drone teams, many environmental sensors and ongoing use of AI-based software to use precision agriculture tools. Cloud services are used for storing and analysing past data, presenting it to users, visualizing information and monitoring from anywhere. All of these components are part of a flexible architecture that supports ongoing environmental monitoring, forecasting, two-way communication and automatic actions in the field. The framework, by combining digital progress and sustainability, provides a strong answer for agriculture that can weather climate change and reduce risks of disasters.

Keywords: Drone-based intervention, IoT communication, Nutrient leaching management, Rainfall prediction, Smart agriculture.

1. INTRODUCTION

Agriculture plays a significant role in sustainable development.

Advances in digital technology for farming are providing a useful answer to these problems. Machine Learning (ML) is especially helpful for spotting patterns in big agricultural data and helping with making data-based decisions. ML techniques are now being applied in farming to predict yields, find diseases, manage irrigation and predict climate [6][2]. Deep learning models are able to analyse satellite, weather and sensor information to give quick insights into the health of soil and crops [5]. As a result of this advance, nutrient movements can be predicted in different rainfall situations, making it possible to take steps to reduce leaching before it occurs. Meteoritic data with GPS and IoT sensors can closely observe and monitor the state of fields in real time. Meteoritic data are used to monitor the weather and environment and also to apply sprays and covers to protect crops that need them. Reduced nitrogen input in rice has allowed scientists to track physiological traits linked to nutrient use efficiency to make rice cultivation more productive [8]. Thanks to these rich data environments, ML models can learn from recent field information which boosts the reliability of predictions and supports effective use of intervention plans. In addition, adding pesticide and climate data to ML-based models has

already led to better predictions in various cropping systems [3]. There is a big difference in technology use between rural and urban areas, mainly in developing countries such as India. The spread of advanced technologies is limited in the regions that need them most by problems like digital illiteracy, poor infrastructure and social and economic barriers [7]. Because of this, it is important to create a strong method for translating predictions into actions that people can take. Using mobile applications, SMS alerts and multilingual voice systems based on ICT can help both farmers and agricultural authorities get warnings and advice quickly.

Here the three goals related to technologies which are meant to reduce the risk of crop leaching caused by heavy rain:

1. Development of a framework to investigate the accuracy and reliability of rainfall prediction within a specified geographic area through the integration of meteorological data with GPS systems.
2. Development of an effective communication framework to farmers and authorities using IoT and ICT.
3. Implementation to assess the feasibility and effectiveness of utilizing meteorological data for the application of thin membrane wrappers to protect crops from damage before or after harvest.
4. The objectives guide the process in which agricultural engineering, remote sensing, data science and rural development are all brought together. First, the review investigates how drone-GPS systems are being combined with ML algorithms to predict rainfall. In addition, it reviews the setup and use of communication methods that enable farmers to use predictive insights. Third, it studies the practicality of using meteorological data to spread thin biodegradable membranes over crops to protect them from rain and nutrient loss.

The review also includes a critical study of soil nutrient estimation techniques from spectral data that are important for precision leaching models [4]. The paper outlines a plan for building scalable and sustainable leaching mitigation systems by exploring the latest machine learning methods and their use with physical and digital infrastructure. It points out the successful pilot projects and applications and outlines the problems with technology and policies that need to be resolved for wider use. The final parts of the paper discuss important challenges such as the lack of inclusive data infrastructure, limited scalable communication models and potential research topics in federated learning and low-energy sensor networks. These add to the research on digital agriculture and precision sustainability and give useful suggestions to those working to make farming systems more resilient to nutrient loss caused by climate change.

2. LITERATURE REVIEW

Over the past few years, research on rainfall-induced crop leaching and how to prevent it has shifted toward using data and precision agriculture. Losing nitrogen through crop leaching is still a major issue in sustainable agriculture because it affects soil health, the number of crops grown and the environment. The increasing impact of extreme weather on rainfall in some regions means that traditional fertilizer management methods are not enough, so adaptive technologies and ML are needed. The link among heavy rainfall, nutrients leaving the soil and soil health has encouraged scientists to build more advanced, automated systems that detect changes in the environment and predict what will happen [11]. It is important in crop leaching studies to study how nitrogen which can move easily, behaves in different farming and weather conditions. Researchers [10] thoroughly examine the way nitrogen moves from the soil to plants, pointing out that poor management can result in lower plant growth and also add nitrates to water. Biodegradable mulch films and organic amendments seem to help control runoff and

maintain nitrogen in the soil, especially when there is too much rain. In organic horticulture, biodegradable plastic films reduce water contact and help crops take up more nitrogen [15]. Spectral imaging is now playing a bigger role in finding leaching and understanding crop stress. The meteorological data collected from satellite to compute NDVI and PRI, two high-resolution indices that indirectly show signs of nutrient deficiency, waterlogging and leaching [9]. Although satellites can observe over a long period, meteorological data are more precise in space and can be used more often. It is important to have this flexibility when trying to spot the early effects of rainfall on nutrients in field crops. Now, researchers are combining different types of sensors such as optical and thermal, to spot crop stress that is closely tied to nutrients in the soil. Machine learning is increasingly being used to forecast and model leaching events. Using weather, soil and farming data, and in [17], built a strong ML model that could predict nitrate leaching on Dutch agricultural fields. Rather than linear regression, the model they built using Random Forest and Gradient Boosting proved to be more successful in finding complex nonlinear relationships. Researchers [18] agree with these findings by using ML models and IoT sensor data to design smart farming systems that predict yields and check soil quality. Their studies pointed out that data from soil moisture, conductivity and rainfall sensors, collected in real time, can guide farmers to use resources wisely and reduce nutrient loss. In rural areas, farmers often face difficulties using new technologies because of their social and infrastructure conditions. Researchers [14] used the multivariate analysis in India and discovered that literacy, the size of land a person owns and previous experience with digital tools all affected technology adoption. The difference between new ideas and their use shows why user-friendly, culturally appropriate interfaces and strong mobile alert, community and local knowledge systems are needed. Another important aspect in reducing leaching is using the best irrigation strategies. In monsoon weather, not scheduling irrigation well can cause nutrients to leach deeper into the soil as it becomes too saturated. Researchers [13] found that using adaptive irrigation to control soil water storage kept nitrogen losses low and allowed the crops to grow well. This result suggests that smart irrigation systems based on ML predictions can help manage both water and nutrients in the soil in unstable weather. Global changes in climate such as more heatwaves and unusual rainfall, are making it harder to predict leaching. Researchers [12] point out that climate extreme can change the way soil behaves and moves nutrients, suggesting that we should use predictive modelling to support climate-smart agriculture. By combining climate forecasting with ML technology, farmers can be prepared for bad weather and use helpful measures like rain shelters, thin wrappers and soil treatments. In new technology, it is important to assess both the economic and environmental effects of decarbonisation and sustainability. The authors of the study examined the link between climate-smart agriculture which includes leaching mitigation and reducing carbon emissions. They discovered that precise actions help the environment and are cost-efficient in the long run, mainly when backed by policy benefits and carbon credit programs. The research area is showing a strong move towards using machine learning, sensor networks and drone-based membranes together with smart irrigation systems to address the problem of crop leaching. Although science in this field has improved and predicting nutrient loss is now possible, the next major step is to make these tools accessible to all, ensure they work with other systems and introduce them to farmers in local communities. This synthesis forms the base for reviewing the technical, environmental and social aspects of the goals detailed in the following sections.

2.1. FRAMEWORK FOR RAINFALL PREDICTION VIA METEORITIC DATA SYSTEMS

2.1.1 Sensor Deployment and Data Acquisition

For rainfall prediction at the farm or sub-regional level, we need reliable, timely and detailed weather data. Though weather stations and regional meteorological services have given key information for a long time, their readings are not always detailed enough to show how rainfall changes across small farms and plots. Because these stations are far apart, fixed in location and designed for broad-scale forecasting, they are not very helpful for making farming decisions on the ground. Because climate change causes local weather to become more unpredictable, there is now a greater demand for advanced technologies that can provide very local weather forecasts in real time.

The meteorological data or Unmanned Aerial Vehicles (UAVs) are now seen as important tools. When fitted with precise sensors, they allow for the gathering of detailed atmospheric data at many different locations and altitudes. Meteoritic data are able to survey large areas in just one trip and can be directed to the exact same spot again and again. The use of GPS modules in UAVs helps locate and timestamp all collected data which forms the base for modelling rainfall and changes in the environment. GPS allows multiple drone missions to be synchronized and helps improve the way data is gathered in large or hard-to-reach areas.

Important elements in a strong drone-based weather monitoring system are pressure sensors, altimeters, humidity sensors and temperature probes. The sensors are attached to microcontrollers and these are then linked to data loggers on the aircraft. In addition, GPS-enabled modules collect location data and also ensure the dataset is precise in time by logging everything with sub-second accuracy. Data packets are sent wirelessly using LoRaWAN, Zigbee or cellular IoT modules like NB-IoT or LTE-M to either ground control stations or remote cloud servers for analysis at the time or after a delay [20]. The sensors on these meteorological data are carefully adjusted to detect minor changes in the air; humidity, pressure and temperature; that usually mean rain is coming. This sensitivity allows them to forecast short-term rain or snow events with confidence at the microclimate scale. By using several meteorological data at once in a swarm, it is possible to monitor different plots in the atmosphere and backup each other if some data is missing or a device fails. UAVs are more advantageous than satellites when it comes to remote sensing. Most satellites are found at heights of hundreds to thousands of kilometres and give resolutions from 250 meters to several kilometres which isn't good enough for detailed farming management. Unlike satellites, meteorological data fly between 20 and 120 meters, giving a centimetre-to-meter resolution that is best for studying small changes in the field. In addition, meteorological data are easy to control; they can be sent up whenever needed and flown again and again over the same points, collecting data that is both regular and tied to the current situation. A lot of agricultural meteorological data today can fly on their own or with partial human control, collecting data along the way as they follow a set path.

Weather events such as cloud formation, wind shear, layered temperature changes, and rapid shifts in humidity affect operational flexibility and must be captured in real time. Figure 1 shows the main structure of this drone-based weather data collection system. It shows how each environmental sensor is linked to the UAV's main processing, navigation and communication systems to make up an integrated atmospheric sensing system. The figure illustrates the complete process, from receiving sensor data to sending it to the ground station, showing how all the technology must work together for quick, local rainfall forecasts in smart agriculture.

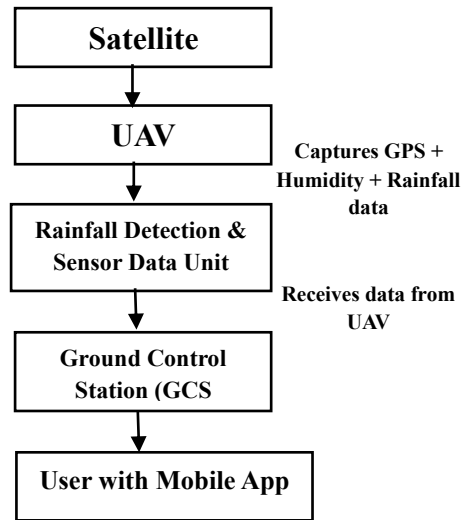


Figure 1. UAV-GPS Sensor Framework for Localized Rainfall Monitoring

When the atmospheric data has been collected using meteorological data, it is passed through machine learning pipelines that can spot complicated, nonlinear connections between different weather elements and rainfall. The purpose is to turn a lot of high-frequency, location-based data into useful rain forecasts. Unlike standard statistical models, ML approaches can learn from data by themselves, respond to new data and find patterns that are not easy to notice using traditional rules. Therefore, they are very useful for dealing with the unpredictable rainfall in farming. Both basic supervised learning models and advanced deep learning architectures have been used. RF and SVM are considered two of the most commonly used traditional methods. RF uses multiple decision trees, averages their predictions and does so to reduce overfitting and make predictions more reliable. SVM is able to map non-linear data into high-dimensional feature spaces which helps it identify the small changes in the atmosphere that often signal an upcoming rainfall.

UAV based weather data changes rapidly over both time and space, the model must be able to account for both these aspects. At this stage, LSTM, GRUs and CNNs from the deep learning field show clear benefits. Every model contributes its own advantages to rainfall prediction. The memories like LSTMs and GRUs can help us follow how atmospheric conditions change before a rainfall occurs. CNNs can recognize spatial information and local patterns using the equation (1), including how clouds are moving, how temperatures differ and the moisture found in particular regions.

$$Y(i, j) = \sum_m \sum_n X(i + m, j + n) \cdot K(m, n) \quad \text{--- (1)}$$

Where:

- $Y(i, j)$: Output feature map value at position (i, j)
- $X(i + m, j + n)$: Input value at position shifted by (m, n)
- $K(m, n)$: Kernel (filter) weight at offset (m, n)
- $\sum_m \sum_n$: double summation over the filter dimensions

The GRU-CNN hybrid model has demonstrated excellent results when forecasting rainfall from data collected by meteorological data. In this way, CNN layers initially spot spatial patterns such as changes in temperature, moisture gradients or cloud pixels in multispectral images from meteorological data. After extraction, the features are sent to GRU layers to examine their time-series changes and find usual indications of rainfall, including decreases in pressure, surges in humidity or changes in wind direction. This

approach allows us to predict both the location and timing of rainfall. Researchers [19] found that GRU-CNN models resulted in more accurate real-time, hyper-local rainfall predictions than either model working on its own. One advantage of these models is that they can learn from raw sensor data without needing much pre-processing or the selection of special features. The benefit of this feature is clear in agricultural fields, as soil, topography and microclimate may be very different just a short distance away. When these models use information from UAV sensors on raw barometric pressure, temperature changes and humidity, they are able to respond to new data and improve their predictions. In [21] performed a detailed study comparing different ML models for rainfall prediction with real drone data. It was found that deep learning models, especially GRU-CNN hybrids, always performed better than SVM and RF in both accuracy and speed, mainly for forecasts within the first 6 hours at sub-regional levels. They were also discovered to deal well with noise and missing data which often affect wireless sensor networks in real-world settings. Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and accuracy percentages or F1 scores are used to see how well the model is performing provided by equations (2), (3), (4) & (5). They allow us to compare how well the model works in diverse environments and with different drone data.

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \text{ ---- (2) } MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i| \text{ ---- (3)}$$

where

y_i = Actual value

$\hat{y}_i$ = Predicted value

n = Number of observations

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \text{ ---- (4) } F1 \text{ Score} = 2 \times \frac{Precision \times Recall}{Precision+Recall} \text{ ---- (5)}$$

Where

TP = True Positives

TN = True Negatives

FP = False Positives

FN = False Negatives

Where

Precision = $TP / (TP + FP)$

Recall = $TP / (TP + FN)$

In table 1 summarizes the main points of several ML models applied to UAV-based rainfall prediction, including their advantages and disadvantages as mentioned in recent studies.

Table 1. Model Performance Comparison for Rainfall using Meteoritic Data [19] [21]

Model	RMSE (mm/day)	MAE (mm/day)	Accuracy (%)	Comments
GRU-CNN (hybrid)	0.98	0.65	94.3	Best performance, handles both space & time
Random Forest	1.23	0.85	89.1	Strong for binary rainfall classification
SVM	1.47	0.98	85.6	Sensitive to feature scaling and overfitting
LSTM	1.12	0.75	91.5	Good for time-series, less so for spatial data

2.1.2 Accuracy and Comparative Performance

When drone-GPS systems are combined with machine learning models in practical use, they greatly improve rainfall prediction compared to traditional approaches. Legacy methods for weather monitoring, including satellites and fixed weather stations, are not always accurate enough or fast enough for agriculture. In comparison, when drone-enabled platforms are combined with modern ML algorithms, farmers can get instant and very precise forecasts for their immediate needs.

The accuracy of this approach was confirmed by trials led by [19]. The model they used which combined GRU and CNN, reached over 94% accuracy by processing UAV sensor data in real-time, much better than the usual satellite systems that have a resolution of hundreds of meters and a delay in data. The strong accuracy means that farmers can make real decisions based on the insights. Because of precise forecasts, people in agriculture can stop watering the fields, decide when to gather crops and cover their fields with protective membranes in advance of any problems. Additionally, a thorough worldwide study by [23] found that the areas with the most UAV use in farming are those that need quick feedback about the environment, for example, for rainfall, pest detection and disease monitoring. They placed importance on the advantage of using GPS modules together with ML inference engines. GPS marks the location of environmental data and ML algorithms work on it live to suggest relevant advice close by. Because of this combination, farmers can decide which areas need membranes based on rainfall which saves them resources. Researchers [22] added to the discussion by describing the ability of such systems to help people make decisions. Meteoritic data, according to their framework, can process data in real time and automatically perform actions. If a drone senses a storm approaching, it could automatically put up protective covers above crops at risk and switch off remote irrigation. In this model, sensing, analysing and acting are all connected within the same platform, so there is less delay and better precision in the response. As a result, this integration creates event-driven agriculture, in which decisions are guided by real-time information and analytics, not just set routines. It gives meteorological data and IoT devices the ability to respond to immediate dangers on their own, before they become more serious. Yet, there are still some problems that stand in the way of making such systems more reliable and scalable. Having multiple sensors or working over a large area puts a big strain on battery life. The load time of a typical UAV is only 20–40 minutes, so they are not suitable for long missions unless they can be recharged with swappable batteries or solar energy. Besides, rain, wind gusts and fog can all be predicted and these can cause meteorological data to stop working when it is most needed, sometimes halting critical missions. Model generalization is still a problem as well. A model developed for one agro-climatic area may not work properly in another unless it is retrained, because soil, altitude, vegetation and weather are not the same. As a result, it is important to frequently update the models and develop region-specific data which cannot be done without local technical support and infrastructure. Sensor calibration and making them work with other instruments are also difficult. The more accurate the prediction is, the more precise the input data. When sensors are not well maintained or are too cheap, they can create mistakes and having various types of sensors can make it hard to standardize models. Also, restrictions in policy and logistics such as no-fly zones, little government help for buying meteorological data and not enough training for users, prevent broad adoption. Because of these challenges, it is important to use flexible hardware, regularly improve models based on local data and rely on government policy, public-private cooperation and extension services to help with drone-based ML. To make the most of autonomous meteorological data in agriculture that can resist climate change, we need to handle these issues as a whole.

2.2 IOT AND ICT FRAMEWORK FOR COMMUNICATION

2.2.1 Network Architecture and Sensor Layer

Rainfall intensity is becoming more unpredictable, and farmers need better ways to communicate and monitor their crops.

i) Soil and Weather Sensing Infrastructure

Soil health and the amount of moisture in the soil show how much rain has fallen and if nutrients will be washed away. They play a role in today's plant health and also shape future soil fertility and water management. Modern IoT technology in farming allows farmers to keep a constant and accurate watch on these conditions by installing sensors throughout the farm. Such systems use advanced technology to capture and send data quickly, so farmers can see in detail how their soil changes during and after it rains.

A smart agriculture sensor set includes capacitive moisture sensors that estimate the amount of water in the soil by measuring changes in its dielectric permittivity. They help you know when the soil is waterlogged and water is seeping below the roots. Electrochemical nutrient probes add to this system by detecting if and how nitrogen, phosphorus and potassium are present. As a result, farmers can tell if recent rain has taken nutrients away before the plants use them. pH meters and EC (electrical conductivity) sensors monitor the soil's acidity and salt levels which may be affected by leaching and can seriously impact both the yield and health of crops. Sensors are usually set at different levels to observe vertical water flow, so that rainfall leaching can be recognized afterwards [28].

The information from the soil sensors is enhanced by the use of weather monitoring nodes. The sensors in these nodes measure ambient temperature, relative humidity, barometric pressure, the amount of solar radiation and rainfall intensity. Modelling evaporation, transpiration and rainfall is possible thanks to these important atmospheric variables. When connected to soil sensors, weather nodes allow for the creation of reliable models that explain the effects of environmental conditions on underground water and nutrient movement. Usually, soil and weather sensors are combined with cheap but effective microcontroller platforms such as Arduino, Raspberry Pi and ESP32 boards. They function as small processors at the site, acquiring data in real time, filtering it and sending it wirelessly. Because they are small and use little energy, they are a good choice for use in agriculture far from the grid. They are compatible with different communication protocols such as Wi-Fi, Zigbee and LoRaWAN, depending on the design of the field system. Using microcontroller boards such as Arduino and Raspberry Pi together with environmental sensors makes it easy to collect and process data on-site.

All of these devices together are called a Wireless Sensor Network (WSN); an easy-to-expand system meant for continuous environmental observations. Each node in a WSN can manage itself and send its data to a central hub or cloud server which provides the main structure for digital monitoring. Such networks help respond quickly to situations in the field and also save large amounts of data for use in predicting future trends, studying past patterns and making farming decisions. WSNs are necessary in agriculture because they link the physical events on the farm to automated, smart actions. In figure 2 explains how the sensors, microcontrollers and data pipes all work together for processing, displaying and advising farmers.



Figure 2. IoT Sensor Topology in Smart Agriculture for Rainfall-Related Monitoring

ii) Communication Protocols and IoT Gateways

The sensor data is collected from soil and atmospheric nodes, it should be transmitted safely to processing units, either close by or far away, to be saved, analysed and used for making decisions. In vast agricultural areas where it is hard to connect, we need energy-saving communication methods that work well over long distances in rural areas. In this area, LoRa (Long Range) is being used widely because it is inexpensive, uses little power and is easy to scale. Because LoRa is designed for sub-gigahertz unlicensed bands like 868 MHz in Europe and 915 MHz in North America, it can send data over distances from a few kilometres in cities to more than 15 kilometres in open rural areas. The low power consumption of IoT is very important in agriculture, as sensors often need to work without maintenance for a very long time. Devices that have LoRa transceivers can send small pieces of data such as soil moisture or rainfall intensity, at set times without overloading the network. Therefore, LoRa is well-suited for ongoing, real-time tracking of spread-out factors such as nutrient leaching, the level of groundwater and microclimate conditions in plant canopies. Many agricultural studies have shown that it works well in remote and low-infrastructure areas [27].

At the heart of this system is the IoT gateway which gathers data from all the sensor nodes and allows them to connect with external networks. The IoT gateway serves several different functions. It not only collects data from many end devices but also cleans it, changes the format and applies simple programs on it locally. A gateway can be set to send local alerts or SMS messages if soil moisture rises above what is optimal for the crop which might indicate a danger of leaching or overwatering. As a result, the gateway can act as both a data line and an initial decision-maker, helping the system react fast even when there is no internet connection. Besides, adding edge computing modules to the gateway architecture allows for early analysis or AI inference to happen at the field level. When the connection is slow or real-time action is crucial such as using meteorological data to put on protective membranes before heavy rain, local processing is very valuable. More and more, these smart gateways are combining machine learning microcontrollers or AI accelerators which makes it harder to separate sensing, communication and decision-making tasks.

Many smart agriculture systems now use a combination of LoRa and either Wi-Fi or BLE (Bluetooth Low Energy) to improve both the range of their signals and the speed of sharing data locally. In this design, LoRa is responsible for sending telemetry data from sensors out to the main station, whereas Wi-Fi is used for quick, local communication

between meteorological data, gateways and mobile devices used by field operators. Thanks to this design, broad areas can be covered without slowing down local communications and this design is particularly helpful in mission-critical farming, for instance, for early detection of nutrient leaching, flood alerts or drone control [25].

Also such systems can handle failures and remain reliable. As an example, when the cellular network stops working due to bad weather, the LoRa system will still function on its own and after connectivity returns, it will send the local data to the cloud. Thanks to this, the system is smart, flexible and can handle disruptions which are important in regions regularly hit by unpredictable rainfall or cyclones. All in all, the use of LoRa for long-range sensing, intelligent gateways and hybrid communication methods is the main structure of modern data transmission in smart agriculture. With this strong design, vital sensor data on soil, weather and crops is collected, sent and used quickly, helping farmers and agronomists make smart decisions about their farms, regardless of the condition of the infrastructure.

iii) Edge-Fog-Cloud Architecture for Scalability

For a long time, cloud-based systems were the main way to analyze data and make decisions in IoT-based agriculture, but today, new distributed computing methods are making it easier to handle data on-site. This change matters a lot in smart agriculture, where quick responses, energy savings and stable operations are key. As a consequence, deploying edge, fog and cloud nodes together is now the most common way to support intelligent farming. Here, edge nodes are the first group of intelligent devices, located directly next to the data sources, usually found in IoT gateways, sensor hubs or drone-mounted microcontrollers. They are intended to do some initial processing, including filtering, lowering noise, setting up alerts and temporarily storing data. For instance, an edge node may review the soil moisture information it receives and instantly stop irrigation or deploy the membrane if the moisture level is too high just after rain. Being near the source, edge nodes remove the need for round-trip communication and make it possible for the system to respond quickly to changes. By using the edge, fog nodes create a middle layer for computing and are commonly found in community-level places such as cooperative data centers or agricultural offices. Fog nodes gather and handle data from different edge devices found in several farms, conducting mid-level analysis, discovering cross-farm trends and starting machine learning processing. In this way, a fog node might use rainfall data to forecast nutrient leaching risk for the entire district or propose group-based actions based on the combined soil profiles. These nodes help connect the fast edge systems with the powerful, but farther-away, cloud servers.

Cloud servers are the most important part of the hierarchy for making major decisions. They manage the storage of important data, train and refine complicated machine learning models and run detailed simulations such as rainfall prediction and nutrient movement over vast landscapes. Cloud services are also used for storing and analyzing past data, presenting it to users, visualizing information and monitoring from anywhere. In addition, models that have been created and confirmed in the cloud are moved to fog or edge computers for live prediction and local use. By using this loop, real-time insights and past records are combined to aid field-level decisions.

Using this edge-fog-cloud hierarchy makes operations more efficient than using a cloud-only system. Most importantly, it reduces the time needed to perform urgent tasks, keeps the system working during internet downtime and allows for more resources as needed. Such features matter a lot in rural and remote areas because the network is often not very reliable or simply missing. According to [25] such frameworks help smart farming systems perform better and adapt to real-life conditions.

In addition, performing data aggregation, compression and simple inference at the edge and fog allows these systems to use less bandwidth, consume less energy and reduce the cost of sending data to the cloud. As a result, the system is better for the environment, more efficient economically and more advanced in technology, especially for large-scale farms or cooperatives operating many sensor networks and meteorological data. All in all, using edge, fog and cloud nodes in agricultural IoT makes the system more flexible, efficient and smart. It enables smart farming platforms to change from being reactive to being proactive, as real-time data triggers local actions and long-term plans are formed in the cloud.

iv) Power Management and Deployment Considerations

Sufficient power utilizing is still a major challenge when building and up keeping big IoT-based farming sensing networks. It is very important to provide reliable, renewable power to sensor nodes in developing countries with limited infrastructure, so that data is always available and uninterrupted. In order to tackle this problem, the majority of IoT devices used in agriculture now rely on solar energy to generate their power which fits the open and sunny environment of fields. Typically, solar panels are connected to lithium-ion or lithium-polymer batteries and the batteries are controlled by battery management systems (BMS) that maintain the charge, stop over-draining the batteries and monitor temperature to keep the system running all the time [26]. Meanwhile, both hardware and software power consumption is managed by using ultra-low-power microcontrollers such as ESP32, STM32 or ARM Cortex-M chips that are in a sleep-wake cycle, use just a few milliwatts when not active and wake up to take and send measurements. Using power-aware programming, firmware is made more efficient by turning off unneeded modules, compressing data and only activating certain sensors when certain thresholds are passed. Using these techniques, sensor nodes use much less energy, allowing them to work without much maintenance or charging for months.

There is now research into energy harvesting that uses vibrations, piezoelectric materials and Thermoelectric Generators (TEGs), in addition to solar. They use vibrations caused by wind or machinery or the difference in temperature between the soil and air, to make usable electrical energy. Even though these technologies hold much promise, they are not yet ready for use and are still limited by their small power output and difficulty in scaling up. Still, combining them with other energy sources can give extra power and help keep the system stable when there is not enough sunlight. How a sensor network is laid out in the field depends on the area's shape, the types of crops and the terrain. The most commonly used topologies are star and mesh and which one is best depends on the application. All sensor nodes in a star topology send data directly to a single central node which is usually an IoT gateway. The design can be easily used, has limited firmware needs and performs well in flat-field environments where all nodes can talk to the gateway. Still, if the main gateway fails, the whole network will fail.

Mesh networks are set up differently, as every node can share data with other nodes in the network. As a result, there are many ways for communication, making the system more reliable and useful in challenging or blocked areas. Mesh networks are perfect for hilly areas, orchards and polyculture plots since a clear path to the gateway cannot always be provided. If a node fails or its battery runs out, they make it possible to automatically re-route the signals, making the system more reliable. The cost of sensors is a key element in deciding if and how farmers can use them, mainly for smallholder farmers with limited resources. According to [27], using low-cost IoT devices made from open-source hardware and ready-made sensors can greatly reduce the costs involved in running a business. The results showed that combining smart sensor placement with efficient firmware design could reduce the total setup cost by more than 30% without affecting the

quality or performance of the data. With these systems, small-scale farmers and cooperatives can use smart farming technology without the expense of building large-scale infrastructure. In short, dealing with energy issues and designing networks will benefit both agriculture and the people involved. By using renewable energy, designing systems for efficiency and adapting the network to the situation, sensor systems can become strong, inexpensive and suitable for a wide range of users and farms.

2.2.2 ICT STRATEGIES FOR FARMER COMMUNICATION

A successful smart agriculture system can collect and analyze data and then share relevant, useful and trusted information with farmers promptly. A strong ICT framework helps send critical notices to farmers and authorities in real time, so they can prepare for or deal with issues related to rainfall and leaching. This part examines the format of real-time communication platforms, the part played by localized voice-based systems and how behaviours influence the adoption of such technologies.

i) Real-Time Alerts via Mobile and Web Platforms

With better digital infrastructure in rural areas, mobile-based advice for farmers can now be used more widely. Most of these systems rely on cloud-based analytics to check sensor information and send alerts by SMS, push notifications, mobile apps or USSD codes. One of the best things about these platforms is that farmers can receive alerts immediately after a threshold is met, for example, if the soil becomes too wet or if heavy rainfall is forecast. New research points out that involving farmers in the process helps make the platforms easier to use and more relevant to their culture. For example, [29] carried out participatory research in India to develop a mobile service that fits how farmers decide and what they prefer to know. According to the study, platforms that considered behavioural factors such as usefulness, social influence and fear of risks were adopted by a much larger number of users. Messages that were easy to understand, used local information and gave practical advice were more helpful than usual weather reports. There are many places where more than 70% of the population has a mobile phone, but access to the internet is not widespread. To solve this, advisory systems typically make use of hybrid structures that connect offline apps, send messages through bulk SMS and store content for regular updates which helps them deliver alerts in places with little internet connection [31]. Most of these tools use AI and big data to keep their models updated and to send different alerts for farms and crops.

ii) Local Language Voice Prompts and the Ability to Serve Customers in Several Regions

The high illiteracy among some smallholder farmers means that voice-based ICT systems are necessary to make sure all can use them. With Interactive Voice Response (IVR), these systems provide pre-recorded rainfall alerts and advisories in the local language, set off by data from sensors. If rain is expected within 24 hours, the system can suggest that the farmer use thin film covers or postpone pesticide use to avoid nutrient loss from the soil. According to [32], voice-based tools are important for helping people become digitally literate and more trusting. Researchers found that farmers who received information via IVR systems remembered and used the recommendations more than those who received the same information by text. The researchers pointed out that interactive communication, where farmers could ask questions or make notes, helped users become more engaged and learn more. These tools work well in many different regions. The software can automatically adjust its content and language to match the information in a user's GPS profile. For users in India and Sub-Saharan Africa, "Awaaz De" and "Viamo" use AI to automatically translate messages and adjust when they are sent to each user.

User interface (UI) design continues to be an essential aspect of scalable ICT systems. Low-literacy farmers tend to use applications that feature icons for navigation, use traffic light; style color alerts and allow them to align their planting with calendar events. This allows forecasts and advisories to be presented visually, so no textual reading is required. The architecture that connects mobile, IVR and web is shown in Figure 3.

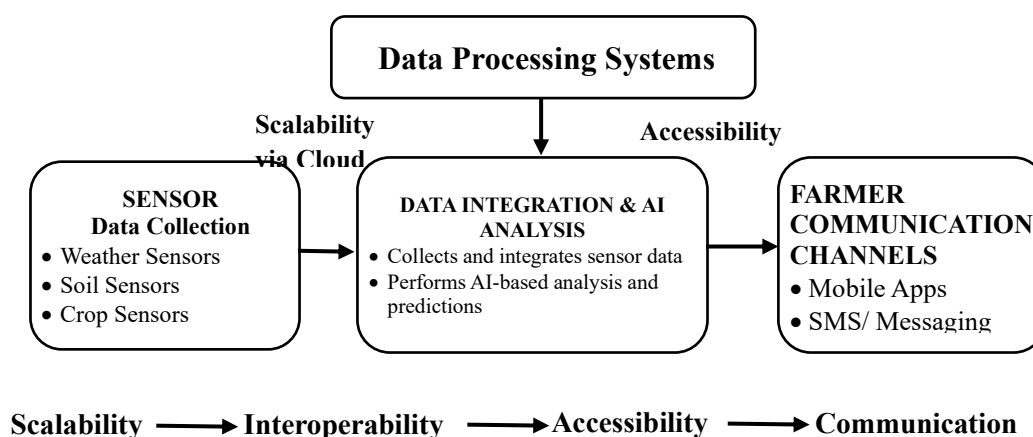


Figure 3. Scalable ICT Framework Linking Sensor Data to Farmer Communication Channels

iii) Behavioural, Social, and Institutional Factors

While ICT tools are available and can work, they depend on being designed for people and trusted by the community. Researchers [30] used bibliometric analysis to show that early warning systems in Southern Africa delivered by extension agents or cooperatives were 35–50% more effective than those delivered only by apps. With social support, training and village presentations, farmers are more likely to respond to digital advisories. In addition, the fear of losing money and the influence of others' behavior are important factors. According to [29], a system can still fail if it does not suit local beliefs, if it is not trusted or if people have had bad experiences with similar technologies.

The use of ICT platforms together with existing workflows, for example, crop insurance or online government services, improves the lasting use and sustainability of these systems. Alerts that reach local extension officers or community leaders can help everyone respond better to rainfall-related problems and can influence decisions about irrigation and subsidies for fertilizer.

2.2.3 INTEGRATION WITH AUTHORITIES AND POLICY BODIES

While machine learning, IoT and predictive analytics are valuable at the farm level, their real impact on the system comes when they are used together with government and policy leaders. With the use of ICT tools in smart and e-Governance, government bodies can address crop risk, changes in rainfall and nutrient leaching both before and after they occur. Good integration helps in centralized monitoring, responding to policies and cooperating as a community to achieve sustainability and food security targets.

i) Smart Governance for Agricultural Risk Management

Smart governance means using technology and data-based systems in public administration to achieve better efficiency, accountability and service delivery. Government decision-making can use environmental data in real time, thanks to smart frameworks in the field of climate-resilient agriculture. Researchers [33] suggest using big data to design a governance system in Ceará, Brazil, so that agricultural policies can

help achieve the SDGs. If AI models and sensor outputs are used, regional authorities could manage fertilizer distribution and rainwater harvesting benefits during the most risky times of the year. When drone-GPS data on rainfall is used and matched with regional e-governance, officials can rapidly determine at-risk areas and give suitable advice. This may mean limiting the use of urea, putting crop covers on early or alerting farmers at certain locations about weather insurance. Governance is integrated; policies can be guided by automated analytics, maps and an analysis of past trends, rather than simply by administrative reports. It enables us to react more quickly and objectively to problems caused by soil erosion and leaching [36].

ii) Public Dashboards for Multi-Stakeholder Transparency

Creating interactive dashboards for the public is now a key part of modern agricultural intelligence systems that support governance and policy work. They make it possible to turn complex data into useful information that supports decisions for many people involved in smart farming. They connect sensor data to practical actions, providing a single platform for accessing, understanding and using agronomic, environmental and meteorological information in real time. They bring together data from the soil, nutrients and the local climate gathered by sensors placed on each farm or group of farms. They are then connected with drone-gathered information on the environment, like the direction of temperature and possible rainfall and open data from government climate and weather sources. As a result, there is a single, organized overview of crop health, climate risks and what actions are needed, available to policymakers, researchers and farmers.

Geospatial intelligence is used in dashboards of AgriStack and Krishi portals in India, so users can look at rainfall patterns, where fertilizers are applied, pest pressure zones and nutrient loss on a map. With geotagged visualizations, district agricultural officers and extension agents can find localized issues such as areas with missing nutrients or future rainfall and compare this information with reports from the field or automated advice from AI. These dashboards are now at the heart of digital agricultural governance, serving as the main tool for deploying and overseeing government programs and farm activities. Dashboards are useful because they turn passive data into tools that help users make decisions. Many advanced interfaces feature action buttons for particular zones, so you can plan drone flights, send fertilizer advice and alert farmers with SMS messages. As a result, dashboards help manage both monitoring and operations, so problems can be addressed more quickly in the field. Additionally, such platforms provide tools to analyse past trends, letting users see how rainfall, soil quality and nutrient movement have changed over the years. These features are very useful for policy researchers, who can examine the lasting results of agricultural schemes, propose new steps to take or supply evidence for making budget decisions and designing programs. It is now easier for all users to access dashboards, as new designs add multi-language support, are mobile-friendly and use simple traffic-light colours and icons to show risks. As a result, frontline field workers and literate farmers can use the dashboard without having to be expert in technology. A sample user interface mock-up is given in Figure 4, illustrating a design that combines information on zone-specific rainfall, nutrient stress and buttons meant for regional government officials. The design demonstrates how digital tools can allow everyone involved in farming to use advanced analytics.

These platforms also promote institutional transparency and participatory governance. By making predictive insights publicly available, dashboards foster trust in government alerts and minimize misinformation during emergency conditions like floods or extreme rainfall events.

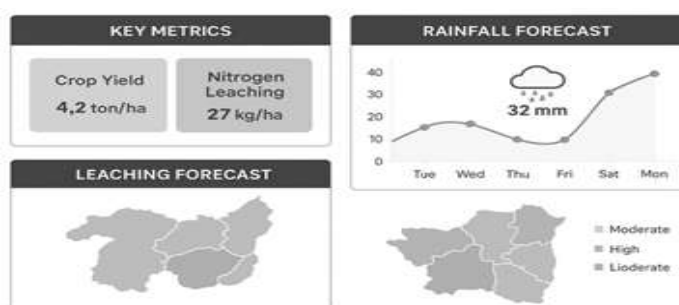


Figure 4. Sample Layout of Dashboard Integrating Rainfall and Leaching Forecasts

iii) e-Governance: From Digital Literacy to Digital Decision-Making

To succeed at integration, governments have to develop digital decision-making systems as well as promoting basic digital education. According to [35], tools for local rural governance should be made easy to understand and multilingual so they support schemes like the Pradhan Mantri Fasal Bima Yojana (PMFBY) and the Mahatma Gandhi National Rural Employment Guarantee Act (NREGA). Also, officials should provide digital training for local workers; village extension officers, soil health technicians and district agriculture officers; to translate scientific data from models and deliver it in ways farmers can understand. Rainfall predictions are simplified for users by actors who produce advisory bulletins, set up relevant subsidies or advise on managing soil.

Dashboards used in governance settings should record every piece of exchange, prediction logging and notice delivered using blockchain. It guarantees decision-making is reliable and can be traced back which is crucial for climate management [34].

iv) Institutional Collaboration for Sustainable Development

The governance of digital agriculture should be done together, not apart, from bodies working on sustainability and climate issues. The researchers [36] highlight that better governance makes it possible for technological advancements in Sub-Saharan Africa. Connecting the data across agriculture, disaster and environmental fields allows governments to respond consistently to avoid drought, implement national soil programs and distribute resources fairly in regions at risk.

Using outputs from predictive models in national planning helps governments make their communities more able to withstand threats. When forecast-based analytics are embedded in India's State Action Plan on Climate Change (SAPCC) or in Nigeria's Agricultural Promotion Policy, this would lead to stronger climate-proof farming methods that would directly connect to Sustainable Development Goals such as SDG 2 (Zero Hunger) and SDG 13 (Climate Action). Also such institutions should promote standard APIs and join public-private efforts so that weather predictions and leaching alerts become integrated into government processes for agriculture.

2.3 UAV-BASED THIN MEMBRANE APPLICATION

2.3.1 Membrane Design and Crop Suitability

With increasing rainfall variability due to climate change, it becomes much easier for crops to suffer physical damage, infection by fungi and a loss of nutrients just before harvest. Covering crops with thin, flexible, biodegradable films is a new method used before and after harvest. Together with drone delivery, these membranes make it easy to reach particular areas using a method that is quick, focused, inexpensive, time-saving and helps protect the environment. Yet, how successful this method is largely depends on the material of the membranes, compatibility with plant growing and how these membranes break down over time in the field.

i) Material Composition and Protective Capabilities

Currently, there is more focus in agricultural materials science on biodegradable plastic films to strengthen crop safety and keep nutrients from escaping. For example, films derived from PLA or blends of starch and other materials can keep away too much water from crops and disease, limiting nutrient losses [15]. They also form a boundary for heat and bacteria which helps prevent sickness after rain stops.

Using these membranes as part of leaching prevention lines up with the results [1] found which were higher nutrient loss and more water runoff in fields treated with chicken litter that experienced increased rain. When you cover your crops with membranes prior to expected rain, they are less likely to be over-exposed to water which keeps nutrients in balance and prevents nitrogen issues in spinach, lettuce and strawberries. Also, biodegradable plastic films need a hydrophobic surface, the ability to bend in different temperatures and good tensile strength so they do not tear after drone deployment. Lately, new spectral reflectivity designs make it possible for the films to reflect UV radiation without stopping too much light that plants need to grow [9].

ii) Crop-Specific Suitability and Coverage Strategies

Each crop species has a different ability to respond to water stress and the amount of canopy above it. This was especially observed by [8] when short-term waterlogging approached rice plants after heavy rains which led to less efficient nitrogen uptake and lower crop yield. Membrane sheets applied on the root zones at important nutrient absorption times can prevent such wastage by slowing down saturation and the rate of water evaporation.

High-value horticultural crops such as tomatoes, capsicum and grapes benefit from thin membrane covers because they keep nutrients from washing away, prevent the fruit from breaking and guard against hail or heavy drops landing on the crop. As a result, using aerosol-based films which become thin protective layers when dried, has become popular for drone applications.

For maize and sugarcane, farmers use methods that allow a bit of water on the plastic and still allow the air to move vertically. According to [10], while the bases of vertical crops are protected from leaching, the tall leaves may soften easily and become more susceptible to fungal infection after rainy weather; which membrane technology could limit.

Figure 5 illustrates the link between crop types and the three membrane deployment formats.

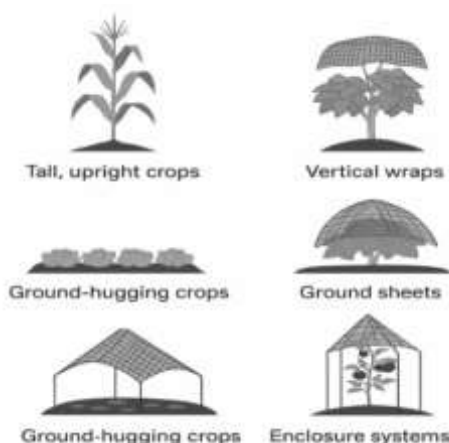


Figure 5. Membrane Deployment Formats Matched to Crop Architecture

- Horizontal membrane wraps for leafy crops
- Semi-permeable films for fruiting plants

- Vertical net-films for tall cereals

iii) Environmental Safety and Degradation Cycles

If membrane deployment is to last, it cannot add residual toxicity or microplastic to the agro-ecological system. As discussed by [15], both the EU and USDA require biodegradable films in organic farming to break down fully after 180 days and leave no harmful residue. Through action by microbes, the films convert into carbon dioxide, water and biomass, leaving the soil unharmed.

It has also been shown that these biodegradable membranes increase nitrogen use efficiency. The microclimate and reduced excess water from rainfall allow them to keep nutrients available to the plants. It is particularly important because nitrate leaching has increased in areas with rainfall increases which were mentioned in the latest global soil-health reviews [17]. Besides, regional temperature, the variety of microscopic life in the soil and the thickness of the paint layers influence how fast the paint wears out. PLA based films are completely decomposed in 60-90 days in tropical areas, coinciding with the normal harvest time of leafy vegetables and short-time legumes, as reported by [13].

2.3.2 AERIAL APPLICATION TECHNIQUES

Covering crops with thin membranes by meteorological data is a major move forward in automation, accuracy and speed for agricultural protection. Membranes have long been applied to soil in both organic and conventional farming, but the process is often difficult, not always reliable and limited by time. Meteorological data can work through these hurdles by delivering to different locations automatically, consistently and regardless of the terrain, especially when it's unclear how much rain will come or the farm is sprawling over many sections.

i) UAV Configuration and Payload Mechanisms

Most agricultural meteorological data used for membrane deployment are large multirotors, prepared to lift about 5–20 kilograms depending on the model and battery used. Equipment on these meteorological data includes servo mechanisms that help with controlled spraying, pressure sensors for accurate release or flexible containers for putting down membrane materials, strips or liquids that turn solid as they interact with surfaces.

Researchers [22] and [23] found that pesticide and liquid nutrient spraying drone-based systems can be adjusted to apply sprayable biopolymer membranes, provided they are low in viscosity and dry fast. If the pressure, angle and altitude are adjusted, the meteorological data can apply the product evenly over a field and avoid waste. In addition, meteorological data that carry cartridges can lay out biodegradable sheets of film on the soil near the plants or along rows, with gravity-assisted rollers and GPS that guides movement.

The handling of these applications is done through automated flight control software, where field maps, specific altitudes and algorithms for adjusting to wind are included. By tracking actual weather, meteorological data are prevented from starting the membrane setup in strong winds or before rain arrives, securing the films.

ii) Precision and Coverage Optimization

Deploying membranes with meteorological data is most effective when the targeting is accurate and this accuracy depends on using remote sensor data, indexes for soil moisture and information about the weather. Researchers [5] stress that drone routes should account for both how wide an area is and how much the ground varies biologically. So, fields that tend to get waterlogged will be treated with two layers or at an early time and higher parts may require a partial application or be sprayed later.

Meteorological data use geotagged rainfall data or start-up NDVI maps from UAVs to decide the membrane's thickness and area of deployment. Average flight paths are similar to

lawn mowers and how high the UAV flies depends on the crop and the material of the cover. Today's advanced meteorological data use LiDAR sensors or rangefinders to dodge collisions with tall plantings or farm irrigation equipment [23].

One main way to measure the performance of an application is the Effective Coverage Ratio (ECR) which shows how much of the selected area is coated by how much membrane is applied. Meteoritic data that are set up well have been shown to achieve ECRs higher than 90%, suffer very little drift and show a small amount of overlap [22].

Table 4. Comparison of Drone-Based vs. Manual Membrane Application Methods [5][22]

Parameter	Drone-Based	Manual Application
Area Covered (ha/hour)	2.5–4.0	0.3–0.5
Labor Requirement	1–2 technicians	6–8 field workers
Material Wastage	<5% (optimized)	15–20% (due to overlap/error)
Deployment Precision	High (GPS-guided)	Medium
Terrain Adaptability	High (even on slopes)	Low
Operational Weather Limit	Moderate wind/resistant	Rain/humidity-sensitive

iii) Integration with AI and Scheduling Algorithms

CNH has started using artificial intelligence to help farmers create crop application schedules based on weather reports, the state of their soil and the development of crops. Based on data such as the chance of rain, how fast the membrane needs to dry and crop stress levels, algorithms can recommend exact hours for flight [2].

In real time, if there is wind, machines can increase air pressure inside meteorological data or make the flight corridor narrower to stop drift. Scientists are using reinforcement learning to let meteorological data automatically learn the best way to fly over different fields and crops.

iv) Sustainability and Energy Considerations

Using meteorological data instead of manual or tractor spraying saves the soil from becoming compacted and uses less fossil fuel. Researchers in [3] explain that when meteorological data are powered by renewable electricity and supported by data-driven software, they greatly reduce both emissions and cost with repeated harvest missions.

2.3.3 FEASIBILITY ASSESSMENT AND COST ANALYSIS

Drone technology working with thin membrane wrappers for fields is an exciting idea in modern agriculture. Even so, for such systems to be truly useful, they must be practical, profitable, work in various areas and handle different crops and pieces of infrastructure. It expected the most important cost factors, how the service matches local settings, the expected profit and any difficulties with use; especially in developing parts of the world.

i) Capital Investment and Operating Costs

With meteorological data, adoption of membranes in smart farming leads to higher precision and automated crop security. Nevertheless, the price and technical demands of these systems play a major role in deciding whether they will be used, mainly in places where capital and technical help are unavailable.

Getting agricultural meteorological data is the main early cost that drives up expenses. Unlike normal meteorological data, agriculture meteorological data are made to last and come with GPS, rugged exteriors and in many cases, thermal or multispectral imaging to support agronomic uses. Besides, to carry out deployment, meteorological data need to have specialized payloads such as biodegradable membrane rolls, sprays or sheath applicators. Meteoritic data that can lift payloads between 10–20 kg are typically sold for

\$3,000 to \$10,000, depending on if they use advanced GPS, have obstacle detectors, endurance and autonomy features [23]. The meteorological data require these features to perform well in different areas and fly efficiently enough that every inch of the farm is examined without wasting materials. Other than the drone itself, a customization process for membrane applications also involves upfront spending. This group incorporates spreading devices, selecting between applying solutions with nozzle arrays or using rollers for the film option. In many cases, these components must be custom built and tuned because of differences in crop or plant arrangements and deployment positions. For pilot deployments still using unique designs, this part of system design can lead to more engineering expenses.

Any feasibility study should also consider the costs of operating membrane deployment systems. They consist of costs that happen on a regular basis:

- Membrane material costs, they cost between \$250 and \$500 per hectare, depending if they are spray films, wrapped sheets or biodegradable nets and how thick they are. Since their durability, resistance to sunlight and how permeable they are vary, they can often change in price and if they can be used again.
- UAV operator wages or service fees. If farmers hire meteorological data via cooperatives or contractors, the cost of hiring an operator might be determined either by hectare or by the hour. If the regulations in your area are strict, it's important to train and get certified.
- Battery replacement and charging infrastructure, In particular, high-frequency applications call for their use in big farms. Sorties by meteorological data on membrane application are commonly kept to a short distance to prevent bacteria buildup on the membrane which wears the meteorological data's batteries rapidly. Some farms add solar power sources, additional battery packs or portable grid-tied charging stations to power their activities during rainy times.
- Field mapping and weather synchronization services, can be found in the form of aggregated agritech platforms or paid subscription APIs. With these services, including terrain mapping, live weather updates and flight plan algorithms, meteorological data are able to adapt to what is happening in the field, reducing both mistakes and waste.

Even though setting up and operating these systems is very expensive, long periods of study have found that they can save money compared to using people or tractors. Researcher [18] examined several smart farming tools such as UAV-assisted application systems and found that adopting drone solutions had higher initial costs, but ultimately saved money. Because of these, we are able to save money on welding costs:

- Reduced labor requirements, this is very useful for regularly repeated or time-limited work such as applying wind covers ahead of rainfall.
- Higher application precision, by using GPS and real-time sensing, the process is supported so that there is less material wasted and there is even membrane distribution.
- Decreased operational turnaround, making it possible to cover more area in less time require fewer people's involvement.

Not only do they save farmers money, but they also improve farming outcomes by helping farmers protect their yields, offer protection from risky weather to workers on the farm and promote sustainable use of farm inputs. This variety of benefits shows that drone membrane systems are good, but also very costly, for farming and dealing with disasters.

ii) Return on Investment (ROI) and Yield Benefits

UAV-applied biodegradable membranes used in farming offer both ways to benefit the environment and make the business side of farming more profitable for high-value crops. Such vegetation includes fruits (such as strawberries, grapes and pomegranates),

vegetables (for example, tomatoes, bell peppers and leafy greens) and flowering species (for instance, marigold, rose and gerbera) and a tiny loss because of rain damage can bring big declines in revenue. For these situations, early and proper crop protection is worth your money and pays off within a short span. A team of researchers at [15] found that using biodegradable mulch films in organic horticulture can raise yield by 20–30%, as well as increase nitrogen use efficiency (NUE). The results happened because the membrane controlled nutrients, reduced weed growth and kept the soil at an ideal temperature. The efficiency of mulch films is increased even more when they are put down with accuracy and uniformity by using UAVs. Thanks to meteorological data, spraying errors are avoided, there are no large uncovered areas and products can be applied immediately before rains are expected, to improve protection. Apart from horticulture, membrane systems can be used on huge cereal and staple farms found in areas that often receive too much rain or are flooded. In parts of South Asia that grow rice, too much rain can carry away important nutrients such as nitrogen, so that applying fertilizer is less helpful. During main growth stages such as tailoring or booting, planting semi-permeable or biodegradable membranes prevents nitrogen runoff when rain levels are highest. Evidence from [8] supports this connection by showing that strategies to improve NUE work well even when nitrogen input is low. According to their study, making nitrogen available with less loss from leaching can cut down nitrogen fertilizer use by 15–18% each time a crop cycle ends. Over time and on vast areas of land, the savings from no-till farming play a major role in increasing the farm's profits. In addition, using less fertilizer lessens farming's carbon impact and is compatible with climate-friendly agriculture goals.

Besides helping with fertilizer, membrane solutions also lower incidence of disease and lessen physical damage. When rain dampens the soil or leaves, *Phytophthora* and *Pythium* fungi do particularly well. They reduce the amount of soil and leaves hitting plants, preventing fungal spores and bacteria from being spread around by the wind. For organic farming, this is outstanding and it helps because synthetic fungicides are usually banned and the main defence against disease is culture and physical efforts.

Using meteorological data for membrane installation saves on labor and makes workers unaffected by bad weather. If rainfall is too unpredictable or heavy, many laborers refuse to harvest plants in the fields, but meteorological data can be used immediately and independently of human commands. Because of this, both efficiency and risk are lowered. We present a comparison table listing the differences in costs, benefits and productivity related to drone deployment of membranes for various types of cropping systems and different agriculture zones.

Table 5. Cost-Benefit Analysis of Membrane Deployment via Drone vs. Manual Methods

Metric	Drone-Based	Manual Application
Membrane cost (USD/ha)	250–500	180–400
Labor cost (USD/ha)	20–40	120–200
Yield improvement (%)	15–25	5–10
Membrane wastage (%)	<5%	10–20%
ROI within first season	Yes (in high-value crops)	Unlikely

iii) Regional Scalability and Infrastructure Needs

Even though using meteorological data in deploying membranes has clear agronomic and economic advantages, getting them used in resource-constrained conditions is still difficult and comes with many hurdles. Things that hold back wide use of such

technologies in places like the Global South are unreliable infrastructure, lack of training for farmers, financial problems and poor cooperation among organizations.

Researchers [6] state that numerous closely related constraints are holding back the digital revolution in rural India and similar areas. Having low digital literacy is the biggest obstacle for farmers who try to work with meteorological data, weather information and specialized control programs. Since land has been passed down over many generations, resulting in fragmented holdings, farming with small meteorological data is too expensive for the average individual smallholder, as the plots don't suit the investment. A further problem is that reliable electricity is not always available, especially for recharging drone batteries. Due to a lack of grid power and changing solar conditions in rural areas, maintaining drone readiness is tough, especially when membranes have to be installed during monsoon season.

Drone strategies should be part of general programs that overcome problems related to financing, operations and information. Combining drone activities and support services locally at the community or regional level is being seen as a strong option. You will often see these models coming as a bundle:

- **Farmer cooperatives sharing drone fleets:** When communities join forces, smallholder farmers are able to share UAV services and avoid big financial burdens. Working with plots side by side, you can plan the flights more optimally and pay less per hectare for operations.
- **Subsidized membrane distribution programs:** The assistance of the government or an NGO can mean that vulnerable farmers don't have to pay for biodegradable membranes. Some of these programs apply subsidies linked to how the farmer performs; such as partial reimbursement linked to crop or rainfall risk.
- **Drone pilot certification programs in rural areas:** Gaining new skills benefits the operations of remote-control meteorological data. Preparing rural youth and pioneer farmers in the handling and upkeep of meteorological data, according to national guidelines, helps build an indigenous workforce and offers potential jobs in the world of ag innovation. In cluster farming, where many small plots are combined, bundled services have proven successful for managing, observing and acting on the plots together. In these systems, both regional extension offices and third-party agritech businesses take care of organizing, operating and maintaining meteorological data to guarantee agricultural work is done on time, safely and effectively. To make this model work, ICT platforms are integrated so that when new membranes are needed, the timing is driven by data, not just by following a schedule. Rainfall, soil moisture and crop growth alerts are brought together by these systems, resulting in automatic advice to deploy meteorological data for applying the membrane. Connecting recent sensor information to logistics in the field means farmers get place-specific and timed solutions, avoiding broad and undirected guidance [29]. Achieving wide-scale use of drone-applied membrane technology in different agroecological regions will depend on bringing together policies, private-public alliances, sound infrastructure and local support.

iv) Policy Incentives and Environmental Gains

When people cannot buy these new technologies by themselves, public support is key to incorporating drone-based membrane systems into agriculture. If farmers and agricultural institutions do not get the funds and support needed, highly effective technologies may only be used by rich farmers, increasing the gap between large businesses and those who need help the most. To address this challenge, necessary policies and public financial support cannot be done without.

Using climate-smart farming tools such as environmental UAVs and automatic deployment systems in subsidy programs can make it much easier for smallholders to

afford them and ensure everyone can benefit. The schemes may involve capital subsidies for buying meteorological data, tax breaks for companies innovating inexpensive meteorological data or support for rental services where farmers use meteorological data only as needed. Just as with insecticide products, sharing costs for biodegradable mulch films or membrane materials can help with the spread of sustainable crop protection methods, mostly for crops that are at higher risk.

Because such systems are good for the environment and for development, there is a strong reason for their policies to be aligned with worldwide and national sustainability plans. Lowering nutrient runoff and leaching of chemicals into neighbouring areas boosts the farm's profits, improves water and keeps soils healthier. Improvements in agriculture due to these outcomes support both Zero Hunger and Climate Action targets by raising food production and helping adapt to climate changes [11]. Membrane application by meteorological data also supports the mission of making agriculture greener, a growing priority both nationally and globally. Traditionally, applying membranes using tractors or manual methods needs many fuel-powered passes in big or diverse fields. Unlike others, meteorological data are light and run on batteries, letting them use less energy and create fewer greenhouse gases. In addition, zero-runoff ways to grow plants make sure nutrients are retained, optimally using fertilizers and thus reducing the production of nitrous oxide (N₂O) which is an important greenhouse gas.

Investment in these technologies by the government leads to additional benefits. Offering training and certifications for drone operators is a way that governments can boost agri-tech jobs, strengthen entrepreneurial opportunities in remote areas and discourage young people from leaving farming communities. If digital extension services are used alongside, digital agriculture programs can also develop farmers' data knowledge and better prepare them for other technologies. Overall adding public sector backing to drone-based membrane systems adds to technology, protects the environment and promotes economic development. Because climate change causes weather to become less predictable in farming, this kind of support is necessary to keep food systems sustainable, just and able to handle any situation.

3. INTEGRATED SYSTEM FRAMEWORK

Because rainfall has become more variable and nutrients are leached more easily, predicting and communicating in agriculture are now very important. The system proposed here, based on (1) rainfall prediction with meteorological data and ML, (2) communication through IoT and ICT technologies and (3) drone-delivered membrane installation, detects, warns about and handles risks in real-time. Here we describe how the different components of the system interact to make the model ready for disasters.

3.1 Modular Architecture and Data Flow

The system is structured into four interdependent modules shown in figure 6:

1. Sensing and Data Collection Layer: Through meteorological data, data on atmosphere features (such as humidity and temperature) is grabbed and IoT devices on the ground gather data on soil moisture, EC and how hard it is raining. GPS technology is used to tag the data and send it to edge gateways so it can be pre-processed [28]
2. Prediction and Analysis Module: Real and historical weather and soil data are used with GRU-CNNs, SVM and RF models to predict rainfall and determine where leaching may occur [29] [2].
3. Communication and Advisory Interface: Alerts are sent by SMS, telling notes and mobile screens based on the language the user set. The recommendations farmers and other key institutions receive are tailored using these notifications.

4. Actuation Layer: Following confirmation or an automatic mechanism, meteorological data apply biodegradable films to crops and stored produce using membrane equipment which reduces nutrient loss due to rain and helps protect harvested produce [15].

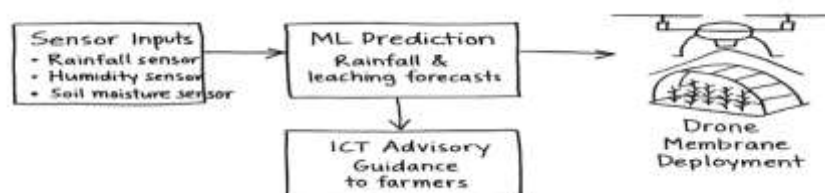


Figure 6. Integrated Framework for Rainfall-Induced Crop Protection Using Smart Agriculture Modules

3.2 System Flow and Feedback Loop

Every module in the integrated smart agriculture system follows a closed loop, using collected information to monitor, guide choices and assist in prompt field actions. The system is capable of handling any environment changes when they occur and can become more accurate, efficient and resilient with every ongoing situation.

The rainfall prediction module starts the feedback loop by constantly studying drone and ground-based weather node data. When the soil moisture sensors and evapotranspiration models tell us the soil will hold more water than expected, an automatic risk alert is sent to inform the team [13]. The communication layer alerts farmers as soon as prediction is received at once by sending an SMS or app notification or using voice technology, to suggest postponing irrigation or fertilization to avoid nutrient leakage.

The system is also equipped to make autonomous choices when humans are not involved. When no action is taken on the risk alert by the farmer within the forecasted time, the system sends meteorological data out to cover vulnerable parts of the crop with protective membranes. These deployments begin after GPS-mapped risk areas are generated, validated using satellite and drone imagery and marked on the field to mark specific risky zones [23].

With the installation of the membrane, the process continues. Consequently, the soil sensors continue their work, checking the moisture, EC and nitrogen levels after the sensors have been installed. When these measurements are back to their best levels, the system logs the event's results before applying the updated information to fine-tune its machine learning models. The system's ability to predict and react to future scenarios improves when historical data is included. But if the process is not stable for whatever reason; for example, if rain keeps exceeding the membrane's ability to store it or unexpected nutrients are lost; the system prepares for another operating sequence. In some cases, this means issuing more alerts, using secondary meteorological data or making sure regional agricultural extension officers are kept informed. Systems within the framework work together to guide event-driven agriculture that is adaptive to all kinds of inputs and unexpected changes.

3.3 Interoperability and Scalability

Making the smart agriculture system compatible with governance, advisory and financial systems is necessary for large numbers of farmers to use it, become visible to institutions and improve coordinated activities. Jointly using technology and services from public organizations promotes a single style of managing disaster risks and sustainability in agriculture. Details on farmers are connected with websites for officials, groups assisting farmers and insurance policies tied to the weather. They improve the way the system works with different stakeholders. For illustration, district agricultural officials can

review dashboards that instantly show the state of their soil, regional weather issues and lists of flying meteorological data. Authorities benefit from metrics present in these interfaces which measure drone use, coverage of water samples and response to alerts, helping to improve the coordination of local advisories [33]. Such detailed disclosure from energy firms supports public agencies in using data to decide on resources, prepare for disasters and take action during severe weather situations. Because the platform is built modularly, it can be rolled out across regions gradually, according to what each area can handle and supply. If there is no UAV infrastructure in a region, the framework can start by setting up ICT advisories, weather sensor nodes for the soil and a dashboard connection. Those features alone are sufficient to add value by monitoring climate in the fields and allowing farmers to share updates. When governments improve technical capacity with their own programs or investors and partners make private contributions, meteorological data and membrane launch systems can be introduced step by step. This process helps decrease the first expenses farmers and local officials must pay, while slowly introducing them to the system.

To make sure different platforms can work together easily and efficiently, the architecture has lightweight APIs included. These APIs allow the system to integrate long-term rainfall records held by the IMD and agronomic data present in soil health cards. When third-party data is merged with sensor and drone information, machine learning is better able to forecast weather, estimate nutrient leaching and schedule membranes. By bringing together different forms of data, the platform's analytics engine improves and allows for better localized model training and checking. Looking at systems engineering, these integration skills mean the platform can link smoothly with many types of applications, be adopted by different groups of users and follow numerous rules across the industry. It does not matter if the platform is used by small farmers, commercial agri-tech companies or by governments; it can still grow significantly over a given area and serve different needs without needing major investments in infrastructure. In sum, by combining e-governance alignment with a modular system and API-aided data sharing, the platform supports technology as well as policy, extension and sustainability goals in precision agriculture.

3.4 Sustainability and Institutional Impact

Combining drone, IoT and machine learning technologies within agriculture provides helpful features for the industry as a whole. Because of these technologies, growers can make better use of resources, cut back on overusing chemicals and take better care of the environment. When soil and rainfall data is used in real time, the system ensures the fertilizer is correctly applied, less runoff occurs and chemical runoff into close water bodies is lower; contributing directly to higher sustainability goals based on recent studies [10] [12].

Using fewer inputs and preventing spills helps improve soil, keep groundwater clean and cut down on greenhouse gas emissions that come from using too much fertilizer. The results achieved are consistent with climate-smart agriculture and are supported by the sustainability goals promoted worldwide and at home. Such frameworks support the real-time tracking of events by government organizations, most notably during emergencies such as monsoonal floods and begins of drought. Because predictive analysis and sensor dashboards are combined, unusual findings are detected more quickly, helping with prompt decisions and field actions. For instance, agricultural departments in each state might use these systems to warn farmers, prepare meteorological data and distribute quick supplies in time for serious weather. Swift action is key in places where weather changes can damage crops or use resources unnecessarily. Additionally, using data visualization and automatic reporting in public dashboards allows systems to support the

formation of policies using facts. By considering historical trends, risk data on maps and measures of the impact of interventions, those deciding on policy can adjust assistance for farmers, land division regulations or what research will be conducted. Researchers [35] state that incorporating data helps government actions support both digital learning and development in rural areas, making it possible for the state to guide agriculture using digital methods. Frequent and more severe effects of climate change in less-developed countries are making it important to create digitized resilience systems. This suggests that with integrated platforms for sensing, analysis, advice and oversight, these countries can leap past many usual infrastructure challenges. This helps farms produce more and also includes disaster management in the way the food system is managed, so daily operations support long-term sustainability and development plans.

4. CHALLENGES, LIMITATIONS, AND FUTURE DIRECTIONS

4.1 Current Challenges and Limitations

While the planned integrated system seems promising for controlling rainfall-induced crop leaching, putting it into practice runs into a range of problems that make its effectiveness and scaling uncertain for farmers. To make a system stable and accessible to all, we have to handle technical inconsistencies, changing environments and socioeconomic differences.

i) Data Collection Inconsistencies

It is the quality, minute detail and continuous gathering of data from the field that decide how strong and accurate the next steps in smart agriculture will be. Machine learning algorithms are trained and rainfall, risks of nutrient loss and drone responses are forecast using these datasets. Maintaining the accuracy of data in various farming environments continues to be a persistent problem, mostly in rural and undersupplied locations. A big challenge comes from sensors breaking down and intermittent communication which often occur in remote systems facing unstable weather, build-up of dust and aging hardware. When sensor nodes have too little sunlight or their batteries don't last long enough, this interrupts their data reporting. These interruptions lower the amount of data in time-series records and make it more difficult for the model to spot short changes in the environment prior to large rainfall or water leaching events. Another problem is that field sensors are not always calibrated correctly. Both the soil moisture probes, pH meters and atmospheric loggers tend to become less accurate as time goes on, particularly in salinity, heavy metal or displacement environments. Large-scale setups, with many sensors covering various hectares, can sometimes have internal differences in sensing due to improper calibration which influences the model's predictions. Uneven depths or odd positions of sensors may create faulty readings that don't reflect the actual state of the field. Unevenness in the soil, elevation and vegetation occur over very short distances on heterogeneous farmland which makes the problem worse.

Technological limitations for UAV sensing are equally as important. The length and frequency of UAV-based environmental scanning missions are limited by how long the batteries will run. A majority of commercial agricultural meteorological data provide between 20 and 40 minutes of operated flight time when carrying additional devices including high-resolution cameras, LiDAR elements or membrane release mechanisms. Therefore, the drone cannot perform consistent, high-frequency monitoring of substantial and non-uniform territories, since the round-trip time exceeds its capabilities. The data collected each time can only be as detailed and useful as the type of sensors and available payload the UAV can accept. Using several kinds of sensors, for example hyperspectral cameras, thermal imagers and ultrasonic rangefinders, can make data collection much deeper, but it also results in more weight and a faster drain of power which cuts down on

battery life and means recharging after each flight given by equation (7) & (8). A major challenge in UAV-aided farming is deciding how different sensors will affect the time a UAV can stay in the air. UAV Flight Time Estimation

$$T = \frac{E_{\text{battery}}}{P_{\text{base}} + P_{\text{payload}}} \quad \text{---- (7)} \quad P_{\text{payload}} = k \cdot W_{\text{payload}} \quad \text{---- (8)}$$

Where:

- T = Estimated flight time (in hours or minutes)
- E_{battery} = Total energy available from the battery (in watt-hours, Wh)
- P_{base} = Base power consumption (in watts) of the drone without any additional payload

P_{payload} = Additional power draw due to sensors/payload (in watts), which increases with weight and complexity

Payload Impact on Power Consumption

Where

W_{payload} = Weight of the payload (kg)

k = Power consumption constant per kg (W/kg), depends on drone design and aerodynamic efficiency

UAV platforms and sensor companies commonly use unique standards which make it hard for members of the community to work together. Because each manufacturer has its own data methods, optimization algorithms and communication systems, datasets get mixed up when several meteorological data need to function together. Such systems cannot be used on a wide scale or join up with key government-run platforms or important agronomic databases because they are not interoperable. Because of these obstacles, accurate machine learning models are hard to train and can fail when the data arriving for inference is incomplete or erratic. With data that is not very accurate or neat such models may overlook some threats or report false danger in situations that are swiftly changing or near the edge of dangerous weather. Data analysis in today's farming is limited by security issues, balancing decisions and standardization problems. To overcome these issues, more work is needed in standardizing calibration steps, using open data formats, creating light ways to merge data and boosting UAV energy efficiency; each of which is important for successful, scalable and practical agricultural intelligence.

ii) **Limited Generalizability of Machine Learning Models**

Machine learning (ML) is very useful for predicting rain, tracking nutrient leaching and automating farm decisions, one main problem is that it struggles to work well in many agricultural zones. A model that works well for one region may not perform as well in another because of differences in environment, farming methods and climate. Because machine learning results can't always be trusted, there is a risk of critical mistakes when predicting and responding to events. To illustrate, a GRU-CNN developed using high-resolution meteorological and soil datasets for the Indo-Gangetic plains; soils are loamy, the main crops are rice and wheat and rainfall comes from monsoons; won't necessarily work in the Deccan Plateau, where black cotton or red loam soils are dominant, irrigation is less consistent and rainfall occurs much less regularly. The same system may have even bigger challenges in the semi-arid regions of Sub-Saharan Africa, where rainfall occurs just once in a flash and millet and sorghum are most often grown. Such variations in environmental conditions can make models misunderstand moisture saturation points, wind speed ranges or rainfall signals, leading to wrong classifications or wrong predictions.

ML models are structured to learn traits from the data they are trained on which includes its biases, patterns of noise and the grouping of its key features. When using data from a region not seen before, models make less accurate predictions. Many types of variation

such as soil texture, nutrient binding, elevation, sunlight and irrigation, are found between countries and sometimes even between connected places inside a country. The fact that few multimodal, open-access datasets labelled for agriculture are available only makes the problem worse. Such information is commonly held privately, scattered in different formats or kept secret because of regulations. This scarcity prevents training models that work in many cases and reduces the benefits of federated learning, transfer learning and domain adaptation methods that need plenty of data. Although pre-trained models that are adjusted for regional data help, they are not the final answer. If the two domains in transfer learning are close, performance will be better. No overlap in the domains of the data may allow erroneous weights to slip through and cause the constructed models to wrongly separate features, leading to more frequent mistakes. As with other approaches, using domain adaptation may address source and target discrepancies, but it always needs labelled dataset samples from the target environment which farmers may not be able to afford in practice. As a result, training and testing models in the region are still the most effective way. Local data must be regularly added to models to keep them both sensitive to the environment and reliable for forecasting. Setting up structures for local data gathering, partnering with nearby agricultural bodies and passing rules that make sharing and standardizing data across regions possible are all important. Even the strongest ML structures can become unreliable if we do not properly manage our models as they are scaled up. Therefore, robust model generalization in agriculture will require both advanced technology and attention to local data control, diverse ways to collect data and practical support for updating the models. These aspects are key to keep ML-driven tools for farming accurate, equitable and effective everywhere.

iii) Weather forecast Monitoring Organization Endurance and Weather Dependency

Meteoritic data are key in precision agriculture because they use on-board sensors to collect environmental data and they also spread protective membranes to prevent leaching after rainfall. Still, both the adaptability and automation of meteorological data are limited by their difficulties with battery endurance and sensitivity to various conditions. Such constraints can reduce how much help a system is able to give, mainly when speedy solutions are required during inclement weather. Flight time is the main problem that aircraft face. Agricultural meteorological data primarily sold today; especially those with sprayers, rollers or multispectral sensors attached; tend to fly for just 20 to 30 minutes when their batteries are fully charged. Because of this limitation, more than one flight or battery exchange is needed to cover a larger area. Using 4–6 flight cycles for a biodegradable membrane over a 5-hectare rice plot will depend on drone speed, the membrane itself and the wind speed. As a result, processing time and workforce synchronization go up, along with the difficulty of events involving batteries and flying again. Regions that have unreliable power infrastructure, mainly remote countryside without reliable grid electricity, are most affected by the endurance challenge. Because solar charging stations, battery swap depots or mobile power units are not always available, subsequent drone flights can be delayed in such settings. Even with backup batteries, power access is crucial because they will not work properly when many meteorological data have to coordinate across different areas. Because of this, it becomes very difficult for the system to respond and scale up during the monsoon season when swift and large-area efforts are key. Compounding this problem is that meteorological data are easily disturbed by bad weather, even though their primary use includes forecasting and dealing with rain. You typically won't see UAVs flying during times of strong wind, hard rain or when there are heavy fog or mist. Such conditions appear not just in monsoon but also when membrane deployment is necessary to keep nutrients and crops safe from damage. Drone systems are sensitive to changes in weather conditions. Wind gusts and bumpy air make flights less stable and may affect the way spray or

membranes are placed. Because the battery-powered motors have to work tougher to avoid falling over, the battery will drain more rapidly. As well as running the chance of short circuits, rain can result in poor data readings from the atmosphere and optical sensors because it absorbs the light those sensors need. Having dense fog in the air can disturb GNSS signals and make it harder for sensors to detect objects. As a result, UAVs in environments with trees, poles or vertical trellising may suffer from mid-flight problems or crashes.

These weak points create serious challenges for how companies work. If the system triggers a rainfall alert, it will try to deploy protective membranes. However, if meteorological data are too unsafe to fly, those may not be deployed. As a result, the model's ability outshines its actual performance, reducing confidence in the system for users.

To solve these issues, companies now use these new approaches:

- Deploying meteorological data in groups means tasks can be done more quickly and there is less work per area.
- Gas-electric models that fly longer are called hybrid meteorological data, but they are rather costly and generally uncommon.
- Meteoritic data built to withstand weather changes, having sealed covers, tough frames and moisture-resistant sensors.
- The ability to plan and trigger functionality offline, providing autonomous launch as soon as the necessary conditions are met.

Nevertheless, the majority of these approaches are too expensive or intricate to use in settings with few resources. This shows that future study should concentrate on better batteries, lighter loads and stronger ability of UAVs to stand up to stresses. New techniques play a key role in reaching the full benefits of drone-assisted farming in light of the expected weather changes ahead.

iv) Infrastructure Gaps and Socioeconomic Barriers

Although companies have developed IoT and AI technologies in agriculture, not all farmers in low- and middle-income countries are adopting them. Currently, digital systems in farming benefit mainly rich commercial farms because common socioeconomic and infrastructural problems prevent wider application to less wealthy farmers.

Lack of sufficient rural infrastructure is a major limitation. Farmers in a number of regions still do not have reliable electricity, cellular internet or smart tools needed to join digital agriculture. Commonly, eventual connectivity can support calls only and it typically does not provide enough bandwidth for drone data, sensors or analytics on the cloud. Researchers [14] found that in Indian rural areas, a farmer's digital participation was most influenced by their literacy rate, how much they earned and whether they had access to extension programs. When these variables are low in a community, the rate of adoption for new agricultural technology is still slow and steep. Starting costs for installing smart technologies are a big obstacle to making them more widely used. It is necessary to invest in drone teams, many environmental sensors and ongoing use of AI-based software to use precision agriculture tools. Almost all of the smallholder farmers that only farm between 1 and 3 acres and make little extra money, usually cannot pay those prices without extra help from cooperatives, NGOs or government programs. In the absence of such systems, digital agriculture could instead be controlled mainly by big agribusinesses, putting small-scale farms at an even greater digital disadvantage. Too many institutional voids can lead to slow acceptance. Many extensions in rural areas don't have enough resources or the skills to provide digital and AI training to farmers. Where no such support is available, farmers will not trust technology and few will take up new methods, no matter how useful

they are. In addition, people's attitudes and habits are significant challenges too. In those places where farmers have been using the same traditional ways for generations, they are reluctant to trust decisions made by algorithms. A strong barrier to resisting shocks is that most dashboards and advice systems are designed for English or unfamiliar languages and opportunities for training often don't match the needs of people living in the countryside. Most importantly, people in these networks are hesitant to trust AI-suggested recommendations. A lot of farmers are doubtful of models or forecasts that they do not see connected to their everyday activities. If their advice contradicts what the people living there already know, these systems are often ignored. This affects the responsiveness of the digital ecosystem and in time may damage its standing.

To deal with these obstacles, specially designed treatments are required. Such examples are:

- Interfaces and advisories available in local languages as well as in spoken form.
- Rural extension frameworks are strengthened by including capacity-building programs.
- Test plots that show farmers how meteorological data and data-based irrigation can be helpful on their farms.
- Offering digital tools for smallholders at different price levels for one season or per each time they use them.

All the necessary technologies for precision agriculture are easy to access, but their effective use needs the removal of different barriers. Unless there are inclusive design plans, subsidy frameworks and trust-building efforts, smart farming tools will unlikely reach those who can gain the most from them.

5. CONCLUSION

Artificial intelligence, meteorological data and IoT technologies working together provide a new and effective route to stronger and healthier farming. This study examines a modern agriculture system that brings together drone-based GPS for rainfall prediction, live communication through IoT and ICT and drone spraying of thin membrane wraps on crops to prevent them from getting damaged by rain. Each goal takes on a role; predictive, communicative or preventive; that in combination helps the farm detect, assess and control problems as they occur. Linking environmental observations, machine learning and automated field work, this system both handles fast-acting weather hazards and helps achieve lasting sustainability in agriculture. Its design as separate modules, flexibility in use worldwide and ability to link with agricultural policies make it possible for the digital innovation to reach both large farms and small communities, promoting food safety and environmental health throughout the globe.

References

- [1]. Alves, A. S., Schultz, N., Conforto, B. A. A. F., Zonta, E., & de Carvalho, D. F. (2023). Soil, water and nutrient loss under simulated rainfall patterns in an area fertilised with chicken litter. *Journal of Hydrology*, 620, 129543.
- [2]. Chlingaryan, A., Sukkarieh, S., & Whelan, B. (2018). Machine learning approaches for crop yield prediction and nitrogen status estimation in precision agriculture: A review. *Computers and Electronics in Agriculture*, 151, 61–69.
- [3]. Hoque, M. J., Islam, M. S., Uddin, J., Samad, M. A., De Abajo, B. S., Vargas, D. L. R., & Ashraf, I. (2024). Incorporating meteorological data and pesticide information to forecast crop yields using machine learning. *IEEE Access*.
- [4]. Jain, S., Sethia, D., & Tiwari, K. C. (2024). A critical systematic review on spectral-based soil nutrient prediction using machine learning. *Environmental Monitoring and Assessment*, 196(8), 699.

- [5]. Kamilaris, A., & Prenafeta-Boldú, F. X. (2018). Deep learning in agriculture: A survey. *Computers and Electronics in Agriculture*, 147, 70–90.
- [6]. Liakos, K. G., Busato, P., Moshou, D., Pearson, S., & Bochtis, D. (2018). Machine learning in agriculture: A review. *Sensors*, 18(8), 2674.
- [7]. Sindakis, S., & Showkat, G. (2024). The digital revolution in India: bridging the gap in rural technology adoption. *Journal of Innovation and Entrepreneurship*, 13(1), 29.
- [8]. Srikanth, B., Subrahmanyam, D., Sanjeeva Rao, D., Narender Reddy, S., Supriya, K., Raghuveer Rao, P., ... & Neeraja, C. N. (2023). Promising physiological traits associated with nitrogen use efficiency in rice under reduced N application. *Frontiers in Plant Science*, 14, 1268739.
- [9]. Berger, K., Machwitz, M., Kycko, M., Kefauver, S. C., Van Wittenberghe, S., Gerhards, M., ... & Schlerf, M. (2022). Multi-sensor spectral synergies for crop stress detection and monitoring in the optical domain: A review. *Remote Sensing of Environment*, 280, 113198. <https://doi.org/10.1016/j.rse.2022.113198>
- [10]. Giordano, M., Petropoulos, S. A., & Roupheal, Y. (2021). The fate of nitrogen from soil to plants: Influence of agricultural practices in modern agriculture. *Agriculture*, 11(10), 944. <https://doi.org/10.3390/agriculture11100944>
- [11]. Kazimierczuk, K., Barrows, S. E., Olarte, M. V., & Qafoku, N. P. (2023). Decarbonization of agriculture: The greenhouse gas impacts and economics of existing and emerging climate-smart practices. *ACS Engineering Au*, 3(6), 426–442. <https://doi.org/10.1021/acsengineeringau.3c00021>
- [12]. Khan, M. R., Abubakar, M., Tahir, A., Dilawar, M. W., Hassan, H. M. A., Ahmad, S. R., ... & Chand, M. U. (2024). Escalating global threat of heatwaves and policy options for adaptation and mitigation. *Journal of Asian Development Studies*, 13(3), 980–995.
- [13]. Lu, Y., Wang, E., Zhao, Z., Liu, X., Tian, A., & Zhang, X. (2021). Optimizing irrigation to reduce N leaching and maintain high crop productivity through the manipulation of soil water storage under summer monsoon climate. *Field Crops Research*, 265, 108110. <https://doi.org/10.1016/j.fcr.2021.108110>
- [14]. Mittal, S., & Mehar, M. (2016). Socio-economic factors affecting adoption of modern information and communication technology by farmers in India: Analysis using multivariate probit model. *The Journal of Agricultural Education and Extension*, 22(2), 199–212. <https://doi.org/10.1080/1389224X.2014.997255>
- [15]. Samphire, M., Chadwick, D. R., & Jones, D. L. (2023). Biodegradable plastic mulch films increase yield and promote nitrogen use efficiency in organic horticulture. *Frontiers in Agronomy*, 5, 1141608. <https://doi.org/10.3389/fagro.2023.1141608>
- [16]. Schaeffer, A. H., Schaeffer, O. A., Silveira, D. C., Bertol, J. A. G., Rocha, D. K., dos Santos, F. M., ... & Lângaro, N. C. (2020). Reduction of ryegrass (*Lolium multiflorum* Lam.) natural re-sowing with herbicides and plant growth regulators. *Agronomy*, 10(12), 1960. <https://doi.org/10.3390/agronomy10121960>
- [17]. Spijker, J., Fraters, D., & Vrijhoef, A. (2021). A machine learning based modelling framework to predict nitrate leaching from agricultural soils across the Netherlands. *Environmental Research Communications*, 3(4), 045002. <https://doi.org/10.1088/2515-7620/abf42a>
- [18]. Sundaresan, S., Johnson, S. D., Bharathy, V. M., Kumar, P. M. P., & Surendar, M. (2023, March). Machine learning and IoT-based smart farming for enhancing the crop yield. In *Journal of Physics: Conference Series* (Vol. 2466, No. 1, p. 012028). IOP Publishing. <https://doi.org/10.1088/1742-6596/2466/1/012028>
- [19]. Akilan, T., & Baalamurugan, K. M. (2024). Automated weather forecasting and field monitoring using GRU-CNN model along with IoT to support precision agriculture.

- Expert Systems with Applications, 249, 123468.
<https://doi.org/10.1016/j.eswa.2023.123468>
- [20]. Camarillo-Escobedo, R., Flores, J. L., Marin-Montoya, P., García-Torales, G., & Camarillo-Escobedo, J. M. (2022). Smart multi-sensor system for remote air quality monitoring using unmanned aerial vehicle and LoRaWAN. *Sensors*, 22(5), 1706. <https://doi.org/10.3390/s22051706>
- [21]. Kumar, V., Kedam, N., Kisi, O., Alsulamy, S., Khedher, K. M., & Salem, M. A. (2025). A comparative study of machine learning models for daily and weekly rainfall forecasting. *Water Resources Management*, 39(1), 271–290. <https://doi.org/10.1007/s11269-024-03712-w>
- [22]. Sharma, A., Chahal, A. S., Singh, K. K., & Pathania, R. (2024). AI and drone technologies in agriculture. In *Advances in Agricultural Engineering and Artificial Intelligence* (pp. 109–126). Springer. https://doi.org/10.1007/978-3-031-40967-2_6
- [23]. Teixeira, K., Miguel, G., Silva, H. S., & Madeiro, F. (2023). A survey on applications of unmanned aerial vehicles using machine learning. *IEEE Access*, 11, 117582–117621. <https://doi.org/10.1109/ACCESS.2023.3305581>
- [24]. Haseeb, K., Ud Din, I., Almogren, A., & Islam, N. (2020). An energy efficient and secure IoT-based WSN framework: An application to smart agriculture. *Sensors*, 20(7), 2081.
- [25]. Alharbi, H. A., & Aldossary, M. (2021). Energy-efficient edge-fog-cloud architecture for IoT-based smart agriculture environment. *Ieee Access*, 9, 110480–110492.
- [26]. Olivares Garcés, D. (2020). Energy-Efficient Operation of IoT Sensors in Precision Agriculture (Master's thesis, NTNU).
- [27]. Swain, M., Hashmi, M. F., Singh, R., & Hashmi, A. W. (2021). A cost-effective LoRa-based customized device for agriculture field monitoring and precision farming on IoT platform. *International Journal of Communication Systems*, 34(6), e4632.
- [28]. Prakash, C., Singh, L. P., Gupta, A., & Lohan, S. K. (2023). Advancements in smart farming: A comprehensive review of IoT, wireless communication, sensors, and hardware for agricultural automation. *Sensors and Actuators A: Physical*, 362, 114605.
- [29]. Adla, S., Aravindakshan, A., Tyagi, A., Guntha, R., Ponce-Pacheco, M. A., Nagi, A., ... & Pande, S. (2025). Participatory development of mobile agricultural advisory driven by behavioural determinants of adoption. *Journal of Environmental Management*, 374, 124140. <https://doi.org/10.1016/j.jenvman.2024.124140>
- [30]. Agbehadji, I. E., Schütte, S., Masinde, M., Botai, J., & Mabhaudhi, T. (2023). Climate risks resilience development: A bibliometric analysis of climate-related early warning systems in Southern Africa. *Climate*, 12(1), 3. <https://doi.org/10.3390/cli12010003>
- [31]. Hachimi, C. E., Belaqqiz, S., Khabba, S., Sebbar, B., Dhiba, D., & Chehbouni, A. (2023). Smart weather data management based on artificial intelligence and big data analytics for precision agriculture. *Agriculture*, 13(1), 95. <https://doi.org/10.3390/agriculture13010095>
- [32]. Rickards, C. B., Otieno, W., & Marennya, P. (2025). Enhancing farmer learning and adoption of digital extension: A case study report of sorghum and millet farmers in western Kenya. CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS). [Forthcoming].
- [33]. Furtado, L. S., da Silva, T. L. C., Ferreira, M. G. F., de Macedo, J. A. F., & Cavalcanti, J. K. D. M. L. (2023). A framework for Digital Transformation towards Smart Governance: using big data tools to target SDGs in Ceará, Brazil. *Journal of Urban Management*, 12(1), 74–87.

- [34]. Iqbal, R., & Butt, T. A. (2020). Safe farming as a service of blockchain-based supply chain management for improved transparency. *Cluster Computing*, 23, 2139-2150.
- [35]. Sood, S., & Saxena, N. (2017). Moving beyond digital literacy and towards e-governance in rural India. In *Proceedings of the Special Collection on eGovernment Innovations in India* (pp. 1-5).
- [36]. P.Muthi Reddy, Sirineni Pooja, Guttula Venkat Rohith and V. Bharath, "An artificial Intelligence method for Prediction of Heart Disease using Convolutional Neural Network", *Journal of the Maharaja Sayajirao University of Baroda*, ISSN: 0025-0422, vol. 55, no. 1(9), pp. 192-197, April 2021
- [37]. Ofori, E. K., Ozturk, I., Bekun, F. V., Alhassan, A., & Gimba, O. J. (2023). Synthesizing the role of technological innovation on sustainable development and climate action: Does governance play a role in sub-Saharan Africa?. *Environmental Development*, 47, 100900.