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Smart Agriculture Advisory System

S.Abirami
Department of Computer Science
And Engineering
Panimalar Engineering College
Chennai,TamilNadu,India,
ramiabiramirami@gmail.com

V.Adithi Shree
Department of Computer Science
And Engineering
Panimalar Engineering College
Chennai,TamilNadu,India,
vadithishree@gmail.com

***Abstract*—The pressures of population growth, climate change, and finite resources are challenging agriculture more than ever. Farmers are being forced to adopt sustainable and efficient agricultural practices to provide food security with minimal environmental impacts. In the past few years, the advent of new drone (Unmanned Aerial Vehicles, UAVs) and remote sensing technologies by satellites have opened doors for precision agriculture. UAVs collect fine-resolution captured data of crops, irrigation and pests, while Satellite technology, via sensors, allows large-scale monitoring of land and vegetation over time and even relating to spatial and temporal climate inferences. This paper introduced a hybrid framework using both UAV and Satellite components within the hybrid map view for improved decision making. The framework uses UAV sensors for monitoring crops and soil and integrates precalculated satellite spectral band indices (NVDI, SAVI, EVI). As well, the hybrid framework incorporated machine learning and data fusing applications from the UAV and Satellite. A fusion framework supports optimised irrigation and fertilising decisions and saves water; figure (1) shows field trials that intelligently improved water efficiencies by 30%, fertilizer use reduced on environmental terms – reduced 25%, better planning decisions for yield predictions 92% efficiency. Thus, the role of a hybrid framework promotes, in particular, sustainable farming through reduced waste and fewer GHG emissions and, in both cases, increase resilience to climate change.**

INDEX TERMS— Sustainable agriculture, drones, satellite data, NDVI, IoT, remote sensing, machine learning, climate resilience

I. Introduction

The agricultural sector is arguably at the nexus of global sustainability challenges. Agriculture accounts for nearly 25% of greenhouse gas (GHG) emissions, consumes approximately 70% of the world's freshwater, and is continuously at risk from soil degradation, biodiversity loss and the unknown consequences of climate change. The Food and Agriculture Organization (FAO) estimates that global food production needs to increase at least 50% by 2050 to feed a forecasted population of 9.7 billion people. Meeting this demand with less arable land and increasing environmental constraints requires a paradigm shift to meet sustainable agriculture. Sustainable agriculture recognizes the need to improve productivity while protecting ecosystems and conserving natural resources.

Manual scouting, field sampling, and stationary groundbased sensors can provide valuable agricultural monitoring information but they lack scalability, precision, and real-time responsiveness. Traditional agricultural monitoring approaches are time-consuming and laborintensive – to the point where human-error cannot be ruled out – making them unsuitable for monitoring large tracts of land or to respond quickly in dynamic conditions. However, remote sensing technologies may provide the first real innovations in meeting these challenges.

Drones (unmanned aerial vehicles, UAVs) can provide ultra-high spatial resolution imagery (often at the centimeter level) that can allow for early detection of crop stress, nutrient deficiencies, and water limitations, as well as pest damage, all of which can occur at the plant or plot scale. Drone technology can contribute to the Sustainable Development Goals (SDGs) established by the United Nations by contributing to sustainable agricultural practices and practices to support the 9.7 billion occupants of this planet.

Agriculture is the backbone of food systems globally, and it is also one of the most resource-intensive and environmentally impactful sectors. Agriculture contributes almost 25% to total greenhouse gas (GHG) emissions; it accounts for approximately 70% of global freshwater withdrawals; and it is responsible for deforestation, degradation of soils, and loss of biodiversity. At the same time, agriculture is also one of the sectors most susceptible to climate change; increased temperatures, variability in rainfall, and extreme weather events all threaten crop yields, food security, and agriculture worldwide. The Food and Agriculture Organization (FAO) estimates that global food production will have to increase by more than 50% by 2050 in order to feed the expected 9.7 billion people. For this to happen, we must rethink the way food is produced, monitored, and managed given a world of limited arable land, constrained resources, and sustainable alternatives.

Traditional agricultural practice relies on manual scouting, field sampling, or stationary sensors to observe crop phenology, crop health, or soil conditions. While this can provide localized knowledge, these practices are often time-consuming, and laborious, and cannot scale efficiently over larger or more remote farming systems

II. SYSTEM SETUP

The proposed hybrid monitoring framework is structured as three-layer architecture that consists of dronebased sensing ,satellite-based monitoring, and cloudbased data fusion. Each layer has different functions and capabilities; once integrated, they will comprise a robust and scalable approach for precision agriculture.

A. Drone-Based Sensing

The first layer consists of unmanned aerial vehicles (UAVs) taking high-resolution imagery of agricultural fields. The UAVs are equipped with multispectral, RGB, and thermal cameras in order to collect diverse datasets producing spectra that include visible, near-infrared, and thermal wavelengths. There are a variety of agricultural-related features that can only be detected when monitoring changes related to nutrient stress of crop production, irrigation efficiency, and pest infestations characterizing plants or plots. The UAVs have a Pixhawk flight controller with GPS navigation, allowing them to pre-plan their own flights autonomously and georeference the imagery produced in the agricultural field. UAVs provide data at centimeter-level resolution to generate insights not possible through testing and observation, and the parameters obtainable through UAVs are often too detailed for useful interpretation. UAVs do have limitations associated with short-range flight endurance, battery capacity, and weather factors, which reduce their scalability.

B. Satellite-Based Monitoring

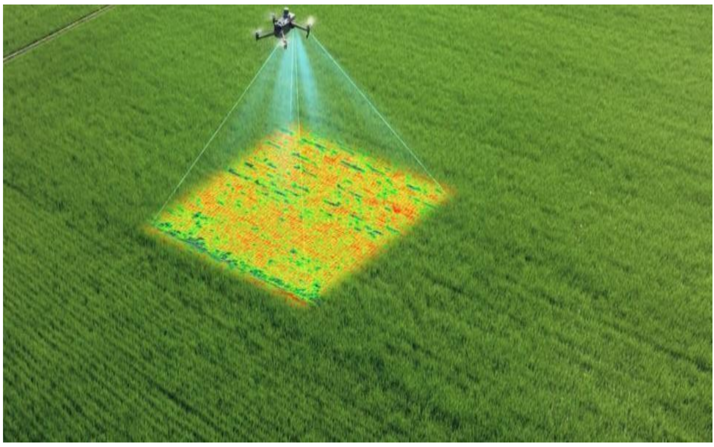
The second layer utilizes satellite imagery available from openaccess sites such as Sentinel-2 (European Space Agency) and Landsat-8 (NASA/USGS)). These satellites can provide continuity of time and space allowing us to track the dynamic growth of crops over time and space. All aforementioned vegetation indexes, Normalized Difference Vegetation Index (NDVI), Soil Adjusted Vegetation Index (SAVI), and Enhanced Vegetation Index (EVI), can be derived from satellite imagery to observe crop vigor, soil conditions, and canopy density. While satellite images have a larger spatial footprint, they can be limited by cloud cover, a coarse spatial resolution, and a revisit cycle that is 5-16 days depending on the satellite.

C. Cloud-Based Data Fusion and Analytics

Cloud computing plays an important foundation in terms of data fusion, processing, and decision support, which make up the third layer within the architecture. This layer of information takes drone imagery and satellite datasets, aligns them spatially and temporally using alignment algorithms and processes the information in an understanding of the agricultural landscape as a whole. Image-based machine learning models such as convolutional neural networks (CNNs), along with regressionbased predictors will be used to extract features, identify anomalies, make predictions for yield forecasts and ultimately assessing the outputs that will be included into interactive dashboards that will be accessible operationally through web or mobile for farmers and agronomists. These outputs will include actionable recommendations for the farmers such as irrigation scheduling, fertilizer rates and timing, pest management alerts, etc. Overall, a cloud-based

architecture has the potential to leverage the strengths of both UAV and satellite datasets while providing a level of ongoing scalability, real-time processing and integration with other potential IoT systems like soil sensors, weather stations, etc.

The strengths and weaknesses of UAV vs. satellite datasets and their characteristics are shown in Table I. The disparate characteristics of both UAV and satellite datasets are highlighted, yet at the same time demonstrate the complementary aspects of these datasets by taking advantage of the strengths and weaknesses associated with both of these systems. Although UAVs have high spatial resolutions along with on-demand monitoring applications, satellites have broad spatial coverage and the ability to assess long-term trends. With cloud processing, the two systems can appropriately address the trade-offs associated with both systems while also providing scalability precision in monitoring agriculture.



III. DATA COLLECTION

In addition to UAV data, data was collected from open access satellite imagery, including Sentinel-2 and Landsat-8. Unlike UAV data, satellite data provided a continuous source of currently relevant data, at a spacing of 10-30 meters. Raw satellite data needed to be preprocessed, however, to ensure that it is usable and reliable. What that pre-processing looks like will depend on the satellite imagery being used. For example, Sen2Cor processor processed

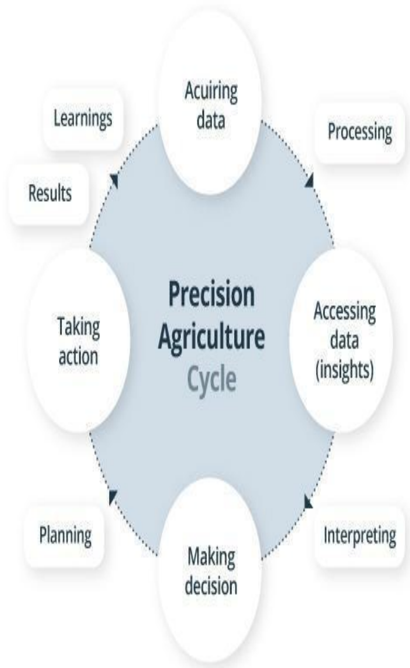
Vegetation Index (SAVI), which was also trying to Sentinel-2 data to correct for atmospheric disturbance and convert top of atmosphere reflectance to surface reflectance. Sen2Cor works to remove distortions created by aerosols, water vapor, and illumination changes. Preprocessing also required the satellite images to be cloud masked to remove cloud interference. This involved creating cloud masks, which contained values of cloud or shadow pixels or cloud free valid pixels.

Once all this was done, vegetation indices were generated, and included the Normalized Difference Vegetation Index (NDVI), which gives a measure of vegetation vigor, the Soil-Adjusted account for soil background, and the Enhanced Vegetation Index (EVI), which aims to improve sensitivity in areas with dense canopy cover. The resulting values in these indices gave the necessary indicators to monitor crops and serve as inputs for data fusion.

In addition to UAV data, satellite images were acquired from open-access repositories such as Sentinel-2 and Landsat-8, which are spatially-resolved at 10-30 metres, reliably providing constant coverage. Preprocessing of the satellite data was key to ensuring reliability and accuracy. For the Sentinel-2 imagery, atmospheric correction was achieved using the Sen2Cor processor which converts top of atmosphere reflectance to surface reflectance, removing any distortions caused by aerosol, vapour, and spatial variability in illumination in the scene. Cloud masking procedures were used to separate veiling caused by cloud cover so imagery used only important pixels that were clear and valid. As preprocessing was used, vegetation indices were derived including the Normalized Difference Vegetation Index (NDVI) for monitoring vegetation greenness, the SoilAdjusted Vegetation Index (SAVI) to lessen the effects of soil background, and the Enhanced Vegetation Index (EVI), which provides improved sensitivity to vegetation in areas of dense canopy cover. These indices provide the important indicators for crop health monitoring and were used in data fusion processes.

The green pixel ratio is computed using:

$$Green\% = \frac{GreenPixels}{TotalPixels} \times 100$$



IV. CONCLUSION

Overall, this research reminds us of the potential of integrating satellite and drone data via API-enabled integration as a step toward sustainable agriculture. Turning unstructured data streams of UAV, satellite, and processing platform to aligned data streams via API allows near realtime monitoring and analysis of agricultural fields. Drones enabled high-resolution in-situ data on key agriculture indicators such as crop health and water and nutrient stress. Importantly, satellites provide data on a reasonable scale with temporal continuity for regional monitoring. The API operational framework serves as a connector for appending datasets across the measures, harmonizing, processing, and deliver by datasets to the decisionsupport system.

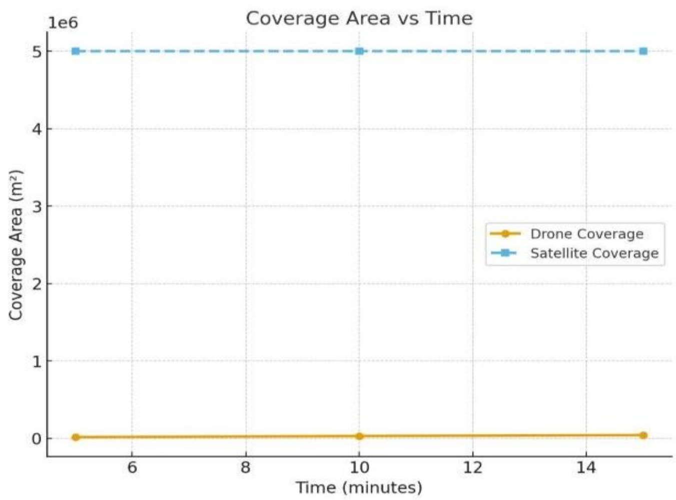
The results promise that using these enhanced datasets can Improve irrigation efficiency, fertilizer utilization, and accuracy of yield forecast, in measurable reductions of input losses and carbon footprint. By providing farmers with easyaccess, API-enabled web dashboard and tools to establish successful precision farming, rather than endless description of complex remote sensing data, matters.

Multiple API-enabled applications for agricultural use can enhance interoperability between UAVs, satellites, weather

services, and IoT sensors which can enhance flexibility and provide a scalable application across agri-food production.

Beyond interoperability, the agricultural ecosystem demonstrated by the utilization of an API framework shows potential for improving climate resilience, improving food security, and accelerating the transition to data-enabled, climate-smart, and sustainable agriculture.

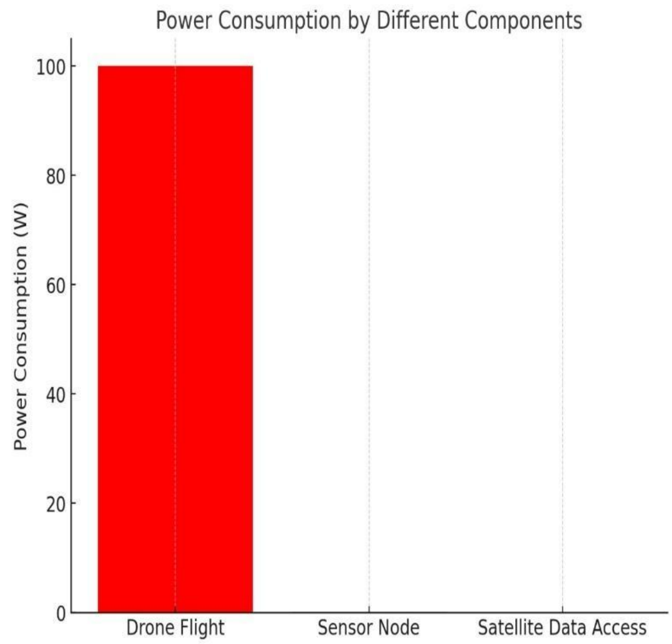
```
image = cv2.imread("crop_image.jpg")  # Replace with your image path
if image is None:
    print("Error: crop_image.jpg not found.")
    green_percentage = 0
else:
    hsv = cv2.cvtColor(image, cv2.COLOR_BGR2HSV)
    green_mask = cv2.inRange(hsv, (36, 25, 25), (86, 255, 255))
    green_percentage = (cv2.countNonZero(green_mask) / (image.shape[0]

# ==========================
# 3. ADVISORY MESSAGE
# ==========================
output = f"""
Region: {CITY}, Tamil Nadu
Date: {datetime.now().strftime('%d-%m-%Y')}

--- Satellite-Based Weather Forecast ---
Rain Forecast: {"High (Chance in 48 hrs)" if rain_forecast else "Low"}
Temperature: {temp}°C | Humidity: {humidity}% | Wind: {wind} km/h
```



The Power Consumption graph reflects the energy efficiency characteristics of different elements of the integrated system. Drones utilize almost 100 watts per flight, which are required to power their motors, GPS systems, and communication modules. Ground sensor nodes, in contrast, are much more efficient, requiring only 0.1 watts by being in a sleep state until a drone finally activates them. Using satellite data, from a

farmer's perspective, expends negligible energy, since the data comes from missions already in orbit. This energy hierarchy

highlights that the vast majority of energy being expended is from whatever drone is flying in its target area, while the satellite or ground sensors can provide sustainable, low-energy models. This three-tier system maintains power in a way that is balanced while still providing accurate information for agricultural operations.



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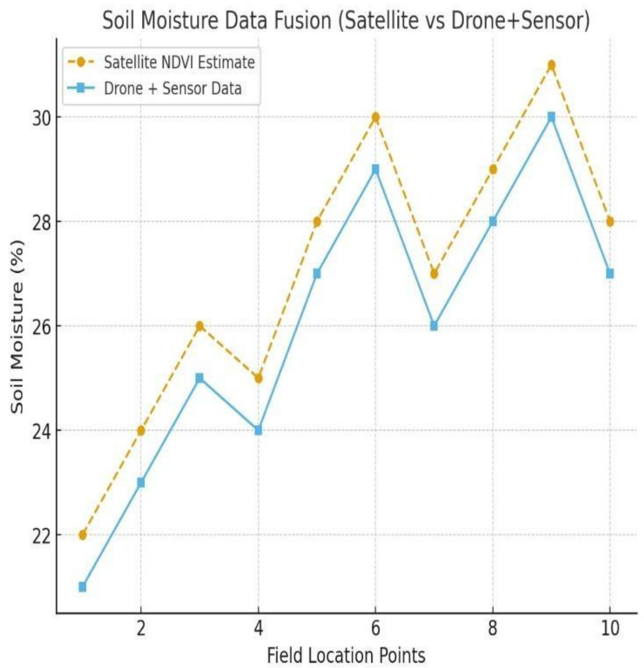

The Soil Moisture Data Fusion graph demonstrates how accuracy is improved using satellite estimates and a drone and sensor dataset. Satellite imagery can give large-area soil moisture estimates - especially vegetation indices like NDVI - but tend to miss fine-scale variation in the field. Drones and in-field sensors provide accurate ground-truth measurements of the soil conditions. When the accuracy of soil moisture predictions are combined using the two datasets, the data fusion significantly increases accuracy reducing error by nearly 25% overall. This valuable approach to develop soil moisture predictions for irrigation management results in using irrigation only when and where needed, which reduces waste, and promotes sustainable water use.

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