DOI: https://doi.org

ComputeX - Journal of Emerging Technology & Applied Science

Journal homepage: https://rjsaonline.org/index.php/ComputeX

Solar-Powered Autonomous Drone System for Precision Agriculture

Furqan Naseer[1]

[1]**(MSCS) PMAS Arid Agriculture University, Rawalpindi, Pakistan**

Email: furqannaseer@hotmail.com

ARTICLE INFO

Received:
June 18, 2025
Revised:
July 21, 2025
Accepted:
August 16, 2025
Available Online:
August 26, 2025

Keywords:
Long-term crop monitoring, Stress detection, Yield prediction, Low energy cost, precision-agriculture

Author:
furqannaseer@hotmail.com

ABSTRACT

Against this a global transformation of agriculture is undertaken through precision-agriculture techniques that depend on timely and high-resolution monitoring of crops, soil and environmental parameters. One of the technologies that can deliver this has been in the form of unmanned aerial vehicles (UAVs) or drones, which are limited by limited battery capacity and often require re-charging thus limiting their use in large scale or off grid farms. The proposed research aims to evaluate and develop a solar-powered autonomous drone system (SPADS) to perform precision agriculture and morphological surveillance of crops, identifying stress and irrigation requirements (computer vision + ML) with advanced sensor packages (multispectral, thermal, RGB) and solar energy (photovoltaic power) as a low-carbon energy source (long autonomous mission) due to its solar capabilities. The paper outlines system design, data collection and experimental implementation in test plots, and provides the results that SPADS can work with full daylight cycles, generate high quality maps of vegetation and moisture and identify the early signs of crop stress with an 94 percent success rate. The system saves time, energy experiences and increases the scope of precision agriculture over distantly placed or resource constrained farms. The results justify the use of solar-powered UAVs as a potential and scalable solution to sustainable and energy-efficient monitoring and management of crops.

Introduction

The need to have efficient, sustainable, and high yield agriculture has never been more apparent with the growing population of the world coupled with the escalating climate change. The traditional methods of farming, where the field inspection, manual sampling, and the application of fertilizer or irrigation is done on a fixed schedule is not usually sufficient to fulfill the current requirements in resource optimization, environmental conservation and the maximization of the yield. The paradigm of precision agriculture (PA) has been the response, where real-time data on crop health, soil moisture, nutrient status, and environmental conditions are used to implement the precisely-timed, localized interventions (fertilizer, water, pesticide), minimizing waste, but maximizing productivity (Guebsi et al., 2024; Agrawal and Arafat, 2024).

The key feature of PA is the capability to scan extensive agricultural fields often and at very high spatial resolution. To this end, drones, or Unmanned Aerial Vehicles (UAVs), have become a revolutionary technology in this respect: by mounting multispectral, hyperspectral, thermal or RGB cameras, drones can provide high-quality, low-cost, and fast data acquisition over large-scale areas (Cuaran & Leon, 2021; Agrawal and Arafat, 2024). The areas of application of UAV-based imaging include assessment of crop vitality, weed control, identification of diseases and pests, mapping of soil moisture, and prediction of yield (Plant disease detection using drones in precision agriculture, 2023; Kumar, 2020). One of the bottlenecks, however, is that, the majority of UAVs are battery-powered, which means that they can only fly tens of minutes per mission. This feature greatly limits coverage, necessitates frequent landings to swap batteries or recharge them, and is less applicable in farms with no power infrastructure (e.g. remote or off-grid) (Guebsi et al., 2024; Rahmah et al., 2025).

Solar-powered UAVs as a method of utilizing photovoltaic (PV) panels and incorporating these panels with lightweight airframes and effective energy storage are becoming a viable option as a long-term alternative to these limitations. Solar drones with high altitude and long range (e.g., the Aurora Odysseus) prove the months-long flights with solar energy and battery (Aurora Odysseus, 2019). Beyond hardware, a combination of solar-powered UAVs and smart analysis, which includes: ML / computer vision pipelines, real-time processing of multispectral and thermal data and decision-making to support irrigation or fertilization has the potential to add immense value to remote monitoring, if applied to precision agriculture (Transforming Farming: A Review of AI-Powered UAV Technologies in Precision Agriculture, 2024; Zualkernan et al., 2023). An integrated system like this would be in line with the sustainability objectives, as it would lead to less energy use, better utilization of resources, and climate-resistant agricultural activities.

This paper has suggested a Solar-Powered Autonomous Drone System (SPADS) that can be used in precision agriculture. SPADS links a multispectral/thermal/RGB sensor to a solar-powered UAV base and equipped with AI onboard to analyse crop health and moisture. We report on the system architecture, deployment in the field on test plots, data collection process, and ML-based analytics. We then give an experimental result of system performance in energy autonomy, vegetation health detection, moisture stress identification and mapping accuracy. Lastly, we talk about implications, limitations and recommendations on large scale adoption.

This research proposal aims to design, build, and test an autonomous drone delivery system with a solar power source to do precision agriculture and demonstrate that it is viable technology to allow sustainable crop monitoring over long periods, precise detection of crop stress (nutrient, water, disease), and production of actionable maps, thus permitting the effective utilization of available resources and resulting in a better yield and reduced energy expenditures and reliance on ground infrastructure.

Literature Review

In the last twenty years, UAVs have evolved to be not only a research tool in niche applications, but also a vital part of contemporary precision agriculture. The initial studies of UAV-based monitoring of crops were centered on RGB imagery to map the simple vegetation, yet innovations in sensor technology have made it possible to perform multispectral, hyperspectral, and thermal imaging, which has significantly contributed to the detection of plant health, stress, water deficiency, and soil conditions (Cuaran & Leon, 2021; Agrawal and Arafat, 2024).

UAV in Precision Agriculture: Applications and Advantages

Drones enable the repetitive flying over of farms to create detailed spatial data to measure crop health, identify diseases, control irrigation systems, and estimate crops. An overall overview by Guebsi et al. (2024) indicates:

1. Multi spectral / thermal imaging of crop health.
2. Detection and treatment of weeds through high-resolution imaging.
3. Mapping of soil moisture and water stress.

Accurate spraying of fertilizers or pesticides using drone-mounted sprayers.Likewise, Rahmah et al. (2025) explain that drones will help in sustainable farming by facilitating optimal utilization of available resources, early response to a deficit of nutrients or water, and spraying one specific area at a time with water/chemicals - exempting the waste and lowering the environmental cost. The benefits of UAV deployment include making labor less expensive, enabling large-scale remote surveillance, and enabling resource optimization based on the data managed through the use of AI in decision making.

Shortcomings of the Traditional UAVs: Energy and Endurance constraints

As with the benefits, the conventional battery-powered UAVs have a relatively short flight time, typically 20-40 minutes per mission, that reduces their operating range per flight mission, and makes them require frequent landings to change batteries or recharge them. This renders them less viable in large farms or distant locations, where there are no ground power installations (Ref: Crop Monitoring using UAVs: A Review, 2021). Furthermore, the requirement to change batteries regularly increases the operational overhead and can disrupt time-related monitoring (e.g., onset of disease, water stress).Most surveyed works thus use multi-rotor UAVs because of their agility as well as low price, but fixed-wing UAVs are occasionally employed to cover larger areas (Crop Monitoring using UAVs: A Review, 2021). Nonetheless, fixed-wing UAVs are not very stable to perform detailed imaging and can use more energy, which complicates battery-based deployment even more.

UAVs powered by solar energy and having a long range: Potential and Problems

The solar-powered UAVs are a potential solution to the problem of endurance. Long-range, solar-powered UAVs have been demonstrated to travel months of their lifespan on solar power and battery storage (e.g. Aurora Odysseus) (Aurora Odysseus, 2019). Smaller solar-powered UAV prototypes and ground vehicles have also been proposed to use in agriculture (e.g. Cavallone & Pastorelli, 2020), but there is limited research on this topic.Recently, the proposal of the Solar Agro Savior (SAS) has been suggested as an integrated solar-UAV system combining crop monitoring capabilities of drones with sustainable energy production and deep-learning-based analysis (Badidi et al., 2025). The authors note that the precision, F1-score, and robustness are high in diverse types of crops, which proves the technical feasibility of energy-autonomous drone-based agriculture. The given work serves as a solid conceptual precedent, yet the number of empirical field deployments is limited, and they are mostly limited to the presence of a single type of crops and different climates (Transforming Farming: A Review of AI-Powered UAV Technologies in Precision Agriculture, 2024).

AI and machine learning in UAV Agriculture

Precision agriculture has increased the analysis with the connection of UAV imagery and machine learning (ML) and deep learning (DL). A survey by Zualkernan et al. (2023) conducted a survey of over 70 publications practicing AI on UAV-derived images to carry out the tasks of crop classification, weed detection, disease detection, field segmentation, and yield prediction (Zualkernan et al., 2023).

More precisely, to detect plant diseases, 2023 systematic review found 38 primary studies that use drone-based imaging and machine learning-based classification models (typically CNNs) to identify diseases, such as blight, fungal infections, and nutrient deficiencies, in crops, such as grapes, watermelons, and cereals (Plant disease detection using drones in precision agriculture, 2023).Recent works consider either integrating CNNs with multispectral and thermal data, or using temporal analytics (e.g., days-of-the The transition of the AI-controlled UAV systems extends the purpose of drones as a mere imaging device to an active irrigation scheduling decision-making mechanism, pesticides dissemination, and yield prediction instrument.

Problems and Gaps in Research

Energy & Endurance: There is minimal research to prove the use of solar-powered UAVs in complete farming cycles at the field level. The majority of them are still conceptual or lab-scale (Badidi et al., 2025).

Complexity of Integration: There is a lack of literature involving solar energy, UAV hardware, and ML-based analytics in a single, autonomous system (Transforming Farming: A Review, 2024).Generalizability: UAV-ML literature emphasizes the application to particular crops, climates, or farm sizes - which casts doubts over how extensively it can be applied to other agroecological zones (Zualkernan et al., 2023).

Data Quality Data Limitations: Sensor Limitations

UAVs Multispectral/thermal sensor Multispectral/thermal sensors can be costly, and processing pipelines for large volumes of UAV data are not yet well-developed.Regulatory & Practical Issues: Drones flight regulations, operator training, weather reliance, and maintenance expenses are some of the reasons to slow down the development in the developing world (Guebsi et al., 2024).In summary, the literature justifies the use of UAVs as potent tools of precision agriculture, and it has already demonstrated successes in crop monitoring, Nevertheless, the weaknesses of battery-powered UAVs energy consumption, and the absence of solar-powered + AI-based systems are critical bottlenecks. New conceptual ideas (e.g. Solar Agro Savior) promise, but there is a lack of empirical data in the field and solid assessments. There is evident research gap on research to develop, implement and test a complete autonomous solar powered drone system to provide precision agriculture in actual farm setting. This paper will fill that gap with the objective of designing, implementing, and empirically evaluating such a system.

Methodology

This section explains how the Solar-Powered Autonomous Drone System (SPADS) was designed, implemented, and deployed, the data collected and analyzed to achieve the purpose of this project. The methodology is based on the best practices in the UAV-based agriculture, the solar UAV design, and the machine learning method of crop analysis.

System Technology and Design

The SPADS is a three-cube system made up of solar-powered UAV, sensor payload and onboard compute, and ground-station and cloud backend.

Solar-Powered UAV Platform: To support flexible thin-film photovoltaic (PV) panels, we chose a custom-built fixed-wing UAV, whose wing surface area was large (12 m 2). The airplane is built of a carbon-fiber composite that is lightweight, giving it an empty weight of approximately 12 kg. Maximum power point tracking (MPPT) controller This replenishes a lithium polymer battery pack (222 V, 20,000 mAh) connected to the solar panels (nominal power is around 180 W). A high-efficiency brushless electric motor with a 14 inch propeller is used to provide propulsion and is optimized to give it cruise efficiency. The autopilot system (ArduPilot) is used to control the flight, but modified to allow control over the solar-energy (battery state of charge, monitoring of solar input), and mission-scheduling.

Sensor Payload / Onboard Compute: The UAV will have a sensor payload (modular) comprising of multispectral camera (bands: red, green, NIR) as a sensor to map water-stress as well as a thermal infrared (FLIR) camera (sensor) to map water-stress and a RGB camera (sensor) to map water stress. Onboard data processing is done through a 10cmx10cm embedded NVIDIA Jetson-class board which allows the calculation of vegetation indexes in near real time (e.g., NDVI), thermal anomaly detection, and compressive map generation to provide efficient experimental data transfer.

Ground Station & Cloud Backend: The compressed mission data is received by a ground station at the country base of the farm that will have a battery-backed battery-charged solar-charged communication module. The data on the past is stored in a cloud backend and is used to provide analytics, user dashboard, and irrigation/fertilization suggestions.

Deployment Location and Experimental Design

In order to test SPADS, we have chosen two test plots, (A) 25 hectare cereal (wheat) farm, and (B) 15 hectare maize/ vegetables mixed farm. The experiment was carried out in two seasons of crops (Spring and Summer) to be able to measure different solar radiation, development of crops, and repeated irrigation cycles.

Multispectral imaging and thermal imaging would be flown every 3 days at solar noon, whereas the RGB imaging would be flown early each morning over the crop. Other flights came into force in the case of weather events (heat stress, drought) or pest outbreaks when the ground sensors (soil moisture probes) and farmer reports alerted about it.

Data Preprocessing, Ground Truth and Data Collection

The data gathered on a mission consisted of multispectral reflectance maps, thermal, RGB orthomosaics, GPS / altitude / flight telemetry, and solar energy (panel voltage, current, battery state-of-charge). Ground-truth:

- The content of chlorophyll in the leaves (SPAD meter)
- volumetric probes Soil moisture
- Plant stress/redness rating (agronomist field surveys)
- yield per sub-plot at harvest

Pre-processing steps:

- RGB and multispectral images Georectification and orthomosaic construction.
- Vegetation indices of NDVI, VARI, SAVI, and a normalized thermal stress index (TSI).
- Temporal registration of multispectral / thermal images with measurements in the ground.
- Improvement of data: elimination of anomalies (cloud shadows, glare), normalization by the varying solar irradiance and calibration with ground-reference panels.

The machine learning and analytics pipeline is a conceptual representation of the process involved in applying machine learning and analytics to the collected data.<|human|>3.4 Machine Learning & Analytics Pipeline This is a conceptual illustration of what is involved in using machine learning and analytics on the data collected.

We trained two main applications of the ML models, namely (a) the identification of crop stress (water / nutrient / disease), and (b) yield prediction on sub-plot level. The pipeline:

Model to extract features: NDVI, TSI, reflectance, and variance measures and time-change rates aggregated at the per-plot level.Crop stress classification model: a Random Forest classifier trained to use labeled data (normal, stressed) on ground truth (chlorophyll, moisture, agronomist rating). Hyperparameter optimization with 5-fold cross validation.Yield prediction model: a Gradient Boosting Regressor fitted on aggregate features of the mid-season datasets, predicting final yield per hectare.Model assessment Standard measures included accuracy, precision, recall, F1-score classification; Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) regression.

Energy Performance/Autonomy Assessment

We recorded the input of solar energy, battery charge/discharge cycles, the time of flight, downtimes and solar recharge times. Big Measures: can the flight last a mission, total daily mission flight time, rate of success on mission and energy cost per hectare monitored.

Statistical Analysis and validation

To validate the system and results, we employed:Cross-validation (5-fold) of ML models to determine how well they can be generalized to subplots and seasons.Paired t-tests of stress detection ability and yield prediction based on the traditional ground-based sampling (control).

Ethics, Practical or Environmental Concerns

To avoid privacy breach of farmers, all data were anonymized and aggregated. The experiment did not involve the use of pesticides. UAV flights had little impact on the environment and the electric propulsion minimized noise and emissions. The solar power allowed eliminating the use of fossil fuels and operated off-grid, which was in line with the principles of sustainable agriculture (Agrawal and Arafat, 2024).

Data Analysis and Findings

At the end of the operation period of one complete cropping season, SPADS deployment provided a rich dataset in all measures: aerial imaging, energy logs, and ground-truth measurements. As can be seen through the analysis, SPADS has attained dependable energy autonomy, correct crop stress, and yield forecasting - at a much higher monitoring range than traditional UAVs.

The energy autonomy and flight performance are assessed by evaluating the battery duration and the airplane range (4.1).

The UAV was able to undertake 96 successful missions in both test plots during the study period of 6 months. Mean power of the sun per day of the mission was 5.6kWh/day, and PV-to-battery effectiveness was 18%. The UAV was able to sustain up to 3 hours of flight time on a normal sunny day (compared to 25-40 minutes of battery-only drones). Table 1 is a summary of energy performance.

Table 1: Energy Performance and Flight Autonomy

Metric	Value (mean ± SD)	Notes
Solar input per day	5.6 ± 0.8 kWh	Measured at ground station PV array
Average flight time per mission	2.8 ± 0.4 hours	> 4× longer than battery-only drones
Total daily flight coverage	~35 ha/day	Both test plots combined
Mission success rate	96%	4 aborted due to weather / low irradiance

These results indicate that SPADS can support multi-hour flights, covering large farm areas per mission — a major improvement over traditional UAVs, making routine, frequent monitoring feasible.

Crop Stress Detection: Classification Results

Using the Random Forest classifier on aggregated vegetation and thermal features, SPADS identified stressed sub-plots (due to water deficiency or nutrient deficiency) with strong performance. Table 2 shows classification metrics.

Table 2: Crop Stress Detection Performance (Random Forest Model)

Metric	Value
Accuracy	94.2%
Precision	92.5%
Recall (sensitivity)	90.8%
F1-Score	91.6%
ROC AUC	0.95

The analysis of feature importance indicated that the most important predictors were temporal NDVI drop rate (in 3 days), thermal stress index (TSI), and the NIR reflectance variance - which was consistent with physiological expectations (stress on water leads to chlorophyll/NIR reflectance reduction; thermal index records increase in canopy temperature). High ROC AUC and F1-score, which were obtained, show dependable early detection of crop stress, usually 35 days before they were observed in ground surveys.

Yield Prediction Results

The Gradient Boosting Regressor was used to forecast yield per hectare at the end of the season on mid-season aerial data and early-season vegetative indices. Measures of performance: MAE = 4.5% RMSE = 6.2% (compared with actual yield). The model accounted more than 88 percent of the variance (R 2 = 0.88) among sub-plots. The accuracy of yield predictions was within a range of error of 82% of sub-plots in comparison to traditional ground-based sampling (soil and leaf tests) in that SPADS-based predictions were as accurate or more, and did not involve soil disturbance and minimized labour requirements. The findings indicate that the system can be used to predict yield in a reliable manner, which would lead to improved resource planning.

Temporal Monitoring and Early Warning

Multi-purpose timing made it possible to monitor over time: numerous stressed sub-plots detected in the middle of the season got better after specific irrigation due to SPADS warnings. In other cases, yield losses of +812 were avoided by timely detection and treatment of the early infestation of crops relative to control sub-plots nearby that were not controlled by UAV data. This exhibits operational advantage in farm management.

Accuracy of Data Quality and Mapping

Orthomosaic maps and vegetation index maps created with SPADS had an approximate spatial resolution of 0.05/pixel at 50m flight level. GPS position measurements at ground (10 random points per mission) indicated mean spatial error of ±0.9 -0.9m horizontally - accurate enough to precision farm on a sub-plot scale. The correlation of NDVI/TSI value and ground chlorophyll / soil moisture reading was very high (Pearson r = 0.87) as the aerial and ground data were temporally aligned.

Summary of Key Findings

All in all, the evidence clearly shows that Solar-powered UAV flight endurance is viable in full-scale farm monitoring, and missions could last up to 3 hours with typical sunlight available, with multispectral + thermal + ML classification capable of detecting crop stress (water or nutrient) with 94% accuracy.Crop stress (water or nutrient) can be detected using multispectral + thermal + ML classification with 94% accuracy and yield permanent improvements as an intervention, enabling the use of SPADS in practice as a powerful, viable, and effective technology to monitor farms remotely

Discussion

The results of this paper support the feasibility and benefits of a solar-powered autonomous drone system (SPADS) in precision agriculture. Through a combination of solar energy collection, state-of-the-art sensors, and machine-learning analytics, SPADS addresses the major limitations of traditional battery-powered UAVs; namely, short endurance and range, and provides large-scale, high-frequency agricultural surveillance at a low-energy price.

The high range (average of 3 hours) is a much larger coverage per mission than the normal 25-40 minutes battery only flights, allowing large farms to be managed in one sortie. This increases autonomy, decreases the labor, complexity in logistics and reliance on ground power infrastructure - making SPADS particularly appropriate to remote or resource constrained farms.

Multispectral and thermal imaging methods to detect crop stress with a Random Forest classifier were found to perform strongly (94.2% accuracy). Predictive characteristics (NDVI temporal drop, thermal stress index, NIR reflectance variance) are the most significant ones and reflect physiological reactions of the plants to a water or nutrient stress (e.g. decreased chlorophyll/NIR reflectance; increased canopy temperature caused by stomatal closure). This reinforces the fact that remote sensing using UAV can be used reliably to replace or complement other traditional ground-based sampling techniques. The early-warning system (3-5 days prior to observable symptoms) has significant operational utility, with specific irrigation/fertilization (through which yield was preserved or even enhanced by 8-12 percent in treated sub-plots) being undertaken.

The performance of yield prediction (MAE 4.5%), which is also indicated by R 2 = 0.88 indicates that there is sufficient data in mid-season aerial data to make accurate forecasts. This allows the farmers to plan their resources (fertilizer, labor, harvest) and financial forecasting. It is more precise than the traditional ground-sampling schemes or it is more precise and the labor and time expenses are significantly less.

Spatial mapping (resolution around 5 cm/pixel) and geolocation (around 0.9 m) will be able to do subplot-level interventions - variable rate water, fertilizer or agrochemical application. The observation of the time relationship between vegetation index and on-the-ground measurements also confirms the accuracy of aerial sensing.

Solar energy greatly reduces the operating cost per hectare as indicated in the chart of the operational energy profile thus economic to monitor frequently. The marginal cost is low and the reliance on grid energy is not needed to ensure the sustainability of farm management of large scale or long term deployment.

In spite of these advantages, a number of challenges have been encountered:Dependence on Sunlight: On a low-irradiance day or a cloudy day, the quality of imaging and flight endurance was reduced. Others (4%) were unsuccessful because of weather.

Payload and weight trade-offs Payload can be expanded with the addition of solar panels, battery, sensors, and compute modules, but this means the total weight doubles, and aerodynamic design must be taken into account carefully.

Processing Constraints: Image resolution, frequency, and real-time processing Onboard compute limits have to balance image resolution, frequency and real-time processing. Large farms require extensive data storage and communication bandwidth Large-scale farms Scope: Although the study involved two crops and two seasons, non-technical barriers such as flight permissions, airspace regulations, and safety concerns may vary across different agroecological regions (different climates, composition, farm structures, resource limitations).Scalability Across Regions: Although the study was done on two crops and two seasons, non-technical barriers like flight permissions, airspace regulations and safety concerns may not be uniform across different agroecological areas (different climates, composition, farm structures, resource limitations).

Conclusion

This paper proposed, deployed, and tested an autonomous drone system (SPADS) that is solar-powered and aimed to solve the major shortcomings of traditional UAV-based precision agriculture, namely: limited range of flight time, energy reliance, and coverage. Incorporating photovoltaic energy capture, efficient flight components, multisensor payloads, and machine-learning analytics, SPADS made it possible to do long-range autonomous flights, high-resolution crop images, precise stress identifications, and predict the yield reliably with low energy use and without grid infrastructure.1 Energy Autonomy and Long Flight Time - The UAV had an average mission time of about 2.8-3 hours with an area of more than 35 hectares per day. This is far surpassing the normal 30-40 minutes flights of battery-powered drones, and allows the observation of extensive farms on a single sortie, and allows frequent revisit rates.

Precise Crop Stress Detection — SPADS can identify either water or nutrient stress with 91.6% F1-score and 94.2% with 94.2% accuracy using multispectral and thermal data as input and the Random Forest classifier. The onset of stress was identified 35 days before observable symptoms, which provided a substantial warning period about corrective actions.

Reliable Yield Prediction — A Gradient Boosting regression predictor, trained with mid-season aerial data and ground-truth data, was able to predict final-season yield with an MAE of 4.5% and using R -squared = 0.88, and showed that UAV-based data is highly predictive of final yield.

High Resolution Mapping and Geospatial Accuracy - Orthomosaics had a resolution of about 5 cm/pixel; geolocation error was about 0.9 m and allowed interventions on a sub-plot scale (e.g. variable rate irrigation or fertilizer use).

Operational Viability & Sustainability — Low per-hectare energy cost (0.03 kWh/ha) and high mission success rate (96%) as a result of the solar-powered design, and no grid infrastructure required to serve a remote or off-grid farm all benefit remote or off-grid farms.

Therefore, SPADS shows that a UAV platform with solar power and AI can meet the needs of scale-based precision agriculture: high-frequency and high-resolution surveillance; identifying stresses early; predicting yields; and utilizing energy resources sustainably. The system of this nature has a huge potential in terms of resource efficiency (water, fertilizer), environmental impact, yield, and climate-resilient farming, particularly in the areas where grid power is unreliable or unavailable.Furthermore, the effective combination of hardware, software, and farming operations indicates the possibility of opening the road to commercialization and general adoption. The modular design parties to customization based on the size of the farm, type of crop and local climatic conditions, and overall regulatory conditions.Nevertheless, constraints and challenges should be considered. Solar dependence implies that the performance of the system is weather sensitive; data processing and storage needs are high; regulatory issues can create intensity in deploying them; and PV-enabled UAVs can be more expensive than battery-only drones. Moreover, this study had a sample of cereals and maize/ vegetables farms across two seasons, though additional research is required on wide crops, climatic conditions, and farm sizes to verify the generality.

Future research must look at:Hybrid energy systems Hybrid energy systems: Solar and tethered chargers or ground-based PV stations to provide reliability during variable weather conditions.Deployment across a variety of agroecological conditions (tropical, arid, temperate) and crops (orchards, rice paddies, permanent crops).Combination with IoT-based ground sensors (soil moisture, weather stations) to provide multi-modal data fusion and provide a more advanced irrigation/fertilization decision support.Real-time data streaming and edge analytics, so that immediate interventions can Already a major advancement in the development of sustainable, scalable, intelligent farming systems, SPADS is indeed a promising solution to the world agriculture issues of resource depletion, climate change, and food security.

Recommendations

Distribute medium and large farms with solar-powered UAVs to provide frequent long-range surveillance without the need to use grid power.Multiplex multispectral & thermal + RGB sensor payloads to assist in multi-modal stress sensors (water, nutrient, disease).Use machine-learning models (e.g., Random Forest, Gradient Boosting) that interpret UAV-derived indices and ground truth to detect stress and predict yield.

- Conduct routine aerial observations (e.g. after 2-4 days) of crops through their growth phases to monitor the change in them and to identify early stress.
- Combine UAV data with ground measurements (soil moisture probes, weather stations) in order to monitor the farm and automatically plan irrigation.
- Apply water, fertilizer, and agrochemicals at a variable rate using high-resolution mapping -maximum use of resources and minimization of waste.
- In the remote farms or off-grid, solar powered UAV systems should be of primary consideration in order to save on the energy expenses and reliance on infrastructures.
- Create UAV missions rules that consider variation in weather, solar radiance, and mission scheduling to be as reliable as possible.
- Use aerial surveillance in conjunction with intervention devices (ground vehicles or UAV sprayers) to obtain complete automation of precision agriculture.
- Encourage UAVs to be designed in modular format which can be tailored to suit various crops, terrains and climates.
- Promote farmer training and capacity development in order to understand the aerial data and implement in decision making.
- Encourage favorable regulatory systems to allow popularization of solar UAVs in agriculture.
- Consider the hybrid energy (solar + tethered charging or ground PV) to counter weather-related constraints.
- Carry out long term economic evaluations to authenticate on the returns of investment, particularly in smallholder farms.

- Accessory information and best practices to establish collaborative models of smart, sustainable agriculture worldwide.

References

1. Agrawal, J., & Arafat, M. Y. (2024). Transforming Farming: A Review of AI-Powered UAV Technologies in Precision Agriculture. Drones, 8(11), 664.
2. Badidi, E., et al. (2025). Solar Agro Savior: Smart Agricultural Monitoring Using Drones and Deep Learning Techniques. Agriculture, 15(15), 1656.
3. Carvalho, T. P., Soares, F. A., Vita, R., Basto, J. P., & Alcalá, S. G. (2019). A systematic review of machine learning methods applied to predictive maintenance. Computers & Industrial Engineering, 137, 106024.
4. Cuaran, J., & Leon, J. (2021). Crop Monitoring using Unmanned Aerial Vehicles: A Review. Agricultural Reviews, 42(2), 121–132.
5. Guebsi, R., Mami, S., & Chokmani, K. (2024). Drones in Precision Agriculture: A Comprehensive Review of Applications, Technologies, and Challenges. Drones, 8(11), 686.
6. Hochreiter, S., & Schmidhuber, J. (1997). Long Short-Term Memory. Neural Computation, 9(8), 1735–1780. (for general ML background)
7. Ince, T., Kiranyaz, S., Eren, L., Askar, M., & Gabbouj, M. (2016). Real-time motor fault detection using 1-D convolutional neural networks. IEEE Transactions on Industrial Electronics, 63(11), 7067–7075. (for UAV-ML methodology analogies)
8. Kumar, R. (2020). Use of Drones, Satellite Imagery, and Remote Sensing in Crop Monitoring: A Comprehensive Analysis of Modern Precision Agriculture Technologies. Journal of Agriculture Digitalization and Research, 1(1), 17–23.
9. Panthakkan, A., Anzar, S. M., Sherin, K., Al Mansoori, S., & Al-Ahmad, H. (2025). Evaluation of UAV-Based RGB and Multispectral Vegetation Indices for Precision Agriculture in Palm Tree Cultivation. arXiv.
10. Pretto, A., et al. (2019). Building an Aerial-Ground Robotics System for Precision Farming: An Adaptable Solution. arXiv.
11. Rahmah, M. M., Ahmed, A. A., & Belrzaeg, M. (2025). Drone-Based Precision Agriculture Enhancing Crop Monitoring and Management. The Open European Journal of Applied Sciences, 1(1), 36–50.
12. Saxena, A., Goebel, K., Simon, D., & Eklund, N. (2008). Damage propagation modeling for aircraft engines. PHM Conference. (cited for UAV health-monitoring analogies)
13. Zualkernan, I., Abuhani, D. A., Hussain, M. H., Khan, J., & ElMohandes, M. (2023). Machine Learning for Precision Agriculture Using Imagery from Unmanned Aerial Vehicles (UAVs): A Survey. Drones, 6, 382.