ENGINEERING Agriculture

REVIEW

2026 / Volume 13 / Issue 4 / 26675

From data to harvest: artificial intelligence and machine learning technologies revolutionizing agrophotovoltaic systems

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KEYWORDS

Agrophotovoltaics, artificial intelligence, Internet of Things, precision agriculture, predictive maintenance, sensors, solar energy optimization

Received August 23, 2025;
Accepted November 3, 2025.

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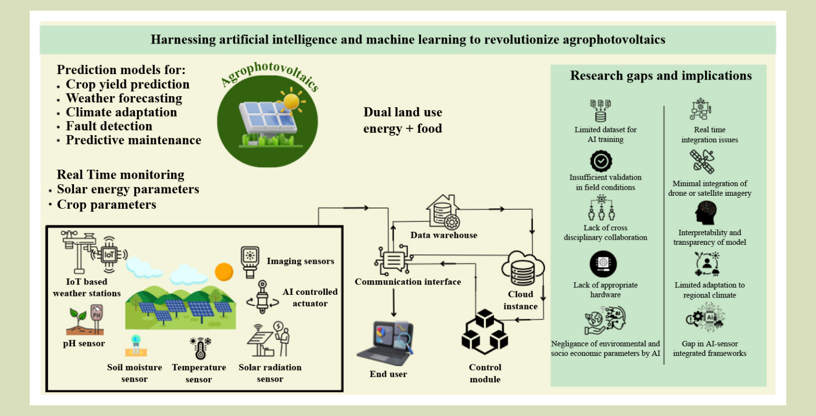
GRAPHICAL ABSTRACT



ABSTRACT

Agrophotovoltaics (APV) integrates solar photovoltaic systems with agricultural production, offering a sustainable solution to meet growing energy and food demands. This review explores the transformative role of artificial intelligence (AI) and machine learning (ML) in optimizing APV performance. Key applications include energy yield forecasting, predictive maintenance, fault detection and crop-energy balancing strategies. Advanced algorithms, such as neural networks, decision trees and reinforcement learning, deliver high prediction accuracy and significant operational improvements. Reported studies show forecasting accuracies up to R^2 of 0.96 for simulated irradiance datasets, representing model prediction performance rather than actual plant energy conversion efficiency. Likewise, AI-driven co-optimization of light distribution and irrigation improved leafy-vegetable yields by 10%–18% in experimental APV plots in India and France. The integration of Internet of Things sensors with ML models enables real-time environmental monitoring

https://doi.org/10.15302/J-FASE-2026675

and dynamic resource management. This review presents the integrated synthesis of AI/ML applications specific to APV systems. It proposes a taxonomy of AI/ML use-cases, a research roadmap, and a quantitative synthesis linking model performance metrics with agronomic and energy outcomes. The study also identifies research gaps in data interoperability, environmental variability, model interpretability, and socioeconomic adoption. Addressing these challenges through interdisciplinary research and policy frameworks can accelerate intelligent APV deployment, advancing renewable energy, sustainable agriculture and climate resilience.

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1 Introduction

With global demand for both food and energy are steadily increasing, advances in renewable energy technologies are enhancing their capacity to meet this growing demand[1]. From 2012 to 2021, the global use and consumption of renewable energy increased significantly, with fossil fuels being increasingly replaced as part of the global energy transition[2]. Renewable sources are rapidly gaining prominence in the global energy mix, now accounting for over one-third of global energy capacity[3]. According to the 2024 global overview, electricity generation from renewables contributed to over three-quarters of the overall increase in heat pumps and road transportation energy needs. This growth is supported by declining costs and consistent governmental policies in more than 130 countries[4]. Solar and wind energy are at the core of the sustainable energy transition. Earth system models are being used to forecast long-term resource availability[5]. In 2023, solar photovoltaics (PV) accounted for about 70% of the growth in renewable electricity generation. Power generation from solar PV reached a record increase of 320 TWh, representing a 25% rise compared to 2022. Global cumulative solar PV capacity surpassed 2.2 TW, with 34 countries each installing over 1 GW of solar capacity and 23 of them exceeding 10 GW in total installed capacity[6].

In parallel with the rapid expansion of solar PV capacity, innovative solutions such as agrophotovoltaics (APV) are emerging to optimize land use by combining solar power generation with agricultural activities. APV involves installing solar panels above crops or grazing land, enabling dual land use. This not only improves land-use efficiency but also offers shade that can enhance crop yields and reduce water evaporation, thereby making farming more resilient to climate variability. The integration of solar energy with agriculture is gaining traction as a sustainable energy solution for the farming sector, which supports over 2.5 billion people globally. Also, field-scale APV trials in Europe have demonstrated biodiversity improvements of 60%–75% in pollinator and ground-flora richness, mainly in low-intensity grazed systems[1]. Despite the benefits, challenges such as variable energy yields persist. However, solar PV continues to be widely adopted for both on- and off-grid applications[7]. The implementation of Industry 4.0 technologies in the agrifood supply chain, including solar energy systems, faces barriers related to technological architecture, data security, management and Internet of Things (IoT)-based infrastructure[8]. Addressing these challenges is crucial for climate change mitigation and food security.

Artificial intelligence (AI) and machine learning (ML) offer potential solutions to many of the challenges of APV systems, significantly improving their efficiency. Recent research highlights the growing role of AI and ML in managing solar energy systems. These technologies are increasingly used to optimize solar power and other variable renewable energy sources. IoT solutions, such as solar-based fertigation systems, can further optimize resource use in APV settings[9]. AI is the broad discipline concerned with developing computer systems capable of performing tasks that normally require human intelligence such as reasoning, perception and decision-making. ML is a subset of AI that focuses on algorithms that learn patterns from data to improve performance over time. Thus, AI here is used to denote the general concept of intelligent automation and ML when referring to specific data-driven learning algorithms.

Although APV offers clear benefits such as dual land use and increased crop yields, it also has challenges including economic feasibility, wind load vulnerability and shading effects[10]. To overcome these challenges, researchers propose open-source AI architectures based on ML paradigms, which simplify the development and deployment of AI models in agricultural environments[11]. These architectures aim to optimize resource utilization, support a variety of IoT protocols for sensor integration and enhance collaboration among data scientists and ML engineers. As global food demand rises, AI-driven APV systems have the potential to significantly improve land-use efficiency and contribute to achieving Sustainable Development Goals[10,11].

Figure 1 illustrates how AI can enhance APV systems through prediction models for crop yield, weather, climate adaptation, fault detection and maintenance. It also illustrates real-time monitoring of solar and crop parameters, highlights key research gaps and emphasizes dual land use for optimizing energy and food production in sustainable systems. APV combined with AI-driven systems enables efficient dual land use, where solar panels coexist with crop cultivation. ML algorithms (brain/chip icon) support crop yield prediction, weather forecasting, climate adaptation, fault detection and predictive maintenance (PdM). Real-time monitoring is achieved via IoT weather stations and sensors measuring soil pH, moisture, temperature, solar radiation and imagery. AI-controlled actuators optimize energy and crop performance, while data flows through communication interfaces, cloud processing, data warehouses and control modules, with end-user interfaces providing actionable insights. Remaining challenges include limited datasets, low drone/satellite integration, hardware constraints, insufficient interdisciplinary collaboration and adaptation to diverse climates, highlighting research opportunities.

1.1 Overview of solar energy technologies in agriculture

Recent research highlights the growing significance of solar energy technologies in agriculture and their role in the clean energy transition. Solar PV systems have gained considerable attention as a reliable power source for various applications, including utility grid supply[7]. The adoption of solar energy in agriculture is largely driven by the need for sustainable practices and improved energy efficiency[12]. These technologies are critical to decarbonization efforts, offering the potential for optimal resource utilization and broader access to clean energy[13].

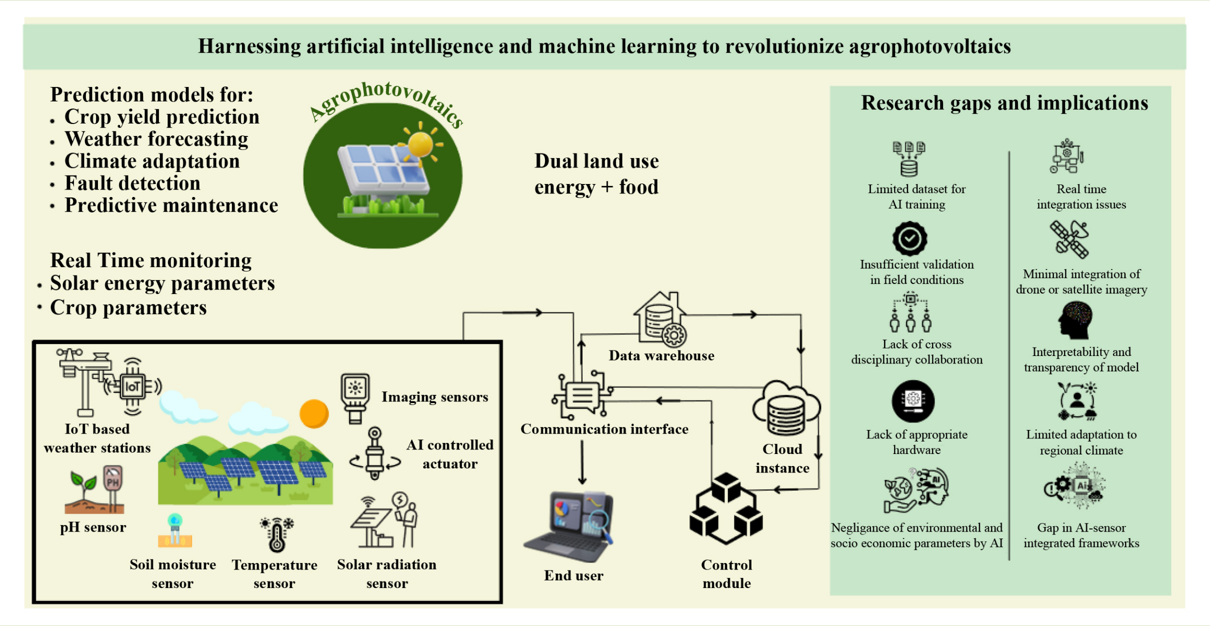


Fig. 1 AI-driven framework for smart agrophotovoltaics systems.

However, challenges such as fluctuations in solar irradiance can affect energy generation, necessitating accurate forecasting methods to ensure system reliability[7]. Additionally, market dynamics and energy policies significantly influence the pace of clean energy adoption. Ongoing research focuses on enhancing energy efficiency, implementing appropriate regulatory frameworks, and evaluating the financial implications of solar energy deployment in agriculture[14].

Table 1 summarizes various solar energy technologies, outlining their applications, benefits and challenges in the context of agricultural productivity and sustainability.

2 Methodology

A comprehensive and precise search strategy was used to ensure thorough examination of all relevant studies. Reputable databases, including Google Scholar, IEEE Xplore, ScienceDirect, SpringerLink and MDPI, were systematically searched. Carefully selected keywords, including APVs, artificial intelligence, precision agriculture, solar energy optimization, IoT sensors and PdM, were used to identify pertinent scholarly contributions.

Figure 2 shows the PRISMA flowchart, which explains the flow diagram of article identification, screening and selection[21].

About 45% of the retrieved studies were published between 2023 and 2025, reflecting the recent research interest in AI-APV integration. Figure 3 presents a bar chart illustrating the number of AI-APV-related publications from 2015 to 2025. Based on data collected from the Web of Science Core Collection, an initial search using the keyword APV yielded about 1750 results. When filtered by publication year, specifically since 2024 and since 2025, the number of records narrowed to 605 and 165, respectively. Also, combining relevant keywords (e.g., APV, AI and solar energy) revealed a marked upward trend in publications, particularly since 2024.

Figure 4 provides a visual summary of the keywords used and the corresponding number of articles retrieved based on various keyword combinations.

As the combination of keywords became more specific, the total number of retrieved articles decreased; however, the proportion of recent publications increased, indicating growing research interest in these focused areas.

To provide conceptual clarity and structure, the diverse AI/ML applications discussed in this review were categorized into a taxonomy of four core functional domains. Table 2 categories reflect the major operational and sociotechnical dimensions of APV systems and highlight how AI techniques contribute across the value chain.

Table 1 Solar energy technologies: applications, benefits and challenges in agriculture

Solar energy technology	Application	Benefit	Typical system size and output/example	Challenge	Ref.
Solar photovoltaics	Powering farm machinery and lighting	Reduces reliance on fossil fuels and enhances crop yield	System size: 6.6 kW Output: ~26.4 kWh·d^{-1}	High initial investment. Intermittent energy supply, Land use conflicts	[15]
Solar photovoltaic thermal systems	Heating for greenhouses and heat recovery on dairy farms	Improves plant growth and enhances thermal efficiency	System size: 24 collectors Output: 4200 kWh	System complexity; weather dependence	[16]
Solar membrane desalination	Providing water for irrigation and addressing water scarcity	Sustainable water source and reduces dependence on groundwater	Capacity: large-scale plants can process 60,000 m^3·d^{-1}	Environmental impact of membranes; energy efficiency issues	[17]
Agrophotovoltaics	Dual use of land for crops and photovoltaics panels	Maximizes land use and enhances biodiversity	Reduces water consumption by 20%–30%	Design complexity; potential crop shading	[18]
Solar greenhouses	Controlled environment agriculture	Extends growing season and reduces energy costs	Can create shaded areas that receive only 20% of solar radiation	Climate dependency; high construction costs	[19]
Concentrated solar power	Large-scale energy production and agricultural heating	High energy efficiency and supplies heat for irrigation	Plants with 15 h of thermal storage can provide near-24/7 power. A single parabolic trough plant can have a capacity of up to 200–250 MW	Land-intensive; high capital investment	[20]

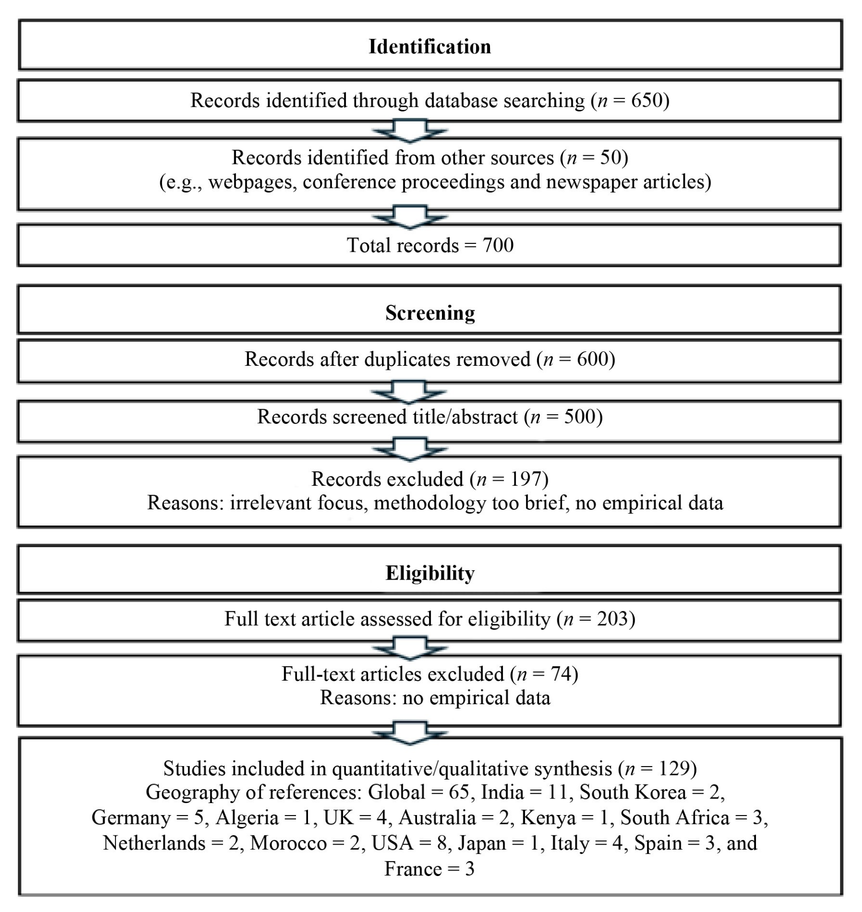


Fig. 2 PRISMA flowchart showing the identification, screening and inclusion of articles.

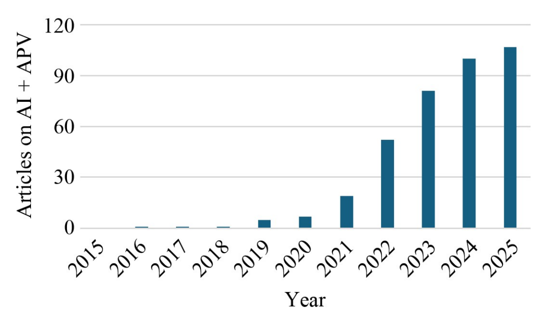


Fig. 3 Number of articles on artificial intelligence (AI) and agrophotovoltaics (APV) since 2015.

Throughout the review process, clearly defined inclusion and exclusion criteria were applied to ensure the relevance and quality of the selected studies. Eligible sources included peer-reviewed journals, statistical reports and official publications from reputable organizations including the Ministry of New and Renewable Energy and the International Energy Agency. Studies were excluded if they were non-peer-reviewed, lacked supporting data or focused solely on energy systems not incorporating elements of AI or ML.

3 Background and history

3.1 Agrophotovoltaics systems

APV systems have evolved from early conceptual designs that simply combined solar energy with agriculture into sophisticated configurations that optimize panel orientation, height and tracking mechanisms based on site-specific

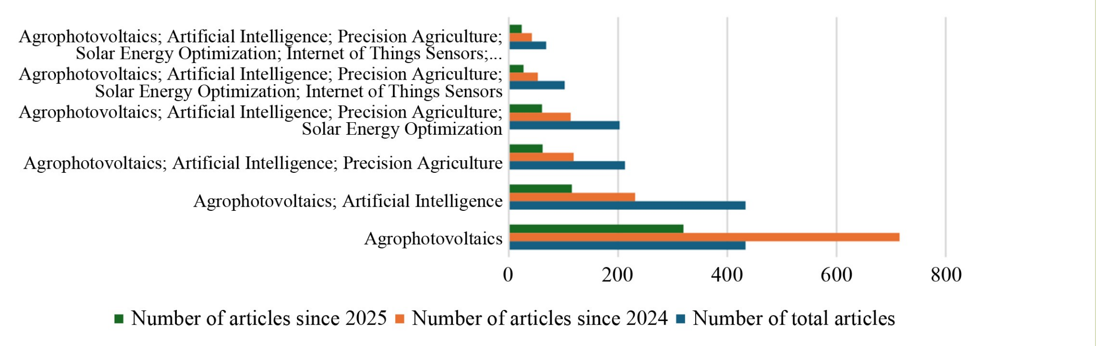


Fig. 4 Keywords used and the number of articles.

Table 2 Taxonomy of four functional domains

Domain	Primary objective	Representative artificial intelligence and machine learning technique	Typical performance metric	Ref.
Forecasting & prediction	Predict solar irradiance, crop yield, and environmental variables to improve planning and grid reliability	Random forests, gradient boosting trees, convolutional neural network-long short-term memory, transformer models	R^2, RMSE, MAE	[22–27]
Control & monitoring	Enable real-time sensing and adaptive management of microclimate, irrigation, and panel orientation	Reinforcement learning, fuzzy logic, Internet of Things-machine learning fusion, Kalman filters	Precision, response time, energy use efficiency	[28–31]
Optimization & co-design	Balance energy yield and crop productivity through spatial and temporal optimization	Genetic algorithms, digital twin models, generative adversarial networks-based simulation, multi-objective optimization	Efficiency gain (%), land equivalent ratio	[32–35]
Predictive maintenance & fault detection	Detect and predict component failures to reduce downtime and costs	Support vector machines, autoencoders, convolutional neural networks, isolation forest	Accuracy (%), F1-score, downtime deduction (%)	[36–41]

Note: F1, harmonic mean of precision and recall, measuring the balance between false alarms and missed detections; MAE, mean absolute error; RMSE, root mean square error; and R^2, coefficient of determination.

conditions. Experimental implementations of APV systems have demonstrated their practical benefits, for example, water efficiency improvements of up to 3.3 times and crop yield increases of up to three times in specific crops such as peppers[42–44]. Simulation and modeling studies have further advanced the development of APV systems, enhancing their performance and adaptability. Figure 5 illustrates the key design models of APV systems.

The vertically mounted bifacial PV modules with a standard

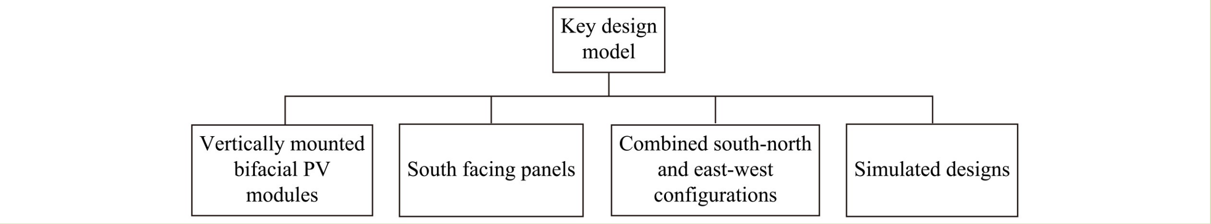


Fig. 5 Flowchart showing the key design models.

configuration demonstrate good energy output but create spatial heterogeneity in crop lighting. One review found that this topology increased the specific yield by 39% compared to standard monofacial systems; however, it necessitates the cultivation of shade-tolerant crops during summer, as electricity generation is prioritized[45]. East to west configured PV farms can reduce water requirements due to their inherent resilience to soiling losses. Also, east to west vertical bifacial modules were found to outperform south to north facing configurations by up to 15% at latitudes below 30°[46]. At low albedo levels (0.25), inclined monofacial systems outperform vertical bifacial configurations[47]. The optimal configuration depends on several factors, including latitude, with east to west vertical systems showing advantages below 30° latitude, while the relationship reverses at higher latitudes[48]. Row spacing is also critical for crop yield, with reductions of about 50% observed as the distance between bifacial module structures decreases from 20 to 5 m[18].

3.2 Advanced materials and storage in agrophotovoltaics systems

Recent research also identifies several limitations and areas for improvement in solar energy harvesting technologies. For example, graphene-based solar cells have challenges due to their band-gapless structure, susceptibility to oxidation and potential toxicity, which require further optimization of the graphene/Si interface and electrical conductivity[49]. To enhance energy density, 3D solar harvesting systems utilizing transparent porphyrin and iron oxide thin films have been developed, enabling multilayer PV and photothermal applications[50,51]. Additionally, nano-enhanced phase change materials have shown promise in improving thermal conductivity and efficiency in solar thermal energy storage systems[52,53]. Electrochemical storage methods, such as batteries, offer space-efficient alternatives to current large-scale storage systems, helping to address the intermittency of distributed renewable energy sources, particularly in urban settings[54].

These technological advancements aim to overcome current limitations and unlock the full potential of solar energy harvesting and storage systems[55]. The benefits of APV systems include reduced dependence on fossil fuels, lower greenhouse gas emissions, improved energy security and increased income for farmers[56]. APV can also contribute to temperature control, water conservation and soil management[55,57]. However, challenges persist, including high initial investment costs, the need for technological adaptation, social and regulatory barriers and potential shading effects on crops[10,55]. Also, wind loads pose a significant structural challenge to APV installations, necessitating further research into effective mitigation strategies[55]. Despite these challenges, APV represents a promising solution for sustainable agriculture and renewable energy production.

3.3 Artificial intelligence and machine learning concepts

ML is increasingly being used to complement or, in specific tasks, even outperform human-led modeling in various systems due to its superior speed and accuracy[58]. In recent years, AI techniques have emerged as transformative tools for managing and optimizing renewable energy systems. These technologies are applied across various domains, including solar, wind and marine energy generation[59]. AI methods such as genetic algorithms, support vector machines (SVM) and neural networks have been widely adopted for power generation forecasting, fault detection and grid integration in smart energy networks and microgrids[60,61].

Deep learning has provided significant potential in predictive analytics and enhancing waste management practices in PV power plants[62]. For real-time monitoring and evaluation of solar irradiance, temperature and panel efficiency, AI algorithms can assist in determining the optimal operational parameters of solar systems[63]. These intelligent systems enable adaptive control strategies, maximizing performance while minimizing operational costs.

Despite their advantages, several challenges persist. These include the need for explainable AI models to ensure transparency, issues related to data quality and availability, and broader ethical concerns around AI deployment. Future research should prioritize the development of energy-efficient and interpretable AI models, scalable algorithms capable of processing large datasets and privacy-preserving mechanisms to ensure the ethical and sustainable deployment of AI in renewable energy applications[62].

APV systems, ML and AI techniques are critical for dynamically tuning design and operational parameters to optimize both solar energy output and crop yield[64]. Table 3 summarizes the algorithm types commonly used in APV

Table 3 Prediction accuracy and energy improvement potential of different machine learning (ML) algorithms in agrophotovoltaics systems

Algorithm type	Energy improvement	Prediction accuracy	Ref.
ML	–	$R^2 \approx 0.99$	[16]
Genomic optimization of the algorithm	29% optimization of combined crop and energy production	–	[17]
Genetic algorithm optimization	260 Wp panels generated 80% crop yield with 379 kWp nominal power	–	[18]
Computational fluid dynamics-based ML (RFR, GBT and SVR)	–	RFR and GBT: RMSE < 2 °C; SVR and LR: RMSE > 3 °C	[19]

Note: GBT, gradient boosting trees; LR, linear regression; RFR, random forest regressor; R^2, coefficient of determination; RMSE, root mean square error; and SVR, support vector regression

systems, along with their corresponding prediction capabilities and accuracy metrics. Table 3 summarizes that ML and genetic algorithms are effectively optimizing both energy and agricultural outputs in integrated systems. Key results include a 28.9% optimization of combined production and high prediction accuracy ($R^2 \approx 0.99$) for crop yield. Also, specific algorithms like random forest regressor (RFR) and gradient boosting trees give superior performance in modeling environmental conditions with high precision having a root mean squared error (RMSE) of < 2 °C.

4 Artificial intelligence in agriculture

In addition, ML is increasingly gaining importance in modern agriculture. These technologies are transforming the agricultural industry by improving multiple aspects such as resource management, pest monitoring, crop yield prediction and disease detection[65,66]. ML algorithms can process and analyze large volumes of data from diverse sources, offering valuable insights that enhance decision-making in agricultural systems[67,68].

Practical applications include crop classification, soil analysis and irrigation management, all of which enhance productivity and operational efficiency. Additionally, AI-powered unmanned aerial vehicles equipped with thermal, multispectral and hyperspectral sensors are increasingly used in precision agriculture to improve monitoring and decision-making. However, their performance can be affected by data drift and may not always generalize effectively across contexts. Despite their potential, challenges such as high initial costs and limited battery life continue to impede widespread adoption. Also, the reluctance of some farmers to adopt new decision-support tools and digital technologies remains a significant barrier to AI integration in agricultural practices.

Figure 6 illustrates the various applications of AI and ML in agriculture, demonstrating their potential to support sustainable and efficient farming practices. AI and ML in agriculture enhance crop management by interpreting data like weather, soil conditions and crop growth metrics. These technologies enable precise irrigation, fertilization, disease detection and yield prediction, leading to smarter, more efficient, and sustainable farming practices.

4.1 Artificial intelligence and machine learning in solar energy

AI techniques, particularly ML algorithms, are revolutionizing solar energy systems by enhancing efficiency, improving forecasting accuracy, optimizing maintenance, and streamlining the overall management of solar power generation. These technologies enable precise prediction of solar energy output, optimize system performance and facilitate proactive maintenance strategies, thereby significantly improving system reliability and cost-effectiveness.

In particular, ML is transforming PdM through the use of advanced algorithms combined with real-time data collected from IoT sensors. Recent studies highlight the effectiveness of hybrid AI models that integrate domain expertise with data-driven approaches to detect issues such as soiling, sensor errors and electrical faults at an early stage. For example, a hybrid AI model developed in a recent InnoSuisse-funded project successfully identified the causes of energy loss and optimized maintenance scheduling, thereby minimizing downtime and energy losses[69]. Also, drone-based thermal imaging provides

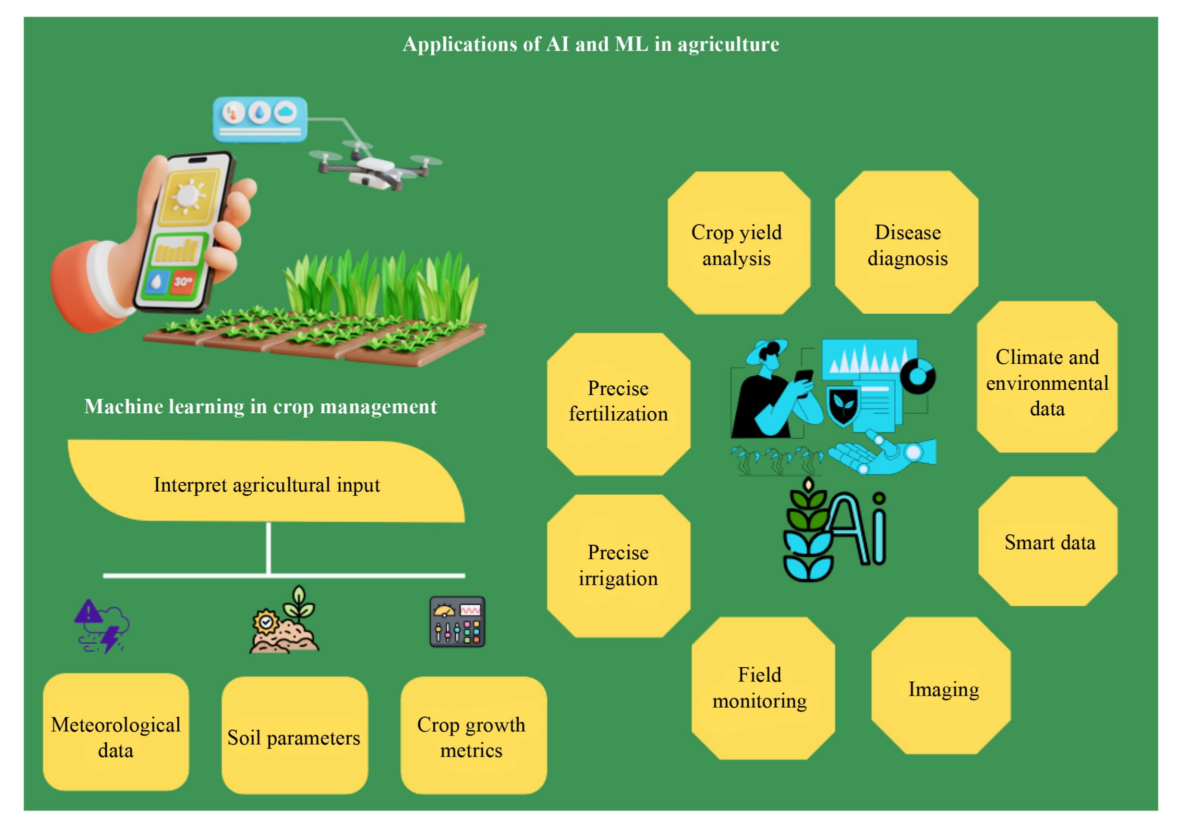


Fig. 6 AI and ML in agriculture.

high-resolution temperature data, enhancing the ability of the ML algorithm to detect faults. This technology enables the rapid identification of damaged cells and hotspots, even across large-scale PV farms. convolutional neural networks (CNNs), a deep learning approach and a specialized branch of ML, have demonstrated superior performance compared to standard ML methods in analyzing thermal and infrared imagery for PV defect diagnostics[36].

ML algorithms such as RF, SVM, artificial neural networks and extreme gradient boosting have shown significant improvements in prediction accuracy over standard statistical models, particularly in solar irradiance and energy yield forecasting. For example, a comprehensive study conducted in Rajasthan, India, reported that the RFR model outperformed linear regression and decision tree models, achieving an R^2 of 0.64 and a low RMSE of 0.59. This study also highlighted the critical influence of meteorological factors, especially wind speed and surface temperature, on solar irradiance[37]. Research conducted in Ghardaïa, Algeria, demonstrated the superior performance of hybrid deep learning frameworks that combine CNNs with long short-term memory (LSTM) networks for direct normal irradiance forecasting. The CNN-LSTM model consistently outperformed alternative approaches, including feedforward back propagation, convolutional feedforward back propagation and SVR methods, achieving exceptional accuracy with an R^2 of > 0.999, along with lower error rates and higher detection coefficients[38]. While this result underscores the potential of hybrid deep learning architectures for capturing complex spatiotemporal dependencies in solar data, a value approaching 1.0 necessitates a discussion on validation rigor to preclude the risk of model overfitting[22]. The reported performance would be substantially strengthened by clarifying the sample size of the dataset, the temporal range of the data, and, most critically, the cross-validation methodology used. For example, robust techniques such as k-fold cross-validation ensure that model performance is consistent across different subsets of data and is not the product of a fortuitous single train-test split[23]. Also, the application of additional error metrics such as RMSE and mean absolute error provides a more holistic view of model accuracy, as they quantify prediction errors in the original measurement units, offering a tangible sense of forecast deviation[22].

This superior performance of hybrid CNN-LSTM architectures aligns with broader findings in the field, where such models have been shown to outperform standalone deep learning approaches, albeit with longer training times[24]. Hybrid CNN-LSTM architectures consistently demonstrate superior performance compared to standalone approaches across multiple studies[25]. The reported near-perfect accuracies necessitate robust validation methodologies to ensure model generalizability. These technological advances in solar irradiance prediction, if properly validated, are crucial for optimizing renewable energy integration, maintaining grid stability, and supporting effective energy resource planning[24].

AI-driven optimization further enhances the operational performance of solar PV systems. Recent studies have used generative adversarial networks to generate realistic synthetic scenarios of solar irradiance and load demand. These scenarios are incorporated into robust optimization frameworks that dynamically adjust system controls. However, the impressive these networks and their optimization performance claims are primarily derived from simulation-based studies, rather than field deployments, with the research explicitly conducted using scenario-based simulations using 1000 operational profiles on high-performance computing clusters. This two-phase optimization approach has resulted in remarkable improvements, including up to 96% energy efficiency, 20% cost reductions, 30% decreases in carbon emissions and a 50% reduction in annual operational downtime in PV-grid integrated systems. The baseline comparison represents standard scheduling strategies using historical data without the support of synthetic scenario generation versus their generative adversarial networks-enhanced framework. Additional improvements include energy costs reduced from 0.15 to 0.10 $\text{USD}\cdot\text{kWh}^{-1}$ and carbon emissions decreased from 850 to 760 $\text{t}\cdot\text{yr}^{-1}$[26]. Such models enable adaptive decision-making that mitigates the variability and intermittency inherent in solar power, thereby increasing system flexibility and reliability.

Also, data-driven AI models have optimized inverter efficiency and solar panel tilt angles, maximizing energy capture and minimizing performance losses caused by shading and environmental fluctuations[27].

Supervisory ML algorithms have provided exceptional precision in fault detection and diagnostics within PV systems. Comparative analyses indicate that K-nearest neighbors (KNN), decision trees, logistic regression (LR) and naive Bayes models can classify faults, including partial shading, open and short circuits, and degradation, with accuracies exceeding 99%. Of these, KNN demonstrated the highest precision at 99.2%[39]. Also, explainable AI approaches and deep learning-based CNN architectures have been developed to detect anomalies caused by dust, bird droppings and other physical defects, achieving over 91% accuracy and providing intuitive interfaces to aid maintenance decision-making[36].

Cybersecurity is a critical concern for smart grids connected to solar energy sources. Recent reports recommend multilayered security strategies including strong authentication methods, network segmentation, real-time intrusion detection and frequent vulnerability assessments. AI-driven threat detection systems offer automated identification of network irregularities and potential cyber threats in solar plant operations, thereby safeguarding system integrity and continuity[69]. By integrating these advances. Figure 7 illustrates the diverse applications of AI in solar energy systems. These applications rely on inputs like meteorological data, soil parameters, and crop growth metrics to enable smarter and more sustainable farming decisions.

4.1.1 Forecasting solar energy production

AI algorithms analyze vast meteorological and operational datasets to generate accurate solar power forecasts, addressing the challenges of intermittency and variability in solar energy. ML models, including deep learning architectures and CNN-LSTM networks, are used to capture complex spatiotemporal patterns, thereby enhancing prediction accuracy across various forecast horizons, such as nowcasting, intraday and day-ahead forecasts. Accurate forecasting is critical because solar energy is inherently weather-dependent, making reliable predictions essential for grid stability and energy planning[40].

For solar energy prediction, different models are typically evaluated using R^2 and RMSE metrics to determine the most

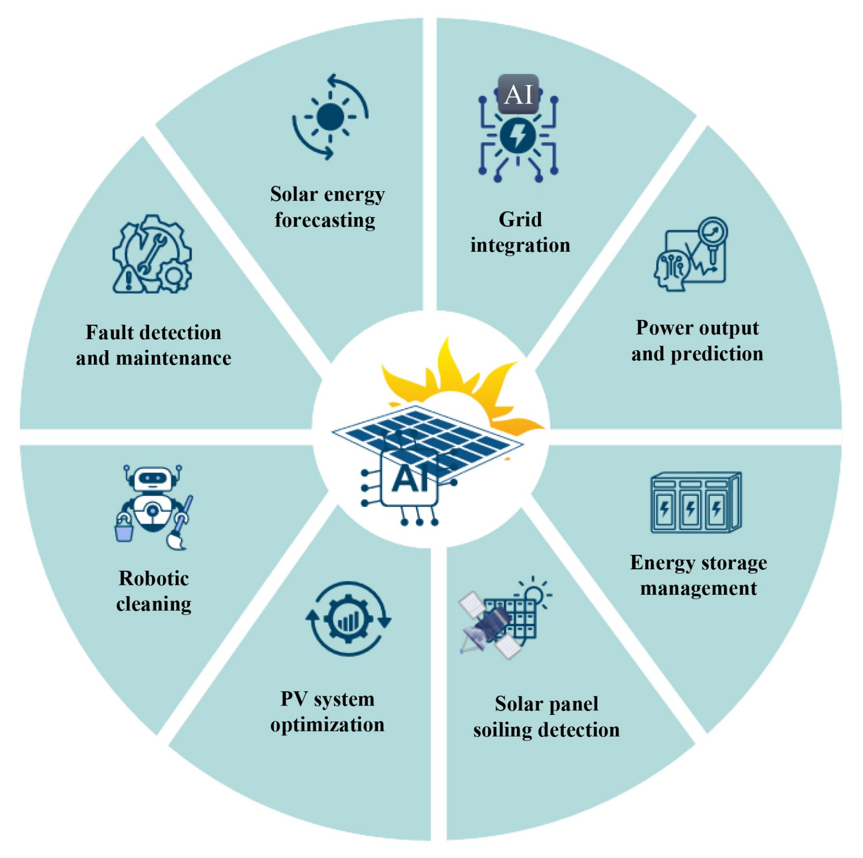


Fig. 7 Artificial intelligence applications in solar energy.

effective approach. Several studies have demonstrated the high predictive accuracy of AI and ML models for solar energy forecasting. For example, ensemble learning approaches have achieved R^2 values up to 0.96 for simulated irradiance datasets under tropical conditions[41]. However, these results primarily reflect model prediction performance rather than actual real-world energy conversion efficiency, highlighting the importance of field-level validation, particularly in APV applications.

Table 4 gives the overall efficiency score of different models at predicting solar energy with ML. Models adapted for zero-inflated data, which handles frequent zero-value outputs (e.g., no solar generation at night), show a significant performance drop (lower R^2 and higher RMSE) despite high preprocessing, suggesting the this is problem is challenging. The efficiency score is a composite metric that balances model accuracy against its computational and data preparation costs. The efficiency score is computed as a composite metric where a high R^2 and a low RMSE value contribute positively to a higher final score. Conversely, the computational burden is incorporated by assigning a numerical preprocessing-cost value to each level of complexity, from low to very high, which penalizes the score. The ultimate balance between rewarding accuracy and penalizing complexity is determined by the weights (w_1, w_2 and w_3) assigned to each of these factors as:

$$\text{Efficiency score} = w_1 \times R^2 + w_2 \times \frac{1}{\text{RMSE}} - w_3 \times \text{Preprocessing cost} \quad (1)$$

These data illustrate a clear trade-off between model performance and complexity. The CNN-LSTM model achieves the highest efficiency score (9.8) by delivering top-tier accuracy (R^2 = 0.96) and the lowest error (RMSE = 0.09), which outweighs its very high preprocessing cost. Similarly, the random forest (RF) model scores highly (9.2) by achieving comparable accuracy with only a medium preprocessing

Table 4 Efficiency of different models for solar energy prediction[40]

Model	Technique used	Data transformed	Mean R^2	Mean RMSE	Data preprocessing need	Efficiency score
Logistic	Regression	None	0.63	15.8	Low	3.5
XGBoost	Ensemble DT	Power transform	0.83	0.40	Medium	7.0
Gradient boosting (Reg)	Boosted trees	Power transform	0.86	0.37	Medium	8.0
RF	Bagged DT	Power transform	0.96	0.20	Medium	9.2
94RF+XGBoost (Ensemble)	Hybrid boost + Bagging	Power transform	0.96	0.20	High	9.4
CNN-LSTMD	CNN-LSTM (Spatiotemporal deep learning)	Power transform	0.96	0.09	Very high	9.8
RF (ZI)	Ensemble DT	ZI + Scaling	0.80	10.70	High	6.8
Gradient boost (ZI)	ZI	ZI	0.77	11.10	High	6.3
LSTM (Zero-inflated)	ZI	ZI	0.64	15.50	High	5.0

Note: CNN, convolutional neural network; DT, decision tree; LR, linear regression; LSTM, long short-term memory network; RF, random forest; R^2, coefficient of determination; RMSE, root mean square error; XGBoost, extreme gradient boosting; ZI, zero-inflated model.

requirement, making it a highly efficient choice. In contrast, zero-Inflated models score significantly lower, as their reduced accuracy and higher error are not sufficiently compensated by their specialized data handling, resulting in a lower net efficiency despite high preprocessing requirements. CNN-LSTM models outperform RF in complex APV prediction tasks by capturing both temporal dependencies through memory cells and spatial patterns via convolutional layers, yielding higher accuracy in high-dimensional datasets[70]. However, this superior performance is offset by higher computational demands, limited interpretability and the need for large sequential datasets, whereas RF models remain more transparent, computationally efficient and adaptable to smaller or mixed-type datasets[71]. Recent studies report hybrid CNN-LSTM-RF frameworks achieving R^2 values up to 0.92 on real solar power datasets[72] and CNN-LSTM consistently outperforming standard models using real PV data from Morocco[25].

Most APV-focused evaluations still rely on computational fluid dynamics simulations, which may not fully capture dynamic crop-panel interactions, variable microclimates, and soil feedbacks, highlighting the need for field-scale validation under real APV operating conditions.

4.1.2 Predictive maintenance and fault detection

AI-driven PdM is transforming solar energy systems by reducing expenses and enhancing overall system performance. PdM systems leverage real-time sensor data, maintenance logs and advanced ML techniques such as RF, SVM and deep neural network to detect anomalies and predict equipment failures before they occur. This enables solar plant operators to shift from reactive or preventive maintenance toward a proactive, condition-based strategy, optimizing maintenance schedules and minimizing unplanned downtime.

Studies report that PdM can reduce maintenance costs by 25%–40%, cut unplanned downtime by up to 70%, and extend the lifespan of critical solar components by 20%–40%[73]. Real-world implementations have shown improvements such as a 27% increase in energy yield due to early fault detection, faster maintenance response times (from 72 to 4 h), and significant environmental benefits including reductions in CO_2 emissions and water use. For example, a case study at Solar Tech Solutions 75 MW solar installation demonstrated maintenance cost reductions of up to 25%, alongside extended asset lifespan through timely interventions.

Table 5 summarizes the benefits and prediction accuracies of various AI algorithms used in solar energy systems.

AI algorithms, including CNNs, AE-LSTM, RNNs and others, have demonstrated high effectiveness in solar energy applications by enhancing fault detection (achieving F1 scores > 90%) and enabling real-time anomaly detection. These models contribute to reduced maintenance costs, extended asset lifespan and minimized downtime, particularly when applied to thermal imaging and sensor data from PV systems.

The implementation of AI-driven PdM in solar energy systems

Table 5 Algorithms used in solar energy systems

Model	Reported benefit	Accuracy	Case study detail	Ref.
RF, SVMs and deep neural networks	Up to 25% maintenance cost reduction and extended asset life	Case-specific accuracy > 90 %	RF, SVMs and deep neural networks	[74]
AE-LSTM, Facebook prophet and isolation forest	Real-time anomaly detection and reduced downtime	Precision/recall metrics (TP = 216, FN = 13, FP = 0, and TN = 12)	PV system sensor data	[75]
CNN	Improved fault detection accuracy (up to 91.5%)	F1 score > 90%	Thermal imaging of PV panels	[36]
Recurrent neural networks and CNN	Lower maintenance costs and reduced unplanned downtime	F1 score > 90%	Wind farm, thermal power plant and solar power plant	[73]

Note: AE-LSTM, autoencoder–long short-term memory; CNN, convolutional neural network; F1, harmonic mean of precision and recall, measuring the balance between false alarms and missed detections; FN, false negative, missed faults (undetected actual faults); FP, false positive, incorrectly detected faults (false alarms); PV, photovoltaic; RF, random forest; RNN, recurrent neural network; SVM, support vector machine; TN, true negative, correctly identified no-fault cases; TP, true positive, correctly detected faults.

requires large volumes of high-quality, clean and integrated data from multiple sensors and historical records. This necessitates rigorous preprocessing to manage noise and inconsistencies effectively. Additionally, the complexity and black-box nature of some AI models, particularly deep learning networks, raise concerns about transparency and interpretability, which are critical for building trust and ensuring adoption in maintenance decision-making.

To overcome these challenges and enable the widespread adoption of AI-driven PdM for solar installations, advancements in explainable AI, edge computing, IoT integration and digital twin technologies are promising solutions. As these technologies mature, PdM is expected to become standard practice in solar energy operations, leading to further cost savings, enhanced reliability and more sustainable energy production[70].

4.1.3 Energy yield prediction and performance optimization

Recent studies underscore the significant potential of AI in optimizing solar energy management and forecasting. Deep learning models, particularly LSTM networks, have demonstrated capacity to enhance grid reliability and increase solar energy production[76]. Advanced techniques such as autoencoders are outperforming standard ML models in forecasting key solar power plant characteristics, contributing to the development of smarter, more efficient grid systems[77]. Also, hybrid models that combine LSTM with novel optimization algorithms, such as the adaptive dynamic squirrel search optimization algorithm, have delivered superior performance in predicting hourly skewed solar irradiance compared to standard methods. These innovations emphasize the unique value AI offers in improving the efficiency and management of renewable energy systems[78].

4.1.4 Artificial intelligence in solar forecasting and grid integrity

The integration of renewable energy sources, particularly solar PV systems, into electrical grids presents significant challenges related to power quality, stability and reliability. The inherent intermittency and variability of solar energy, driven by weather patterns, cloud cover and diurnal cycles, can cause voltage fluctuations, frequency deviations and grid instability if not properly managed[79]. AI technologies have emerged as valuable tools for addressing these grid integration challenges through advanced forecasting capabilities, real-time grid management and intelligent control systems[80].

4.1.5 Solar power forecasting for grid stability

Accurate solar power forecasting is essential for maintaining grid stability and enabling efficient dispatch of standard power plants. AI-based forecasting systems use multiple data sources including satellite imagery, numerical weather prediction models, ground-based meteorological stations and historical power generation data to predict solar irradiance and power output across various time horizons[81].

Deep learning architectures, particularly RNN and their variants such as LSTM and gated recurrent units, have shown superior performance in capturing temporal dependencies in solar irradiance patterns[82]. A recent study found that ensemble methods combining CNN-LSTM architectures with attention mechanisms achieved mean absolute percentage errors below 5% for day-ahead solar forecasting, significantly outperforming standard statistical methods[83]. Also, transformer-based models adapted from natural language processing have shown promising results in multi-step ahead solar forecasting, with some implementations achieving R^2 values exceeding 0.95 for hourly predictions up to 48 h ahead[84].

4.1.6 Grid integration and stability management

The variability of solar power generation necessitates sophisticated grid management strategies to maintain power quality and system stability. AI-driven grid management systems use real-time optimization algorithms to coordinate distributed solar resources, energy storage systems and standard generators. These systems use advanced ML techniques including reinforcement learning and multi-agent systems to adapt to changing grid conditions and optimize power flow. Voltage regulation represents a particular challenge in high solar penetration contexts, where rapid changes in solar output can cause voltage violations. AI-based voltage control systems use predictive models to anticipate voltage disturbances and proactively adjust reactive power resources, including smart inverters and distributed energy storage systems. Research has shown that ML-based voltage control can reduce voltage violations by up to 85% compared to current control methods[28,29].

4.1.7 Frequency regulation and ancillary services

Solar power integration affects grid frequency stability due to the displacement of standard synchronous generators that provide inertial response. AI systems are being developed to coordinate fast-responding resources such as battery energy storage systems and demand response programs to provide frequency regulation services. Advanced control algorithms use ML to predict frequency deviations and optimize the dispatch of ancillary services[30].

Recent developments in virtual power plants leverage AI to aggregate distributed solar resources and provide grid services currently supplied by large power plants. These systems use ML algorithms to forecast the availability and output of distributed resources, optimize bidding strategies in electricity markets and coordinate real-time dispatch to meet grid service requirements[31,32].

AI is being used in virtual power plants to aggregate distributed solar resources and deliver grid services. A techno-economic study demonstrated this on a 90-bus industrial feeder. The VPP was used to purposefully generate islands during grid disruptions by combining rooftop solar PVs and using demand-side control. Reliability was greatly increased by using this technique to power the functioning sections of the grid feeders that were separated by automatic reclosers. According to the findings, the VPP installation directly improved grid reliability for a particular feeder with a high solar penetration rate by lowering the expected energy not supplied score[33].

4.1.8 Cybersecurity and grid resilience

The increasing digitization of solar power systems and grid infrastructure introduces cybersecurity vulnerabilities that could compromise grid integrity. AI-based cybersecurity systems for smart grids use anomaly detection algorithms, network traffic analysis and behavioral modeling to identify potential cyber threats[34,35]. ML models trained on normal grid operation patterns can detect deviations that may indicate cyber attacks or system malfunctions.

Blockchain technology combined with AI is being explored for secure peer-to-peer energy trading in distributed solar systems. These systems use smart contracts and ML algorithms to optimize energy transactions while maintaining grid stability and security. Reliability was increased by using this technique to power the functional sections of the grid feeders that were separated by automatic reclosers.

4.2 Critical evaluation in artificial intelligence in agrophotovoltaics

Systematic reviews of the literature confirm that AI techniques consistently outperform established methods for fault detection, maximum power point tracking and energy forecasting. Deep learning models, particularly CNNs, achieve higher accuracy and efficiency compared to standard ML approaches such as KNN and RF[85]. Quantified improvements include up to 10% increases in system efficiency when AI is integrated with PV systems. However, high computational costs, extensive training data requirements and long computation times present substantial barriers. The trade-off between accuracy and computational burden becomes especially pronounced with high-resolution datasets, where performance gains come at the expense of increased processing demands[86]. These constraints are particularly challenging in agricultural environments, where real-time decision-making and resource limitations are critical considerations.

A significant research gap exists regarding APV-specific applications, limiting the validity of current evaluations. The available evidence predominantly addresses general PV systems rather than agricultural-specific implementations[29]. APV presents unique challenges, including variable crop shading, integration with farming operations and different maintenance requirements that may not be adequately addressed by current AI/ML research.

5 Artificial intelligence in agrophotovoltaics

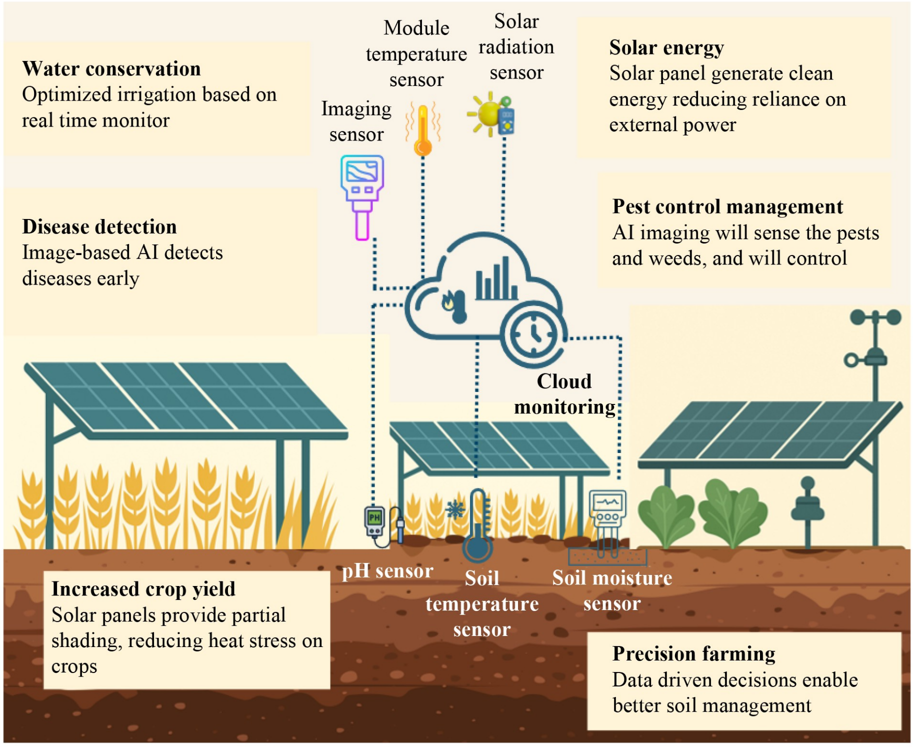
APV solutions leveraging AI significantly enhance system sustainability and efficiency by enabling intelligent control, real-time monitoring and optimized resource management. Figure 8 illustrates the various types of sensors integrated with AI in these systems.

The integration of AI, sensors, and solar energy in agriculture offers several key benefits, including enhanced resource efficiency, reduced dependence on external power and improved crop yield. These technologies facilitate data-driven decision-making, enabling lower input costs, early detection of issues and the adoption of more sustainable farming practices.

Table 6 is a meta-summary contextualizing key performance metrics by comparing their reported ranges across seminal APVs studies. It highlights the critical influence of specific conditions, such as crop type, climate and AI methodology, on the resulting efficiencies, yield gains and economic benefits.

5.1 Control and monitoring

IoT-enabled smart sensors continuously monitor vital parameters such as soil moisture, temperature, humidity, solar



Water conservation
Optimized irrigation based on real time monitor

Solar energy
Solar panel generate clean energy reducing reliance on external power

Disease detection
Image-based AI detects diseases early

Pest control management
AI imaging will sense the pests and weeds, and will control

Increased crop yield
Solar panels provide partial shading, reducing heat stress on crops

Precision farming
Data driven decisions enable better soil management

Fig. 8 Image showing sensors integrated with agrophotovoltaics.

Table 6 Documented co-benefits and performance of integrated agrivoltaic systems, highlighting energy gains, resource efficiency, and AI model accuracy

Metric category	Specific metric	Reported range/value	Context & study details	Ref.
Energy production	Monthly energy gain (with AI-MPPT)	Significantly higher vs non-MPPT systems	AI-based MPPT mitigates shading losses from crops/weather, enhancing overall output	[87]
Water use efficiency	Water consumption	Irrigation water savings contribute to system sustainability	Criteria importance through inter-criteria correlation method for evaluation of irrigation systems	[88]
Land productivity	Land equivalent ratio (LER)	Up to 1.6	LER > 1 indicates land use efficiency; 1.6 means 60% more land would be needed for separate food/energy production	[89]
AI prediction accuracy	Crop yield prediction (R^2)	As low as 0.02	Very low MAE on normalized data indicates high precision	[90]

Note: AI, artificial intelligence; AI-MPPT, artificial intelligence-based maximum power point tracking; LER, land equivalent ratio; MAE, mean absolute error; MPPT, maximum power point tracking; R^2, coefficient of determination.

irradiance and microclimatic conditions, all of which impact crop growth and solar panel performance. These sensors facilitate accurate data collection, enabling data-driven decision-making. Advanced sensor networks allow in-situ monitoring and control of irrigation, fertilizer application and environmental conditions, enabling timely responses to crop needs and system requirements. Integrating AI-driven microclimate forecasting and control into greenhouse/controlled-environment systems enables hourly optimization of light, temperature and irrigation strategies, improving resource-use efficiency and supporting higher crop productivity[91].

5.2 Optimization strategies

Complex optimization methods, including digital twin frameworks and ML models, dynamically balance trade-offs between agricultural production and solar energy generation. These models increase land-use efficiency by optimizing panel tracking, spacing and placement while ensuring adequate sunlight for crops. Additionally, ML manages scheduling for operational and maintenance tasks of both agricultural and energy components to improve overall system efficiency[92].

5.3 Models in agrophotovoltaics evaluation

CNN-LSTM models have significant potential for complex temporal forecasting whereas RF models appear better suited for design optimization tasks in APV systems. Models for APV applications must handle multi-objective optimization, balancing crop yield and solar energy efficiency, while accounting for environmental factors and spatial design characteristics such as panel height and row spacing. In the only available APV study using RF for design optimization, the model successfully predicted panel temperatures with an RMSE of less than 2 °C and optimized panel heights up to 3.2 m, depending on seasonal conditions and ground cover[71].

The strengths of RF for APV applications include excellent interpretability for stakeholder decision-making on panel placement, the ability to handle mixed data types and lower computational requirements suitable for real-time design tools. In contrast, CNN-LSTM performs better for temporal forecasting in related solar applications, with hybrid CNN-LSTM-RF models achieving 92% R^2 [72]. The critical limitation is that no studies have directly compared these approaches within APV systems, creating a significant evidence gap for technology selection in APV contexts.

5.4 Challenges and limitations

APV systems have challenges such as wind load vulnerability, economic viability and potential interference with crop growth. AI can help address some of these issues; however, limitations remain, including difficulties in data collection, variability across field conditions and low replicability due to site-specific factors[55].

The adoption of AI and ML in APV systems is significantly constrained by data governance frameworks that govern ownership, sharing and on-farm edge processing. Research indicates that many farmers are reluctant to share data due to trust issues and uncertain data sovereignty, stemming from unclear legal and regulatory frameworks surrounding data ownership. Concerns about who will profit from the data and how it will be used create additional privacy and security challenges. Promising solutions include privacy-preserving frameworks that enable on-farm edge processing, allowing local data transformation while maintaining farmer control, thereby mitigating privacy risks[93].

Although there are currently few quantitative adoption measures, studies indicate that integrated governance models that combine transparent sharing protocols that foster trust, clear legal frameworks for data ownership and on-farm edge processing capabilities may help AI/ML adoption[94].

APV environments exhibit considerable variability in soil types, microclimates and crop responses to PV shading, necessitating site-specific adaptability and high-quality, diverse datasets for AI models to perform effectively. The complexity and black-box nature of advanced AI models, particularly deep learning architectures, reduce transparency and user trust, limiting adoption among farmers who prefer interpretable decision-support tools. Developing explainable AI methods and user-friendly interfaces is therefore crucial to bridging this gap[95].

Key socioeconomic barriers include limited access to credit, insecure land tenure, insufficient extension services, and restricted market access. Studies consistently show that these barriers reduce adoption intensity among marginalized farmers. While policy frameworks demonstrate potential, significant implementation gaps remain. Research indicates that investment-ready and food-secure small producers are more willing to adopt agricultural technologies. However, systematic reviews reveal that most policy studies focus narrowly on single instruments rather than integrated approaches. Cost-benefit analyses suggest that perceived benefits often outweigh costs, but financing constraints remain problematic. Evidence points to the importance of pluralistic extension services and enhanced financial access as critical enablers of adoption[96].

Additionally, the dynamic nature of APV microclimates, where solar panel shading and cooling alter local light, humidity and temperature regimes, complicates accurate predictions of crop development and energy output. AI models must adequately capture these environmental dynamics. Uncertainties due to climate change and variable weather patterns further challenge the accuracy and stability of AI forecasts. To improve resilience, hybrid modeling approaches that integrate AI with hydrological and physical models have been proposed. Figure 9 presents a research roadmap outlining the challenges and opportunities of AI in APV systems.

5.5 Outlook

In summary, AI and ML hold transformative potential to optimize APV systems by enhancing energy production, crop health and operational efficiency. However, successful implementation depends on overcoming challenges related to data quality, infrastructure, economic feasibility, social acceptance, ethical considerations and environmental complexity. Strategic efforts including improved sensor deployment, development of interpretable and adaptable AI

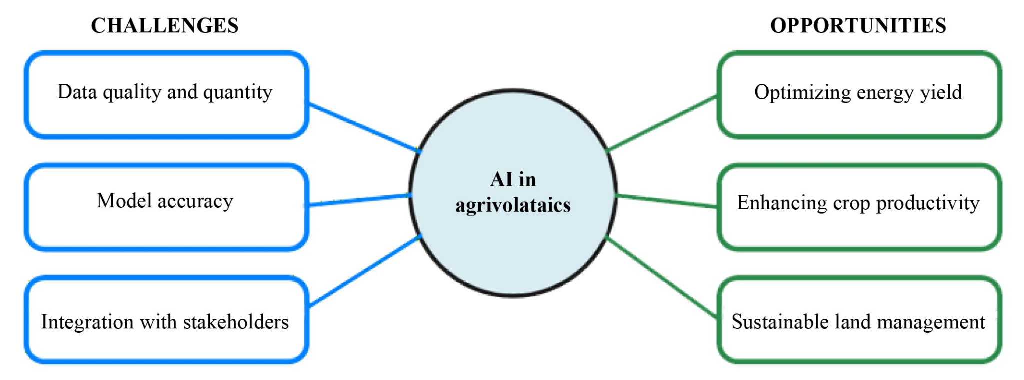


Fig. 9 Diagram illustrates the key challenges and future opportunities for integrating artificial intelligence into agrivoltaics systems.

models, financial support mechanisms, stakeholder engagement and enabling policies are essential to fully realize the benefits of AI-driven APV[95]. Continued interdisciplinary research and collaboration among technologists, farmers, policymakers and community stakeholders will be vital to develop resilient, sustainable agricultural and energy systems for the future.

6 Research gaps

6.1 Short-term priorities

6.1.1 Integration with agrophotovoltaic

A critical challenge lies in integrating AI technologies with existing agricultural infrastructure, especially in rural areas where sensor networks, connectivity and suitable hardware are often lacking. A key question is how can AI technologies be seamlessly integrated into farms that rely on legacy systems and minimal digital capacity. Many farms still rely on outdated tools and practices that are difficult to align with advanced AI systems. This technological mismatch increases implementation costs and complexity, limiting adoption. To promote widespread acceptance, AI tools must be affordable, easy to deploy and seamlessly compatible with legacy systems.

6.1.2 Model transparency

Model interpretability and transparency remain significant issues. The key research question is how can complex AI models, particularly deep learning algorithms, become more explainable and trustworthy for farmers and local decision-makers. Many AI algorithms, particularly deep learning models, operate as black-boxes, making it difficult for farmers and practitioners to understand the rationale behind recommendations or decisions. This lack of explainability undermines user trust and restricts reliance on AI for critical farm management. Research into explainable AI techniques tailored to APV environments is essential to build confidence and facilitate AI adoption as a dependable decision-support tool.

6.1.3 Data sharing and governance

A research question arise in this section will be what mechanisms enable secure, privacy-preserving data exchange among farmers, research institutes and technology developers. Implementing federated learning frameworks and blockchain-based data-sharing systems could allow decentralized yet transparent collaboration without compromising data privacy.

AI integration in APV systems enhances efficiency and optimizes the balance between agricultural yield and energy production through sophisticated data analysis, predictive capabilities and adaptive control mechanisms. These technologies enable real-time monitoring and dynamic resource allocation, improving both crop yields and renewable energy output on shared land.

Research and case studies demonstrate how AI overcomes the common constraints of dual land use by optimizing solar panel positioning and irrigation scheduling, accounting for microclimatic variations and crop-specific needs. Automated control and real-time diagnostics align agricultural and energy operations, minimizing human intervention and maximizing outputs. Providing stakeholders with predictive insights fosters proactive decision-making, enhancing operational planning, risk management and financial viability.

6.2 Medium-term priorities

6.2.1 Economic, technical and environmental implications

The research question arising here will be how can AI/ML systems remain affordable and technically viable for smallholdings with minimal digital infrastructure, Technologically, AI/ML systems offer adaptive management and accurate predictions that enhance solar irradiance utilization, irrigation efficiency, and pest control. Economically, they reduce maintenance costs, minimize resource waste and increase agricultural and energy revenues. However, high initial capital and infrastructure requirements remain barriers, especially for smallholders. Environmentally, these technologies support climate-smart agriculture by optimizing water use and reducing greenhouse gas emissions, aligning with global sustainability goals.

6.2.2 Environmental complexity

The complex interactions between solar panels, crops, soil and microclimates pose modeling challenges. Therefore, the key research question will be how AI can capture the multi-factor interactions of shading, soil moisture and microclimatic variability affecting both crops and solar panels. Factors such as temperature fluctuations, moisture dynamics and shading significantly influence both plant growth and energy production but are difficult for current AI models to capture accurately. Hybrid modeling approaches that combine physical simulations with ML could improve prediction accuracy and system optimization in these dynamic and variable environments.

6.2.3 Broad Impacts on renewable and sustainable energy

The integration of AI in APV and renewable energy systems drives systemic improvements toward global food and energy security goals. These technologies enhance ecosystem management, support biodiversity, decarbonize agriculture, and enable scalable land and resource optimization. AI-powered systems also foster resilient rural development and circular economies by harmonizing precision farming with renewable energy generation, offering replicable models adaptable to diverse climatic and socioeconomic contexts.

6.3 Long-term priorities

6.3.1 Socioeconomic adoption and policy

A central research question arises, how AI-driven APV systems can be scaled equitably across smallholder and industrial farming sectors. Industrial farms typically possess the infrastructure and resources to implement advanced AI and IoT solutions, whereas smallholders often face informational, technical and financial barriers that limit participation. Future research should therefore focus on developing system-dynamics models that simulate technology diffusion under varying socioeconomic conditions. Such models can explore how information-sharing networks, cooperative ownership arrangements, and shared funding mechanisms influence adoption behavior, providing actionable insights for equitable deployment strategies.

6.3.2 Policy and regulatory frameworks

A critical question is which legislative and regulatory tools can encourage broad adoption of AI-driven APV systems while safeguarding data ownership and ethical integrity. Governments and international bodies can facilitate multilevel regulatory frameworks that promote data standardization, cybersecurity and responsible AI use in agriculture. Future research should use multicriteria decision analysis to guide evidence-based policy design, ensuring that regulatory approaches are transparent, inclusive and aligned with sustainable modernization goals while evaluating alternatives across economic, environmental and social dimensions.

6.3.3 Climate resilience and environmental sustainability

Enhancing ecological sustainability and climate resilience in AI-enabled APV systems is increasingly important given rising climate unpredictability. The key research question is how can AI-driven APV systems mitigate long-term environmental impacts and adapt to adverse weather events. Future studies should develop AI-climate coupled models that integrate forecasting with hydrological and environmental data to predict and reduce climate risks. Within the food-energy-water nexus, such systems can enable adaptive management, biodiversity preservation and optimized water use, thereby strengthening farm-level resilience and advancing broader sustainability objectives.

7 Conclusions

The integration of AI and ML technologies in APV systems represents a paradigm shift toward intelligent, sustainable land management, simultaneously addressing global food security and renewable energy demands. This comprehensive review demonstrates that AI-driven APV systems consistently outperform established approaches, delivering substantial improvements in energy efficiency, crop productivity and operational management.

The technological advancements highlighted herein underscore the transformative potential of AI applications in APV systems. Advanced algorithms, including deep learning networks, RF, and hybrid optimization models, have proven effective in energy yield forecasting, achieving R^2 values up to 0.96 for solar irradiance and energy output prediction. Similarly, PdM systems reduce operational costs by 25%–40% and extend asset lifespans by 20%–40%. Also, real-time monitoring through IoT-enabled sensor networks, integrated with ML algorithms, enables precise control of irrigation, fertilization and environmental conditions, optimizing the balance between agricultural output and solar energy generation.

However, the successful implementation of AI in APV systems present several critical challenges that require coordinated research and policy attention. Data quality and availability limitations, particularly in rural agricultural settings, constrain the development of robust AI models. The complexity and black-box nature of advanced algorithms create transparency concerns that hinder farmer adoption and trust. Site-specific environmental variability and the dynamic nature of APV microclimates demand adaptable, interpretable AI solutions that can accommodate diverse agricultural contexts and climate conditions.

Economic barriers, including high initial capital investments and technological infrastructure requirements, present significant obstacles for widespread adoption, especially for smallholders. The development of cost-effective, user-friendly AI tools that integrate seamlessly with existing agricultural practices is essential for democratizing access to these technologies.

To accelerate progress, future research should prioritize actionable directions such as developing explainable AI frameworks that enhance transparency and user confidence among farmers and policymakers. Additionally, the implementation of digital twin systems can facilitate real-time simulation, performance monitoring, and optimization of APV operations under diverse environmental and agronomic conditions. Also, designing hybrid models that integrate physics-based and data-driven approaches will improve both accuracy and adaptability. Collectively, these innovations can bridge existing knowledge gaps and support evidence-based decision-making across technical and policy domains.

Looking forward, the future of AI in APV lies in addressing these challenges through interdisciplinary collaboration among technologists, agricultural scientists, policymakers and farming communities. Priority research areas include developing explainable AI methods specific to agricultural contexts, creating hybrid modeling approaches that combine physical simulation with machine learning and establishing standardized data collection protocols for diverse APV environments.

The environmental implications of AI-driven APV systems extend beyond individual farm benefits to contribute meaningfully to global sustainability goals, including climate change mitigation, biodiversity conservation and resource efficiency. As these technologies mature and become more accessible, they promise to enable scalable solutions for sustainable agricultural transformation while supporting the transition to renewable energy systems worldwide.

Acknowledgements

This research was supported by the collaborative review work under UK–India Education and Research Initiative (UKIERI) and the Scheme for Promotion of Academic and Research Collaboration (SPARC) (UKIERI-SPARC/01/20).

Compliance with ethics guidelines

Shalini Ranganathan, Mehrdad Ghamari, Mahendiran Ramasamy, and Senthilarasu Sundaram declare that they have no conflicts of interest or financial conflicts to disclose. This article does not contain any studies with human or animal subjects performed by any of the authors.

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