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Optimization and Techno-Economic Assessment of Hybrid Renewable Energy Systems for Precision Agriculture: A Review of Tools, Algorithms, and Sustainability

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Abstract

In recent years, precision farming has been leveraging information infrastructure enabled by smart energy use, with designs for irrigation, sensors, automation, and post-harvesting services. In many agricultural regions, it is increasingly clear that, given the high cost of grid extensions and diesel-powered generators, traditional power grids are ill-suited. This corresponds to the rise of hybrid renewable energy systems. This study offers general considerations for optimizing and conducting cost studies of hybrid renewable energy systems in the precision agriculture sector. A comparison of the identified features has been employed to determine which hybrid configurations, their associated control strategies, optimization techniques, and assessment criteria are applicable to a given agricultural application. The summarized results point to a stronger tendency toward cost minimization and a system-oriented, consequently techno-centric design, with disproportionate underuse of explicit and realistic energy–water–crop interactions, real-time decision-making, and compensation for socio-economic aspects. The present article argues for a systems approach to solving the problem of sustainable, resilient precision farming, as well as the use of hybrid renewable energy sources and their smart deployment.

Keywords
Hybrid renewable energy systems, Precision agriculture, Techno-economic analysis, Energy system optimization, Sustainable agriculture

1. Introduction
Precision farming is increasingly characterizing modern agriculture, using high-end sensing equipment, data processing, automated operations, and advanced decision-making tools to achieve higher production levels, optimize resource use, and conserve the environment (Padhiary, Kumar, et al., 2025; Soussi et al., 2024). One of the key success factors of this change is the availability of the necessary energy supplies, since most of the modern agricultural

operations and the use of most of the technologies, including precision image spraying, IoT-enabled sensor-based technologies for soil and crop monitoring decrease and increase, automatic greenhouse management, unmanned aerial crafts, and post-harvest handling and storage (Miao & Khanna, 2020). At the same time, due to these technologies, one can observe that energy consumption in agriculture increases in both intensity and complexity, with fluctuations driven by diurnal and seasonal variations and by seasonal and climatic influences (Ghobadpour et al., 2022). Despite the growing importance of electricity in precision agriculture, the availability of affordable, reliable power remains problematic in many rural and remote cultivation areas. Grid connection to remote agricultural areas is often uneconomical, primarily due to very high installation costs, low load density, and difficult topography; as such, the use of renewable energy sources is viable (Chel & Kaushik, 2011; Stakens et al., 2023). As with many irrigation systems in precision agriculture, these systems require energy, and appropriate and efficient use of such irrigation, particularly in remote farms, is needed. Correspondingly, the combination of these challenges for hybrid energy optimization in agricultural practice is evident, as such systems integrate objective, data-centric strategies that require relevant climate changes to be taken into consideration and proper strategies to be laid down for their efficient use (Amri et al., 2025). However, to achieve encouraging outputs from hybrid renewable energy systems used in agriculture, this focus is not only on technological advances but also on how the systems are designed and operated effectively. Factors in the design of the system, the choice of each component, control mechanisms, and operating schedules tend to be at odds with economic success, technical reliability, and, most of all, ecological sustainability (Zatti et al., 2018). These challenges worsen as renewable energy systems are integrated with agricultural power, which is further complicated by the stochastic nature of renewable energy and the temporal behavior of agricultural energy consumption.

Most studies are more concerned with the general aspects of rural electrification, ignoring the unique needs of precision agriculture (Unde et al., 2025). It is also common for the most general sustainability analysis in this area to include economic appraisal, the dimension of local nutrient utilization, history with other land use forms, environmental consequences in some areas, and welfare issues among farming residents (Hatanaka et al., 2022). The scope of this review includes at least four interconnected things. This paper ultimately presents the review's results and outlines relevant areas for subsequent research, including the need to develop renewable energy strategies to power the mechanization of precision agriculture. The rest of the paper is structured as follows. The next chapter reviews the Energy Characteristics and Systems Requirements for Precision Crop Management. Figure 1 presents the link between water, energy, and food security. The Cyber-Physical Architecture for Smart Irrigation and Energy Management model

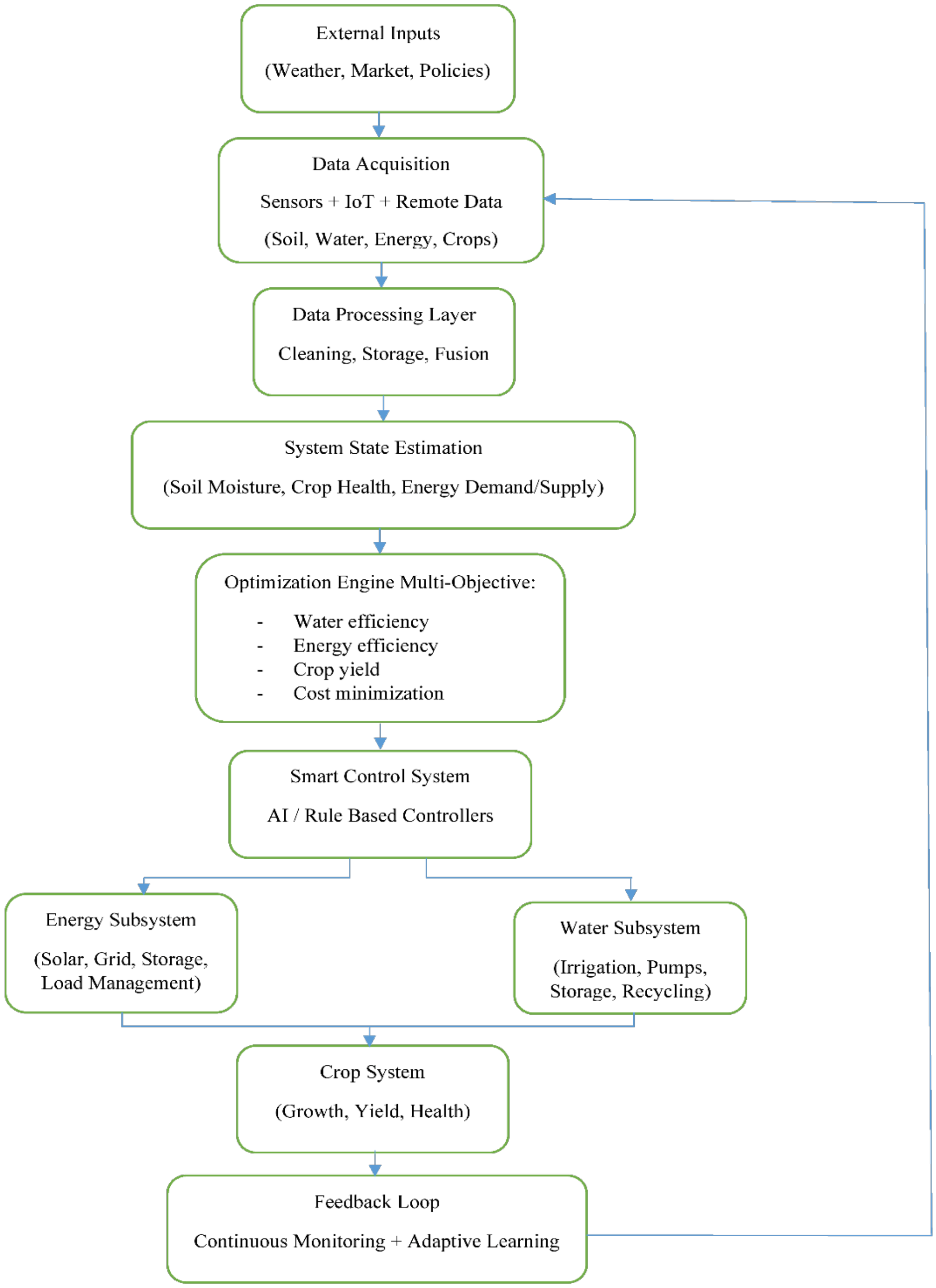

Figure 1. Cyber-Physical Architecture for Smart Irrigation and Energy Management model

2. Precision Agriculture Energy Demand and System Requirements

Within the context of managed grass and pasture ecosystems, human judgment more often than not dominated in specific environmental conditions that had been filled. Climate, including air temperature, humidity, aspect, slope, and ground texture, was a significant driver of all agricultural activities (Asaolu & Ogbemhe, 2009). Certain more advanced precision farming technologies, such as remote sensing and GPS, have, for instance, become part of the mainstream in many countries, including Tanzania, and have advanced in a range of applications (Onyango et al., 2021). However, fewer than 10% of farms use drones and auto-cultivation technologies, though the trend is growing. Apiculture practices have also been influenced by these innovative ideas in precision farming, where farmers are adopting technologies such as "smart" hives with sensors to boost beekeeping efficiency and improve hive management by monitoring and preventing overfeeding. This has been the case despite the fact that bee counts, even to this day, provide only an estimate of their numbers. Ultimately, the most valuable thing an effective technology provides is the capacity of its user to be more accurate. It is very important that smart watering systems rank among the most active types of equipment in applied agronomic methods. Electrical-driven pumping units, control valves, sensors, and communication units are all connected and provide rational water schedules for the plants based on real-time conditions (Daraz et al., 2025). Similarly, IoT networks are permanently active, with spatially distributed sensor nodes, gateways, and data sinks that monitor nutrient levels, temperatures, humidity, and the health of crop soil at intervals (Aldhaheri et al., 2024). Furthermore, greenhouse farming increases power consumption through the use of heating, cooling, ventilation, lighting, and irrigation systems, which are also automated in specific seasons, as in protected agriculture, where typical field problems may not occur (Shamshiri et al., 2021). Besides domestic applications, there are instances of UAV and post-harvest processing activities, such as cold storage, that demonstrate on-and-off usage but consume substantial energy (Dohlman et al., 2024). Within the system's capacity, these and numerous other uses combine to form energy uses that are best characterized by the different segments. Figure 2 summarizes the Precision Agriculture energy demand and system requirements

In precision agriculture, one key factor in the energy needed is its high volatility over any given time period. Such a change in energy pattern occurs in sync with daily shifts, annual cycles, and the duration of a particular crop's growth cycle. Here, in general, these are expected to rise during the day and in most seasons of the year, meaning that, almost regardless of the day and season, digging progresses (Olsen et al., 2015). The rise in energy in crop cycles is paradoxically milder: as more industrial energy is used in such periods, the energy requirement is highest. More energy is indeed required to heat a room in winter than to cool it in summer (Iddio et al., 2020). Smoothing periods, such as the crop cycle, also contribute to variation, as the highest energy needs are realised during the installation, fuller, and harvest phases of growth (Hale et al., 2018). Previous studies have shown that ignoring these dynamics renders sizing somewhat inadequate and the system unreliable (Wang et al., 2026). In addition to seasonal variations, power usage patterns across a precision agriculture system are also significantly dependent on the individual characteristics of the loads. The significance of a load is evident in the fact that some loads are time- and altitude-dependent and require automation to operate continuously; they include running water pumps for irrigation during drought, monitoring greenhouse air temperatures, and storing cold-stored products that can spoil. In such applications, any disruption results in crops going to waste almost immediately and, worse, in the loss of potential profits due to product damage (Babatunde et al., 2019).

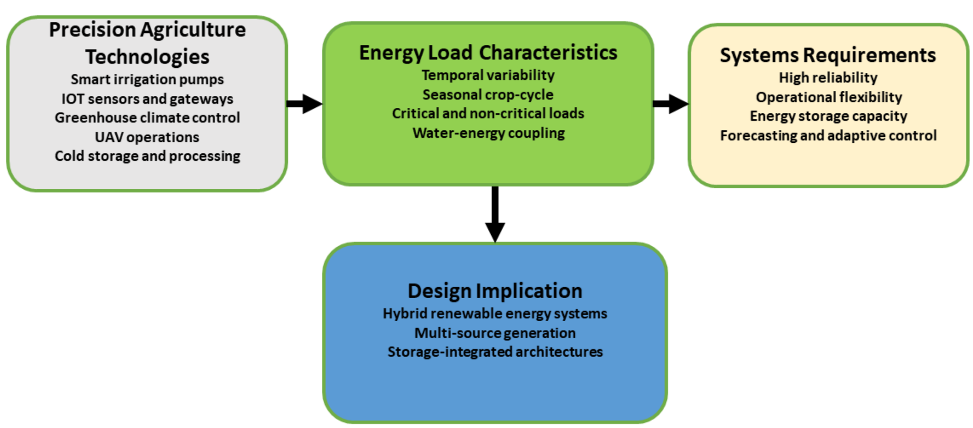

Figure 2. Precision Agriculture energy demand and system requirements

Further implications of the advancement of hydro-power include the increased complexity of the energy required for efficient land use in precision agriculture, especially in areas where agricultural activities are carried out under irrigation. Water is drawn, pumped, transmitted, and distributed using energy, with further operational decisions determining when and how much water to apply to crops, thereby impacting both water use and energy efficiency (Loureiro et al., 2024). The scientific community has recognized significant energy waste in irrigation, and examples have been provided, especially for water extraction systems that pump water from a certain depth in the ground seasonally (Daccache et al., 2014). Irrigation systems that use groundwater pumping are very efficient, but their use is aided by improper irrigation practices, leading to increased energy demand in production (Montazar, 2019). Thus, planning for energy use in agricultural operations should be intertwined with the management of other natural resources, especially water, thereby fueling the development of energy-water modeling frameworks. The needs stemming from yield patterns and their relationship to energy use and costs have implications for the design of weight-saving power-producing plants for agriculture. Such power plants, designed and fueled for agricultural applications, cannot be monolithic but must incorporate diverse energy production technologies. Monolithic energy systems have limited potential to meet highly stringent design criteria, leading to under planned systems with unreasonable structural sizes and cost escalation (Olkkonen et al., 2023).

The management of energy distribution and production is the main aim for any renewable energy system, highlighting the importance of reliable energy substitutes. One key technology that enables the triad (load shifting, peak shaving, and non-interruption supply during renewable energy changes) is energy storage (Areola et al., 2025). This has enabled most of the development of microgrids in a given agricultural activity zone, including the design of a kWh-scale reservoir to reinforce diesel generation. Legitimate sizing of the energy stores in this installation was predetermined from energy storage reliability verification and back-designed (Garcia et al., 2024). Objection-based load estimates serve as a crucial input in optimizing the operation of an energy system. The demand for energy in agriculture also depends on factors such as rainfall patterns, crop type, irrigation schemes, and farm operations, all of which are known to be random (Kocaman et al., 2020). Utilizing very simple or fixed-load assumptions has also been shown to lead to poor-performing systems and elevated operational costs in past experiments (Silva, 2017). Hence, for the efficient management of agricultural output, any technique that relies heavily on data, for example, forecasting and adaptive control, should be given greater importance, as the importance of search and irrigation water in the country will increase. The utility is that the active movement relies on clean energy, which enables the combination to perform both sustainable processes and precision functions. The inverse operation and real-time control play a pivotal role in maintaining power quality and power supply.

3. Hybrid Renewable Energy System Architectures for Precision Agriculture

The photovoltaic battery system represents the most fundamental and widely utilized system for agricultural applications. The combination of solar photovoltaic systems and battery storage creates a sustainable, flexible system that powers irrigation pumps, sensors, and small-scale automation systems. The system benefits from decreasing costs of photovoltaic and battery components and simple system integration (Okomba et al., 2023). The system experiences solar power interruptions because it relies on a single renewable energy source, which becomes unavailable during extended periods of cloud cover and seasonal changes (Kumar et al., 2024). The research findings demonstrated that PV battery systems need to be oversized because they require additional backup systems to ensure operational reliability during their highest irrigation demand periods (Carricondo-Antón et al., 2023). The PV wind battery system solves its deficiencies by using wind power to support its solar energy requirements. Wind resources become more accessible during nighttime hours and seasonal periods when solar energy production decreases, which improves energy distribution and reduces the requirement for energy storage (Soomar et al., 2022).. The system operates at its best when it runs in open farmland areas and coastal agricultural zones that benefit from favorable wind patterns. Previous studies showed that PV wind battery systems provide better power availability at lower operational expenses than systems using only one energy source in rural farming locations (Akan & Akan, 2021). Figure 3 shows energy systems, for precision agriculture. Hybrid renewable energy systems, for precision agriculture combine power from sources, store the power in a central storage unit and run energy management in a way.

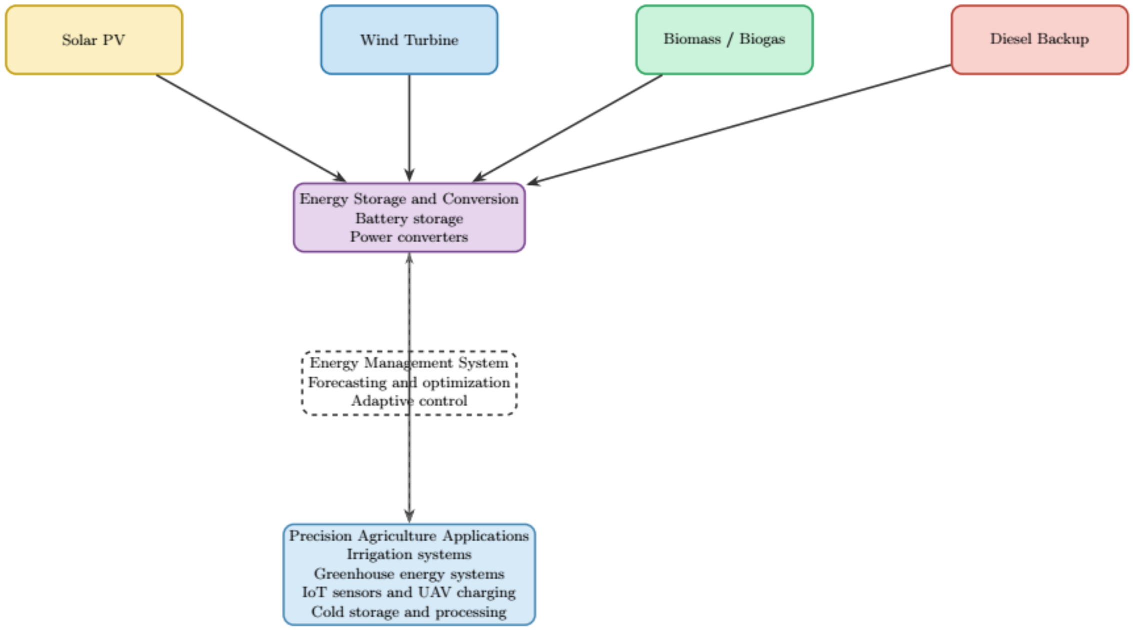

Figure 3. Architecture of hybrid renewable energy systems for precision agriculture

PV-diesel battery systems function as the primary technology which supports precision agriculture operations during the transition from conventional diesel power systems. The system generates power through photovoltaic technology which decreases fuel requirements but diesel engines function as backup power generators during times when renewable energy is not available or when system power requirements exceed maximum capacity (Abdulrazzaq et al., 2025). The system depends on battery storage to manage power fluctuations which results in better generator operation. The hybrid system produces lower emissions and operating costs than diesel systems but it needs fossil fuels to operate and its fuel consumption follows the same pattern as fuel market price changes (Clark et al., 2025; Ericson et al., 2018).

The PV biomass battery system operates by converting agricultural waste products from farming operations and animal waste and industrial waste into its third renewable energy source. Biomass generation produces energy through controlled processes which follow solar energy patterns and enable agricultural circular economy operations (Hellwinckel et al., 2024). The research demonstrated that biomass-powered hybrid systems enable farming communities to become self-sufficient in energy while solving their waste disposal problems (Haji et al., 2024). The three core elements that determine their operational success include access to biomass resources and delivery systems and appropriate conversion technologies for biomass. The development of multi-source hybrid systems now integrates five different energy sources, which include photovoltaic systems, wind power, biomass generation, diesel fuel, and contemporary energy storage technology. The system designs achieve their best performance through complete renewable energy usage at maximum capacity during peak times and they maintain system reliability throughout all operational scenarios (Kenneth et al., 2024). Multi-source systems require complex modeling because they require sophisticated optimization and control systems to operate at maximum efficiency with minimal cost.

3.1 Component-Level Considerations

The implementation of photovoltaic systems is constrained by land-use restrictions because suitable land resources are limited in areas with insufficient agricultural land. Ground-mounted photovoltaic systems compete with crop production, which rooftop systems and agrivoltaic installations help minimize by reducing land-use conflicts (Horowitz et al., 2020). System designers select dual-use design approaches to develop systems which produce energy while continuing to support agricultural operations. The production of wind energy depends on two factors which include local resources and the unique features of terrain and current zoning regulations. The agricultural areas have suitable wind patterns but turbine deployment faces limitations because wind speeds are not strong enough and residential areas are located nearby (Hise et al., 2022; Lopez et al., 2024). The process of wind integration requires specific evaluation for each site, as general findings cannot be applied. The special resource of agricultural biomass for hybrid systems enables waste conversion into valuable energy products. The biomass utilization process faces multiple obstacles because farmers need to collect feedstocks during particular times of the year and because the conversion process fails to reach its highest possible rate (Nguyen et al., 2020). Research findings show that permanent biomass delivery systems serve as the foundation for sustainable biomass-powered hybrid systems because these systems need uninterrupted fuel supply to function properly. The decision for energy storage selection determines how the system will function. The agricultural hybrid systems of today depend on battery storage because it provides fast response times and modular design, and its costs continue to decrease. The storage system of hydrogen provides extended storage duration with superior energy storage capacity but its implementation remains restricted because of conversion efficiency degradation and establishment expenses (Yang et al., 2024). The agricultural sector operates battery systems for their brief to middle-length operations yet hydrogen storage solutions have become popular because they enable both extended and seasonal power storage requirements.

3.2 Application-Driven Architectures

The operational methods of precision agriculture energy system architectures depend on the particular agricultural environment they serve. Irrigation systems require maximum power capacity during times when water resources are insufficient, which they achieve by matching their photovoltaic output to their daytime irrigation schedule. The essential development stages of water supply systems become possible through continuous operation because hybrid systems combine storage facilities with power generation equipment (Amri et al., 2025). The operation of greenhouse energy systems depends on constant electrical power to run their climate control systems and their lighting systems and automated processes. The hybrid system design, which combines reliability with thermal energy integration through biomass and combined heat and power units produces the optimal performance for these systems (Antar & Robert, 2023). The system needs to maintain equal attention between power quality, system resilience and cost optimization requirements. Off-grid rural smart farms enable farmers to execute various agricultural operations through their digital monitoring systems and their ability to control irrigation, process and store crops. The farming operations require energy systems which need to adjust their power output according to the varying energy needs during different stages of production. Organizations use multi-source hybrid architectures with intelligent control systems because these systems help them achieve their operational requirements (Ramkumar et al., 2025). Research on technology focuses on selecting equipment and reducing costs rather than improving agricultural operational efficiency. The evaluation process for system architectures is conducted without regard for farming operations, related practices, specific crop types, or operational requirements. The current solutions face operational challenges due to this mismatch, which should inform the creation of hybrid energy systems that meet agricultural requirements for deployment. The recommended HRES configuration for precision agriculture applications appears in Table 1.

Table 1. Precision agriculture applications and recommended HRES configurations

Agricultural Application	**Dominant Energy Demand Characteristics**	**Recommended HRES Architecture**	**Design Rationale**	**Key Considerations**	**References**
Precision Irrigation Systems	High power demand during daytime; strong seasonal and crop-cycle variability; water–energy coupling	PV–Battery PV–Wind–Battery	Solar generation aligns with daytime irrigation loads; wind complements solar during low irradiance periods; storage ensures continuity during peak demand	Pump sizing and depth variability; irrigation scheduling; battery capacity for peak shaving	(Ismail et al., 2024)
Groundwater Pumping for Irrigation	Intermittent high-power loads; critical operation during dry seasons	PV–Diesel–Battery	PV reduces fuel consumption; diesel provides dispatchable backup during low renewable availability; batteries	Fuel logistics; emission reduction targets; operational cost trade-offs	(Aziz et al., 2019)

			smooth load fluctuations		
Greenhouse Farming	Continuous and stable demand; heating, cooling, ventilation, and lighting loads	PV–Biomass–Battery Multi-source hybrid systems	Biomass provides dispatchable energy and thermal integration; PV supports daytime loads; storage enhances reliability	Biomass supply consistency; thermal energy integration; power quality requirements	(Avwioroko et al., 2024)
IoT-Based Field Monitoring	Low power but continuous demand; high reliability requirement	PV–Battery	Simple and cost-effective solution; minimal maintenance; high reliability for sensor networks	Battery autonomy; communication reliability; modular scalability	(Fadel et al., 2015)
Unmanned Aerial Vehicle (UAV) Operations	Intermittent high-power charging loads; flexible scheduling	PV–Battery	Charging can be scheduled during high solar availability; batteries support rapid charging	Charging infrastructure sizing; load aggregation with other farm systems	(Mohsan et al., 2022)
Post-Harvest Processing and Cold Storage	High and continuous energy demand; critical load sensitivity	PV–Biomass–Battery PV–Diesel–Battery	Biomass or diesel ensures dispatchable power; PV reduces operating costs; storage supports load continuity	Cold chain reliability; backup redundancy; emission constraints	(Rajbongshi et al., 2017)
Off-Grid Rural Smart Farms	Diverse and variable loads; integration of irrigation, processing, storage, and digital systems	Multi-source hybrid systems (PV–Wind–Biomass–Battery or PV–Wind–Diesel–Battery)	Multiple sources enhance resilience and flexibility; high renewable penetration achievable with optimized control	System complexity; optimization and control strategy; scalability	(Shahzad & Jasińska, 2024)
Agro-Processing and Value-Addition Facilities	Medium to high power demand; semi-continuous operation	PV–Biomass–Battery	Biomass leverages agricultural residues; PV offsets daytime energy use; storage stabilizes supply	Feedstock logistics; conversion efficiency; waste management integration	(Niyogi et al., 2025)

4. Optimization Objectives, Problem Formulation, and Algorithms

A research about hybrid renewable energy system optimization for precision agriculture studied three essential elements which included economic performance, system reliability and environmental impact. The research established two economic performance indicators, which worked to minimize both Net Present Cost and Levelized Cost of Energy while maximizing all financial performance indicators including Internal Rate of Return and net profit (Urbano et al., 2022). The two metrics track all costs which include capital expenses and operational expenses throughout the system's entire operational period and investors find them useful because they provide straightforward results for their investment evaluations. The research conducted by Khan et al. (2025) created optimization models which analyzed hybrid renewable energy systems together with precision agriculture while considering three sets of technical, operational and resource-based limitations. The power balance constraints of the system maintain electricity generation, storage levels and consumption areas at their designated power levels throughout the day by considering both renewable energy output and customer electricity requirements. The storage dynamics constraints have developed a system model which explains battery charging and discharging behavior and shows their maximum charge capacity, their power consumption losses and their storage capacity deterioration, according to Li et al. (2025).

The agricultural hybrid renewable energy system modeling process encounters its primary difficulty due to the inconsistent output of renewable energy sources. The generation of electricity through solar and wind power becomes unpredictable because of weather patterns which create challenges for power production forecasting. The first studies employed deterministic methods which used typical meteorological year data to generate average weather patterns for simplified calculations but produced results with insufficient research power according to Gaugl et al. (2025) and Pous et al. (2025). A research study has introduced new methods for representing renewable energy resources that use stochastic modeling and scenario-based methods to accurately capture resource fluctuations and uncertain conditions, as reported by Mi et al. (2025). The operational needs of agricultural work require specific optimization methods which differ from those used in conventional microgrid systems. The operational energy requirements face time-based non-linear energy constraints because irrigation schedules, pumping depth variations, greenhouse climate management and post-harvest processing requirements exist according to Agadi et al. (2023). The optimization models have constraints to connect energy delivery between three elements which include water resources availability, crop development stages and system operational activities thus requiring a more complex model structure. The research study has examined both deterministic and stochastic optimization methods as potential solutions.

The initial design phase of a project benefits from deterministic models because they enable faster computations but stochastic models establish system resilience through their ability to handle unpredictable situations according to Afzal et al. (2024). The researchers selected a modeling method because it would yield more accurate results, but they needed to balance this advantage against the ease with which their system could perform calculations.

4.1 Optimization Algorithms

Researchers have used various optimization algorithms to address problems in hybrid renewable energy systems for precision agriculture. The field of system modeling uses classical optimization techniques when system models permit linearization or discretization, employing three main methods: linear programming, mixed-integer linear programming, and dynamic programming (Zhang & Wei, 2022). The methods provide theoretical guarantees that, when used with them, produce results that complete within a specific time frame and deliver precise outcomes. The methods have been limited in their use because they depend on basic assumptions, including linear cost structures and permanent operational models. Metaheuristic algorithms have become popular because they address these challenges. The hybrid system sizing and operation problems can be solved using Genetic Algorithms, Particle Swarm Optimization, Grey Wolf Optimizer, and Whale Optimization Algorithm, according to research by Bouaouda and Sayouti (2022). The algorithms have proven their ability to solve problems involving multiple objectives and non-linear, non-convex equations without using gradient information. The research results indicate that metaheuristics produce better results than traditional techniques because they decrease expenses while increasing renewable energy use, but require more processing time (Chauhan & Chauhan, 2024). The development of hybrid optimization systems based on artificial intelligence brings together the benefits of traditional and metaheuristic optimization methods. The mathematical programming framework establishes project feasibility through its structural design, while the global search capabilities and adaptability functions of metaheuristics and machine learning methods improve performance (Azevedo et al., 2024). The energy, water, and operational constraints between agricultural systems have shown great success with these methods.

Researchers have begun to investigate reinforcement learning as a solution for managing energy operations in agricultural hybrid systems. The dynamic nature of learning environments makes reinforcement learning agents suitable for developing control policies that they acquire through their environmental interactions (Platero-Horcajadas et al., 2024). The agricultural field has not widely adopted reinforcement learning yet, but the technology shows potential to improve load management, storage control, and renewable energy integration. Table 2 summarizes the comparison of optimization algorithms, objectives, and precision agriculture applications.

Table 2. Comparison of Optimization Algorithms, Objectives, and Precision Agriculture Applications

Algorithm Class	**Representative Algorithms**	**Primary Optimization Objectives**	**Typical Precision Agriculture Applications**	**Key Strengths**	**Key Limitations**	**References**
Classical Optimization	Linear Programming (LP)Mixed-Integer Linear Programming (MILP) Dynamic Programming (DP)	NPC minimization LCOE minimization Reliability constraints (LPSP, LOLP)	Small to medium-scale irrigation systems IoT-powered farms with predictable loads	Fast convergence Deterministic solutions Strong mathematical guarantees	Limited scalability for large systems Requires linearization and simplifications	(Stamou & Rutschmann, 2018)
Metaheuristic Algorithms	Genetic Algorithm (GA) Particle Swarm Optimization (PSO) Grey Wolf Optimizer (GWO) Whale Optimization Algorithm (WOA)	Multi-objective cost–reliability trade-offs Emission reduction Renewable penetration maximization	Off-grid rural smart farms Multi-source HRES for irrigation and processing	Handles non-linear and non-convex problems Flexible objective formulation	High computational cost Parameter sensitivity No guarantee of global optimality	(Agajie et al., 2024)
Hybrid Optimization	MILP–GAPSO-assisted LPGA–DP hybrids	Cost–reliability–emission optimization Storage sizing and dispatch	Integrated irrigation and cold storage systems Greenhouse energy systems	Balances solution quality and feasibility Improved convergence over standalone metaheuristics	Increased model complexity Implementation difficulty	(Ehrgott & Gandibleux, 2008)
AI-Assisted Optimization	ANN-assisted GAML-enhanced PSO	Long-term cost reduction Predictive reliability optimization	Large-scale smart farms Energy–water–crop coupled systems	Learns complex system behavior Reduces computation time in repeated runs	Requires large datasets Limited transparency	(Banluesapy et al., 2025)
Reinforcement Learning	Q-learning Deep Reinforcement Learning	Real-time energy management Storage dispatch optimization Load prioritization	Smart irrigation scheduling Adaptive greenhouse control	Adaptive and self-learning Suitable for dynamic environments	Early-stage adoption Training instability High data requirements	(Padilla-Nates et al., 2025)
Stochastic Optimization	Scenario-based MILP Chance-constrained programming	Robust cost minimization Reliability under uncertainty	Weather-sensitive irrigation systems Renewable-dominant farms	Explicitly handles uncertainty Improves resilience	High computational burden Scenario explosion	(Singha et al., 2026)
Multi-Objective Optimization	Pareto-based GANSGA-IIMOPSO	Cost–emission–reliability trade-offs	Policy-driven sustainable farms Climate-smart agriculture projects	Reveals trade-offs Supports decision-making	Requires post-processing No single "best" solution	(Huang et al., 2025)

5. Simulation, Optimization, and Decision-Support Tools

5.1 Tool Capability Comparison

The HOMER system offers users pre-developed component models together with optimized operational methods which allow fast process assessment yet prevent users from creating detailed models of complex agricultural systems and their specific operational needs (Mbasso et al., 2023). The MATLAB and Python platforms enable users to develop precise component models that facilitate energy demand calculations and control system design for agricultural applications (Guevara et al., 2024; Padhiary, Roy, et al., 2025). Different tools offer varying levels of optimization support, which is their main distinguishing feature. HOMER uses internal search methods together with enumeration methods to solve small and medium-sized problems; however, these methods restrict users from controlling their goal and their obstacle handling methods (Windahl et al., 2019). The MATLAB and Pyomo platforms allow users to create optimization systems that solve single and multiple-objective problems through random elements and advanced ordering methods that combine traditional and modern optimization techniques (Hernández-Pérez & Ponce-Ortega, 2021). The system requires this adaptability because farmers who practice precision agriculture need to control all aspects of their operations, including power consumption, water management, and regular work activities. The two platforms differ in their economic and environmental evaluation functions. The system performs automatic calculations of Net Present Cost and Levelized Cost of Energy, as well as fuel consumption and emission results through HOMER, which enables standardized configuration evaluations (Dykes et al., 2020). The MATLAB and Python-based systems require users to create their own economic and environmental evaluation frameworks, as this function enables them to establish transparency during life-cycle evaluation and impact assessment (Garner & Dehouche, 2023). The need for agricultural database integration has become critical, as precision agriculture depends on obtaining data that is both current and highly detailed. The Python-based tools deliver major advantages because they operate with data analysis software and Internet of Things platforms. The MATLAB environment allows data connectivity through its system, but requires users to use its proprietary tool packages. The system requires HOMER software to develop agricultural operation models through its analysis of standard farming methods and weather data, which restricts its ability to model adaptable agricultural practices (Padhiary, Kumar, et al., 2025).

5.2 Tool Limitations

The present simulation and optimization systems that farmers use in precision agriculture operations face major performance issues due to fundamental design flaws. The system fails to accurately show crop water and energy resource utilization, which is its main operational limitation. Most tools analyze agricultural energy requirements as fixed external factors instead of tracking how these needs develop through irrigation choices, plant development and water supply conditions (Fuentes-Peñailillo et al., 2025). The simplified approach compromises the authenticity of optimization outcomes and imposes restrictions that prevent their use in comprehensive farm management systems. The system has another barrier: it uses artificial intelligence and adaptive control technologies only to a limited extent. Most energy modeling tools require extensive modifications to enable machine learning and reinforcement learning, which function in MATLAB and Python environments (Hanafi et al., 2024). Static control methods and rule-based strategies still prevail because they do not exploit data-driven optimization opportunities (Biagioni et al., 2022).

The majority of available tools continue to rely on static modeling methods to meet their operational needs. Operators define load profiles, resource availability, and system operational functions before operations begin, which limits the system's capacity to respond to current changes in weather and crop conditions and to operational priority adjustments. Recent research has introduced stochastic modeling and scenario analysis methods, but systems that provide real-time decision-making support for precision agriculture are still very rare (Taylor, 2019). The current simulation and optimization tools for hybrid renewable energy system analysis, which already exist, need the development of new platforms that combine agricultural process modeling with advanced optimization techniques and real-time data capabilities (Al‐Shetwi et al., 2025)The current gaps require solutions to develop intelligent systems that will provide sustainable energy for contemporary agricultural needs.

6. Challenges

6.1 High Initial Cost

The high cost of acquisition and installation is a major challenge to the adoption of a hybrid renewable energy system for precision agriculture. The hybrid system components include solar photovoltaic panels, wind turbines, inverters, storage batteries, and other control systems for precision agriculture. The high upfront cost of these components, including installation, increases the overall cost of implementing the hybrid system in precision agriculture (Mamaghani et al., 2016). Also, the sophisticated technologies, such as sensors, the Global Positioning System (GPS), and advanced machines required for precision agriculture, are expensive (Guebsi et al., 2024). These challenges can make hybrid systems for precision agriculture beyond the reach of small- and medium-scale farmers.

6.2 Lack of Skilled Manpower

There is also the issue of the scarcity of skilled personnel needed to install and maintain the hybrid system, especially in rural areas. This manpower shortage increases the cost of installing and maintaining the hybrid system for precision agriculture, beyond the financial means of most small- and medium-scale farmers (Balogh et al., 2021). This is because interested farmers who want to implement the hybrid renewable energy system for precision agriculture will have to bear the cost of searching for qualified manpower, sometimes enticing them with good financial rewards and conditions of service before they agree to do the job.

6.3 Lack of Funding

Lack of funding for precision agriculture can hinder the adoption of a hybrid renewable energy system (Kumar, 2025). It can lead to barriers linked to technical, operational, and socio-economic inefficiencies. The burden of entry costs will be too high for small farmers to bear, thereby cutting them off from adopting it. Also, large farmers may experience long payback periods, thereby hindering their adoption. Furthermore, due to large economies of scale, the hybrid renewable energy system will be expensive for small farmers.

6.4 Weak infrastructure

The challenge of a weak infrastructure slows down the adoption of a hybrid renewable energy system. This challenge has the potential to make the system unreliable, reduce its efficiency, and increase its cost (Shani et al., 2024). The infrastructure is the backbone of the hybrid system, and a weak backbone will lead to an unreliable network, higher investment costs, reduced optimization potential, weakened system communication and control, reduced storage capacity, and reduced grid system integration.

7. Techno-Economic, Environmental, and Sustainability Assessment

7.1 Techno-Economic Metrics

The economic evaluation of hybrid renewable energy systems used in precision agriculture relies primarily on techno-economic assessment. The most common method for evaluating economic performance uses Net Present Cost and Levelized Cost of Energy, which determine total system expenses and energy output over the system's entire lifetime. The two metrics enable system comparison by providing clear information that helps inform investment decisions. Studies have shown that optimized hybrid systems achieve lower lifecycle costs in agricultural applications than diesel-based systems and grid-dependent systems (Caglayan, 2025; Emezirinwune et al., 2024; Okakwu et al., 2023). The financial assessment uses the Internal Rate of Return and the payback period to show which investments offer the best returns and how quickly they recover initial costs. These indicators are especially important for farmers and rural investors who need to keep costs low while managing investment risks (Abu-Nowar, 2024; Ofori-Bah & Amanor-Boadu, 2023). Recent research shows that renewable-dominant hybrid systems achieve shorter payback periods and higher returns as technology costs decrease and fuel prices fluctuate (Bose et al., 2018). The assessment of techno-economic results in precision agriculture requires reliability metrics as essential factors that go beyond cost analysis. Loss of Power Supply Probability and Loss of Load Probability serve as reliability indices that assess how well a system can satisfy its operational needs during various running environments (Amoussou et al., 2024). The criteria for power interruptions show direct impact on irrigation schedules, greenhouse climate control, and post-harvest preservation methods. Renewable penetration refers to the proportion of energy from renewable sources and serves as a common indicator of system robustness and sustainability. High renewable penetration rates attract positive attention, but research shows that systems lose reliability when they reach excessive penetration levels without suitable storage and backup systems (Albhrani et al., 2021).

7.2 Environmental Assessment

The primary goal of environmental assessment for hybrid renewable energy systems is to minimize greenhouse gas emissions and fossil fuel usage. The common method for measuring carbon dioxide emission reductions involves comparing hybrid systems with diesel-only and grid-based reference systems, as demonstrated by Roy et al. (2024). Research shows that renewable energy effectively reduces emissions when it replaces diesel in agricultural systems that rely on off-grid power and irrigation, according to García et al. (2019). The measure of fossil fuel displacement in hybrid systems demonstrates their ability to reduce reliance on traditional energy sources. In rural agricultural areas that face difficulties with fuel delivery, price fluctuations, and disruptions, this metric is highly important (Amri et al., 2025). Farming communities experience improved energy security because increased renewable energy sources reduce fuel use and operating expenses. Life-cycle assessment has emerged as a leading method for conducting complete environmental assessments. Life-cycle assessment measures all emissions and environmental effects that occur during system creation and setup, the operational phase, and end-of-life disposal, according to Massetti et al. (2017). Life-cycle methods help researchers better understand sustainability trade-offs, yet they are infrequently used in agricultural hybrid energy research because data availability and the complexity of research methods make their implementation difficult.

7.3 Sustainability Perspective

The sustainability assessment of hybrid renewable energy systems used in precision agriculture evaluates three areas: economic, environmental, and social and systemic. The Energy Water Food Nexus framework enables researchers to study the interrelated aspects that connect energy supply with water management and agricultural production (Albrecht et al., 2018). The availability of energy resources impacts all irrigation operations, while water scarcity and farming methods create specific energy requirements in precision agriculture. The integrated assessment of these interactions produces system designs that achieve both resource efficiency and enhanced resilience. The sustainability assessment process requires evaluating socio-economic impacts as an essential component. Hybrid renewable energy systems enable rural development by offering lower energy expenses, better energy supply reliability, and enhanced agricultural output (Natividad & Benalcazar, 2023). Through system installation, operation, and maintenance activities, these systems enable farmers to maintain consistent income and reduce their risk from fuel price fluctuations while creating local job opportunities. The benefits of research studies have received greater recognition in recent years, while research studies still apply socio-economic indicators inconsistently (Cartland et al., 2022). Hybrid renewable energy systems receive stronger sustainability justification through their alignment with the Sustainable Development Goals, which implement agricultural systems. The systems enable direct achievement of Goal 2 through better food security, Goal 7 through providing affordable clean energy, Goal 12 through sustainable consumption and production, and Goal 13 through climate action (Hailu et al., 2025). Most studies treat the SDGs as qualitative references because they fail to connect system results with specific measurement criteria.

7.4 Critical Observation

The examined studies show that techno-economic evaluation methods in the literature primarily focus on cost metrics, such as the Levelized Cost of Energy and Net Present Cost. The indicators serve essential functions, yet their widespread use lends them greater importance than they deserve, diminishing their value for reliability, environmental resilience, and socio-economic factors. The sustainability evaluation process focuses on operational emissions reductions while failing to consider life-cycle effects, energy, water, and food connections, and broader socio-economic impacts. Existing research presents an unbalanced view, limiting its ability to support decision-making in precision agriculture. The development of a comprehensive assessment system requires combining techno-economic evaluation methods with environmental assessment procedures and sustainability measurement methods. The proposed method establishes a comprehensive framework for precision agriculture, enabling the development of cost-efficient, sustainable hybrid renewable energy systems that maintain environmental and social equity as well as system effectiveness.

8. Comparative Synthesis, Research Gaps, and Future Directions

8.1 Comparative Taxonomy

The existing literature shows specific patterns that demonstrate how different types of hybrid renewable energy systems match with agricultural needs. The basic operation of photovoltaic battery systems makes them suitable for outdoor IoT systems, small irrigation systems, and distributed sensing applications with low to medium power needs (Olkkonen et al., 2023). The agricultural sector now relies on multi-source hybrid systems that combine photovoltaic technology and wind power, biomass energy, and backup generators to operate greenhouse farms, post-harvest facilities, and off-grid smart farms under changing environmental conditions. The selection process for systems depends on which technologies are available, as agricultural needs remain unaddressed, leading to designs that prioritize technology as their main element.

Research studies evaluating optimization algorithms reveal two distinct patterns as these algorithms pursue their predetermined objectives. The conventional mathematical programming approach sets cost boundaries for system design and creates dependable systems through basic system models that study expected load patterns (Coit & Zio, 2019). The research field uses metaheuristic algorithms and multi-objective algorithms to develop hybrid systems that must achieve three objectives: economic goals, environmental goals and reliability goals (Meng et al., 2022). The present study implements artificial intelligence through reinforcement learning to develop control systems which manage renewable energy system power fluctuations (Xiong et al., 2023). The selection process for algorithms chooses methods which operate efficiently rather than those which fulfill the requirements of agricultural operations. The assessment of simulation tools against decision-support tools reveals that current operational procedures need enhanced organizational systems. HOMER software enables businesses to perform rapid techno-economic evaluations, yet it restricts their ability to model agricultural operations and their associated adaptive management systems. The MATLAB and Python platforms enable users to achieve high-level optimization, integrated data handling, and customized model development, but users need deep knowledge of the systems because they lack standardized agricultural modules. The current set of available tools does not provide a complete solution for evaluating energy systems, water resources, crop production, and sustainability, necessitating sophisticated decision-support systems.

8.2 Key Research Gaps

Scientists continue their research on hybrid renewable energy systems for precision agriculture, but they need to conduct more studies to address outstanding questions. The most critical funding requirement is that scientists need to create a system that unites energy, water, and crop modeling technologies. Research to date treats agricultural energy requirements as an unchanging external factor rather than recognizing their connection to irrigation decisions, plant growth, and water distribution systems. The results of optimization tests become useless due to this separation, which impedes the connection between energy system design and agricultural productivity. The current research problems arise because scientists lack effective methods for implementing real-time adaptive optimization techniques in their studies. Researchers in most studies conduct their analyses using offline methods that operate with fixed load patterns and established control procedures. Research studies have examined artificial intelligence and reinforcement learning, but these technologies exist only in theory because scientists have not tested them in real agricultural settings (Ali et al., 2023). The research has a weakness: it needs both field validation and pilot-scale testing. Simulation methods evaluate only hybrid system designs, resulting in research that fails to show actual farm operational results over extended periods. The researchers cannot confirm their model assumptions, performance metrics, or scaling capabilities because they do not have access to real-world data (Thakur et al., 2023). The current development targets of socio-economic and resilience modeling require additional research to achieve their full potential. Research findings show both cost savings and emissions reductions, but most studies fail to measure how these changes affect farmers' financial stability, workforce dynamics, community support, and the ability to withstand severe climate disruptions. The lack of these elements in precision agriculture solutions that operate in complex socio-technical systems makes new solutions less relevant to policy and less adoptable by users.

8.3 Future Research Directions

Research gaps in existing studies need scientists to create frameworks that use single intelligent systems to generate functional research answers. Digital twins for precision agriculture show great potential because they enable farmers to track their fields in real time and integrate their energy networks with their agricultural operations through data monitoring. The digital representations will allow for ongoing monitoring, forecasting, and automated farm management throughout the entire operational period of the farm (Escribà-Gelonch et al., 2024). Future hybrid energy systems will operate through artificial intelligence-driven predictive and adaptive control systems, which will serve as their primary operational technology. The combination of machine learning and reinforcement learning enables proactive energy management because these systems predict weather conditions and irrigation requirements and crop responses, which results in better operational stability and enhanced system performance when unexpected events occur (El Mghouchi & Udristioiu, 2025). The research needs to study hybrid systems that unite data-driven intelligence with physics-based models to create systems that are both resilient and easy to understand.

Scientists must develop hybrid renewable energy systems to combat climate change and advance their ongoing research. Future systems need to be tested under artificial extreme-weather scenarios, water shortages, and uninterrupted resource-supply disruptions as climate variability becomes more severe. The incorporation of resilience metrics and stress testing into optimization frameworks will improve system performance and agricultural protection (Zidan & Febriyanti, 2024). The implementation of optimization solutions requires both systems that follow policy guidelines and solutions that can scale for broad deployment. Future research needs to use optimization models that incorporate policy instruments, incentive systems, and regulatory requirements to study how institutional elements affect system sustainability. Both national and international agricultural systems require researchers to demonstrate how pilot projects can scale their operations.

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