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Review Article

Energy-agriculture nexus: Exploring the future of artificial intelligence applications

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A R T I C L E I N F O

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A B S T R A C T

Energy and agriculture are two independent sectors that share a mutual coexistence referred to as the energy-agriculture nexus. In an attempt to facilitate the capacity of this coexistence simultaneously, there is a need for involvement of latest technologies such as the artificial intelligence (AI). This research focused on the incorporation of AI along the energy-agriculture nexus, in an attempt to explore the applications, opportunities, challenges and its potential implications for various stakeholders. According to an intensive literature survey conducted, AI applications were found to be on a significant rise since the last decade, specifically in prediction applications and optimization applications, respectively, with research literature focusing mainly on bioenergy (55%), energy use analysis (17%), process value chain (6%), energy-efficient irrigation (6%), energy in greenhouse (6%), livestock management (2%), farm power and machinery (4%) and risk management (4%). Challenges observed in the literature were observed in terms of data availability, data complexity and heterogeneity, computing power, accountability and transparency in decision-making and research focus. In order to fully comprehend the implications of AI integration along the energy-agriculture nexus and to develop strategies and guidelines for maximizing the advantages of this technology while minimizing potential risks and adverse effects on stakeholders, future research works were discussed.

1. Introduction

The tricky interaction between energy and agriculture, in which they are interconnected and have a substantial impact on one another, is referred to here as the "energy-agriculture nexus". Energy is needed in agriculture to power the different operations, ranging from land preparation to value chain of food products, and in modern agriculture concepts like greenhouse and tech powered livestock propagation. The agricultural industry uses a substantial amount of energy. Around 30% of the world's energy is consumed by agri-food systems, primarily in post-harvest stages [1]. On the other hand, since sources that biofuels and biogas are sourced from are crops and livestock, energy production can also be directly reliant on agriculture. With 55% of all renewable energy and over 6% of the world's energy supply coming from modern bioenergy, it is even considered as the most significant source of renewable energy worldwide [2]. More recently, solar energy generation simultaneously from agricultural lands (Agrivoltaics) is on the rise [3].

Moreover, agricultural activities generate organic waste, which, when converted into bioenergy, creates a circular dependency. The efficient utilization of this waste for energy production is contingent on agricultural practices that prioritize sustainability [4,5]. The nexus thus highlights the dependence of the bioenergy sector on specific agricultural practices and waste streams.

A crucial dependency on water resources is established by agriculture's use of water for livestock management and irrigation [6]. The EA nexus thus, through its definition of how efficiently water is utilized in energy-intensive operations of agriculture, such as irrigation water pumping and distribution, have a further direct effect.

The relationship between energy supply and demand, food security, and the environment is considered a part of the energy-agriculture nexus [7]. Although the transition to low-carbon energy sources necessitates a more efficient and sustainable agriculture sector, it also necessitates a secure, inexpensive, and clean energy supply [1]. In addition, a variety of social, economic, and environmental factors, such as population expansion, urbanization, water shortages, climate change, and changes in land use, influence the energy-agriculture nexus. These variables have intricate and frequently conflicting effects on both agriculture and

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energy, emphasizing the necessity for an interdisciplinary and holistic approach to understanding the nexus. Good examples of researches in these regards is studied by [8] in Bangladesh.

Balancing the frequently conflicting demands of food and energy production while also taking into account environmental and social issues is a serious hurdle in the energy-agriculture nexus. This necessitates careful resource management, taking into account the socio-economic effects of energy and agricultural policies and practices, as well as the management of resources such as land, water, and energy [9].

Since the beginning of human civilization, societies have been able to create their own food and energy sources thanks to the development of agriculture and livestock propagation. As a core of its history, the extensive use of steam power and the invention of the internal combustion engine during the industrial revolution of the 18th and 19th centuries changed transportation and significantly raised the energy requirements of agriculture. Following the pervasive concerns about the environmental effects of fossil fuels, in recent decades, there has been an increased quest in renewable energy sources, precision agriculture technologies, demand for bioenergy, smart grid technology, awareness of the impact of agriculture on the environment, adoption of sustainable agriculture practices, and the integration of new technologies into energy and agricultural systems. This tangibly coined the context of energy-agriculture nexus and its significance for the both industries and the globe in general. Timeline of the nexus is summarized in Fig. 1.

The efforts to promote sustainable development and mitigate climate change are intimately related to the energy-agriculture nexus. The Sustainable Development Goals (SDGs) of the United Nations (https://sdgs.un.org/goals) in particular emphasize the significance of tackling the nexus in order to achieve objectives like eradicating hunger, advancing renewable energy, and safeguarding ecosystems. The Paris

Agreement on climate change (https://unfccc.int/process-and-meetings/the-paris-agreement), which acknowledges the crucial roles of renewable energy and agriculture in reaching the aim of reducing global warming to far below 2°C, is likewise centered on the nexus. An akin concept to energy-agriculture nexus could be the integrated energy-food systems (IEFS). IEFS are organizations that deliberately and purposefully link the production, distribution, and consumption of food and energy. In order to increase productivity, sustainability, and resilience while minimizing resource waste and environmental impacts, IEFS aims to build synergies between the food and energy systems [10].

Since it acknowledges the interdependencies and feedback loops between energy and agriculture systems and tries to maximize their interactions for mutual benefit, the idea of the IEFS is considered to be closely tied to the energy-agriculture nexus. However, the IEFS strategy aims to establish deliberate and systematic links between the two systems to improve their interactions, whereas the EA nexus idea acknowledges the interdependencies and trade-offs between energy and agriculture systems.

In addition, the goal of the IEFS strategy is to develop low-carbon and energy-intensive food systems that support sustainable agriculture methods, cut down on resource waste, and improve food and energy security [10]. IEFS is thus a farming system model that integrates, intensifies and increases the simultaneous production of food and energy through the sustainable use of biomass, i.e. essentially for and within agriculture itself. Notwithstanding the contributions of both the IEFS and the EA nexus' goals, in a nutshell, several other technics to optimize energy (through direct or indirect technical and social interventions) use along the nexus are made possible (Fig. 2).

Researchers nonetheless have a lot to learn about the intricate and dynamic relationships between energy and agriculture, despite the energy-agricultural nexus' expanding significance. It will take additional investigation, creativity, and cross-sector cooperation to close these gaps.

Comprehending the complex interrelationships within the energy-

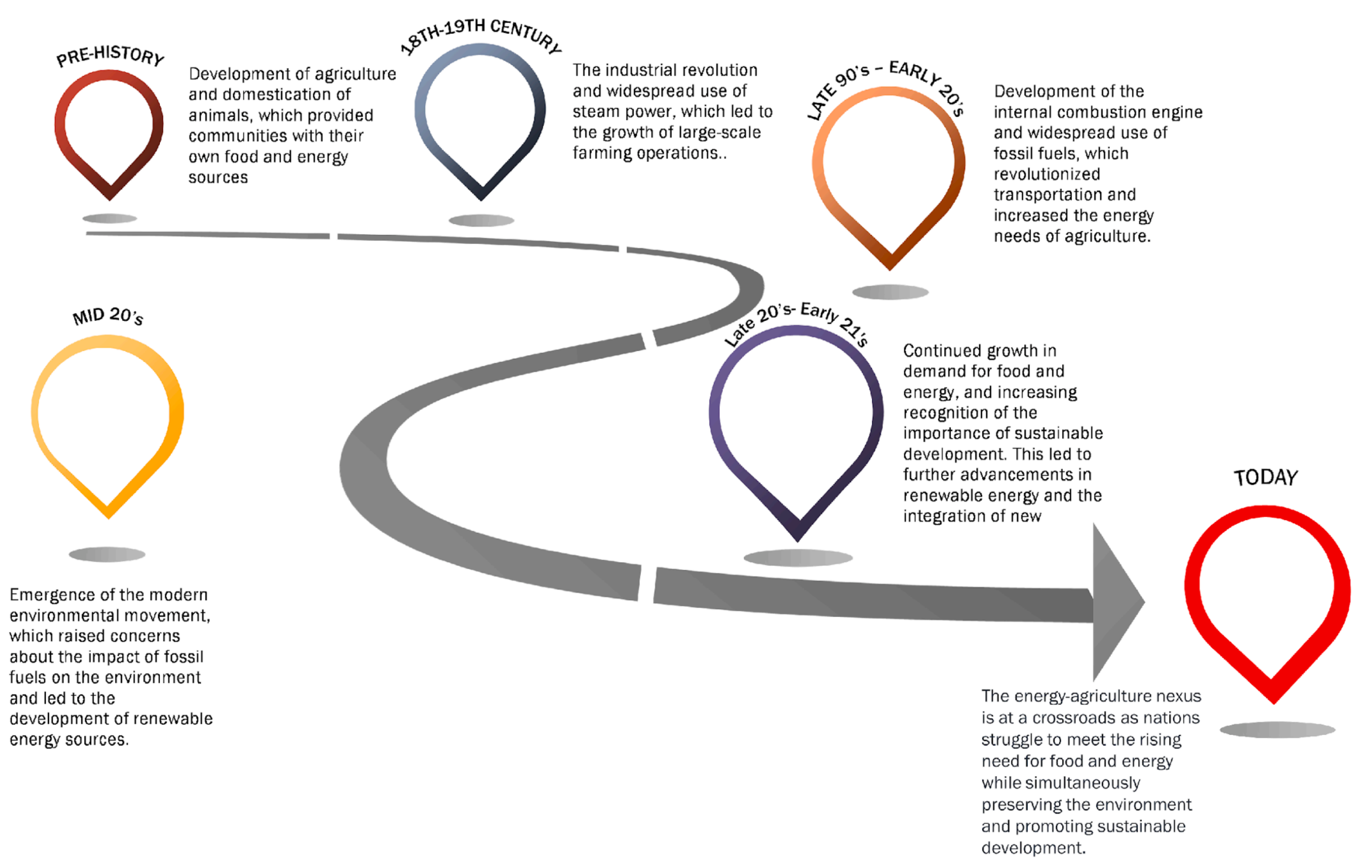

Fig. 1. Timeline of the energy-agriculture nexus.

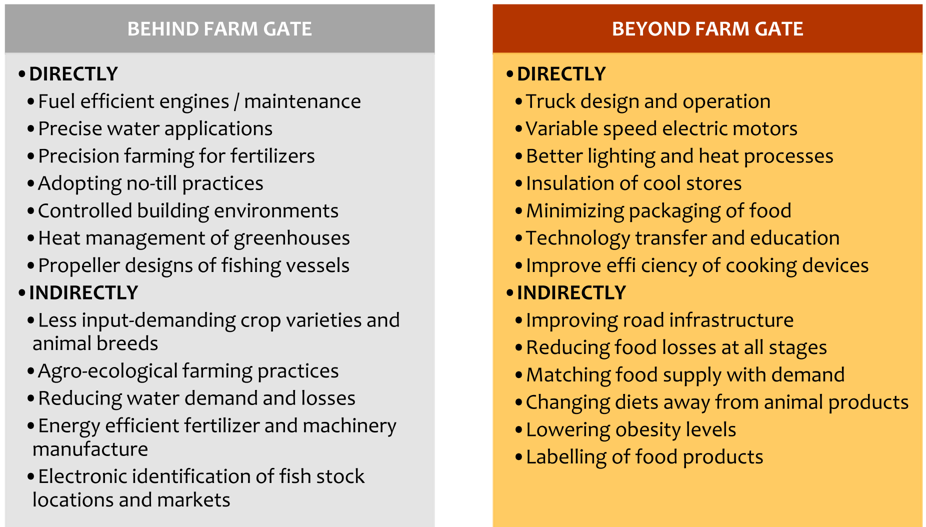

Fig. 2. Some energy efficiency strategies along the food sector [11].

agriculture nexus is essential for promoting sustainable practices and addressing the obstacles presented by a world that is changing quickly. It becomes clear that conventional research methods might not be able to adequately capture this nexus' dynamic character as we work through its complexity. This brought about the motivation for incorporating artificial intelligence (AI) into the research instruments.

AI emerges as an influential tool in understanding the complexities of the energy-agriculture nexus for of its ability to handle large datasets, recognize intricate patterns, and simulate complex situations. AI is capable of identifying hidden relationships, forecasting new trends, and allocating resources as efficiently as possible by utilizing machine learning algorithms. Its application goes beyond traditional limits, providing a comprehensive understanding that complies with the interdependent aspects of agriculture, energy, the environment, and society [12–17].

This comprehensive review aims to provide insight into the potential applications of AI in the energy-agriculture nexus from both methodological and content perspectives. From supply chain management to precision agriculture, the review aims to investigate how artificial intelligence (AI) algorithms were used to promote innovation, improve sustainability, and minimize their negative effects on the environment. AI's ability to work in concert with the energy-agricultural nexus has the potential to completely transform practices and move us closer to a time where energy and agriculture work together to benefit people and the environment. The research is further aimed at adding significant literature that not only reveals the complex relationships within the EA nexus but also steers us towards a more resilient and sustainable future by synthesizing cutting-edge AI applications with interdisciplinary collaboration.

1.1. Overview of AI and its Learning Techniques

With the digitalization of both the worlds of energy and agriculture using the most sophisticated techniques on an individual scope, artificial intelligence, amongst the other key technologies of the 21st century, could standout to fit major gaps of research in the energy-agriculture nexus. AI is emerging as a crucial enabler of a complex innovative, and data-driven industries, energy and agriculture inclusive, giving a key magic tool to boost operational performance and efficiency in an increasingly competitive context [18].

Artificial intelligence (AI) algorithms serve as the foundation for intelligent systems capable of learning, thinking, and making decisions in the same way that humans do. These algorithms are intended to sort data, find patterns, and extract relevant insights, allowing machines to accomplish activities that would normally necessitate human intelligence. AI algorithms are adaptable tools used in a wide range of applications, including picture and audio recognition, autonomous vehicles, and natural language processing [19]. Understanding the various categories of AI algorithm is critical for customizing them to specific tasks and maximizing their performance. The type of learning used by AI systems and the nature of their training data separate them into several groupings. The basic classifications are as follows:

1.1.1. Supervised Learning

Labeled data is used to train supervised learning systems, with each input associated with its matching desired output or target. By generalizing from the labeled examples provided during training, the algorithm learns to map inputs to outputs. Once trained, the model may predict or classify new, previously unseen data. Image recognition, text classification, and regression challenges are examples of supervised learning tasks [20].

Supervised learning can be further divided into two subcategories:

- **Classification**: In classification tasks, the algorithm predicts discrete categories or classes. For example, classifying emails as spam or non-spam, or identifying the species of a plant based on its features. Classifying crops based on satellite imagery for precision agriculture [21] is typical example of this class. Using tagged satellite photos, a model can be taught to distinguish between various crop types. Targeted resource allocation and monitoring can benefit from this classification.
- **Regression**: Regression tasks involve predicting a continuous numerical value. This could be, for instance, Predicting the energy consumption of a specific farm for a given season [22]. Specific case studies are employed generally, using historical data on a farm's energy usage, weather conditions, and crop types to build a regression model that predicts the farm's energy requirements for the upcoming season. This assists in optimizing energy planning and resource allocation.

1.1.2. Unsupervised Learning

Unsupervised learning algorithms train on unlabeled data, which implies they are not given explicit target values. These algorithms, on the other hand, seek to find underlying patterns, structures, or correlations in data on their own. Clustering and dimensionality reduction are two frequent unsupervised learning tasks [23,24]. Utilizing sensors and

Internet of Things (IoT) devices to monitor livestock health, behavior, and surroundings in real time is achievable through unsupervised learning. One example would be the use of sensors on animals to collect ongoing data streams on location, temperature, and heart rate. Real-time processing of this data using streaming analytics enables the detection of anomalies, evaluation of health, and prompt notification for intervention [25]. This can provide light on similarities between farms and aid in the creation of focused energy optimization plans.

1.1.3. Reinforcement Learning

Reinforcement learning is characterized by an agent interacting with its surroundings, taking actions and receiving feedback in the form of rewards or punishments. The agent's goal is to discover a strategy that maximizes cumulative rewards over time. Reinforcement learning, unlike supervised learning, does not rely on labeled data; instead, it learns via trial and error [26]. This sort of learning is useful for activities such as game play, robotics control, and autonomous systems. Applications include decision-making, control systems, and resource allocation optimization in energy and agricultural processes. One such use is the optimization of planting, harvesting, and energy consumption in autonomous agricultural equipment through the use of reinforcement learning in response to current conditions. Over time, the system picks up new skills and modifies its behavior to increase efficiency [27].

These three broad categories of machine learning algorithms provide a complete framework for developing intelligent systems that can learn from data and adapt to new tasks. The type to choose is determined by the nature of the problem, the availability of labeled data, and the intended conclusion [28,29].

Several algorithms are utilized to achieve different AI learning styles, with major ones illustrated based on this research as in Fig. 3. It should be, however, noted that while some of these techniques can be used in both supervised and unsupervised settings (e.g., Neural Networks), they were initially described in the context of supervised or unsupervised learning in this research paper. Additionally, Bayesian Machine Learning was cited specifically for its probabilistic approach to modeling.

1.1.4. Artificial Intelligence, Machine Learning and Deep Learning

Artificial intelligence brought some novelty in the name of machine learning and deep learning which are currently relied on in these regards. Relationships between these terminologies if more of subset nature. While artificial intelligence serves as the general field, the two others portrays subsets within its pools (Fig. 4).

Machine learning techniques were widely used in the research community since the last two decades, when its applications were addressed and applied in several sectors, energy and agriculture inclusive [30]. Conventional machine learning methods, however, still require time-consuming feature extraction for training models [31]. Moreover, it has limited success under some circumstances such as its inability to process natural data in their raw form [32,33]. As a result, deep learning algorithms that automatically extract features as part of their natural operation have been incorporated into research for about a decade [34–36]. According to [37], deep learning has emerged as a more preferred method for some agricultural problems, such as plant disease detection and management, due to its increased computing power, storage capabilities, and accessibility of big datasets.

Deep learning simply learns from datasets of desired images to detect and identify specific features using some sets of complex algorithms (see

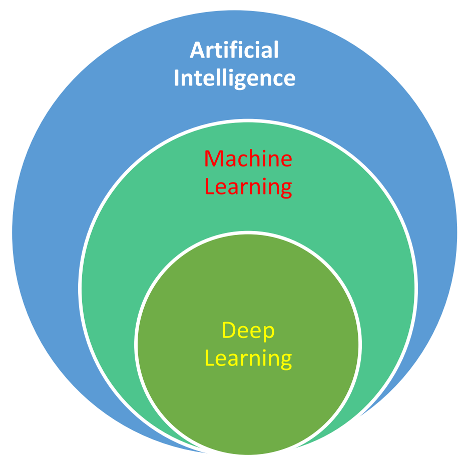

Fig. 4. Relationships within AI, Machine Learning and Deep Learning.

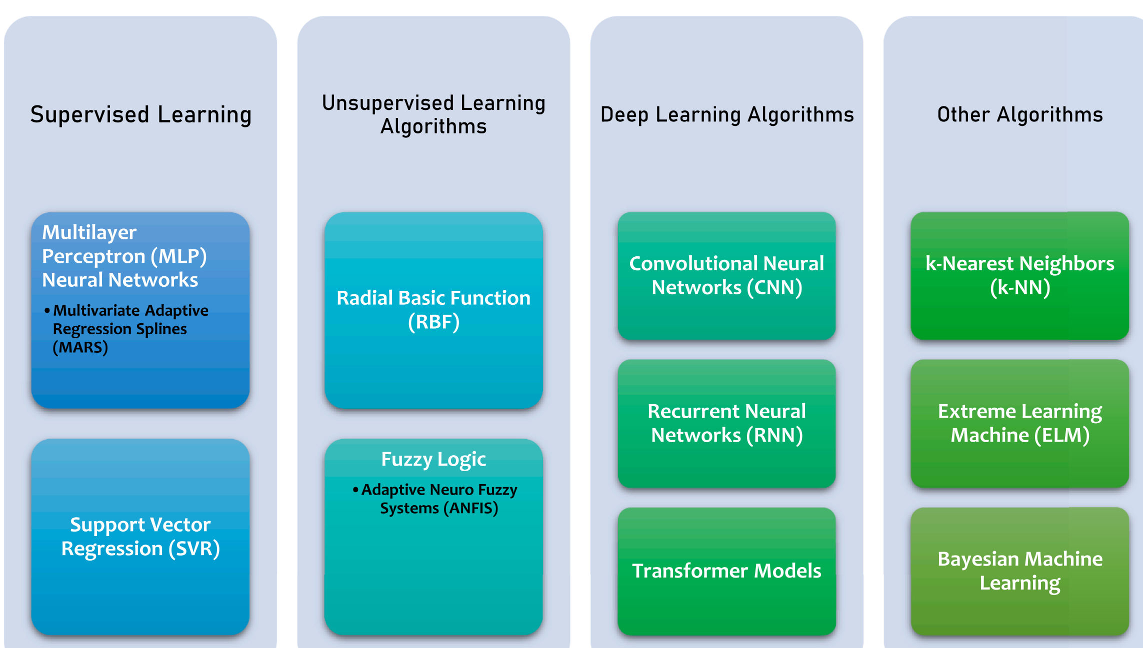

Fig. 3. Algorithmic categorization of AI tools observed in the energy-agriculture nexus' research.

sample algorithms in Fig. 3). As a data-hungry technology, researches in use of deep learning battle with datasets preparation for individual applications. This necessitates a crucial need for datasets to be prepared by the respective scientific research communities, simplifying the path for model developments, learning and knowledge sharing.

Though a lot has been done using AI in energy and agriculture sector individually, little concerns were observed in collective works suitable to fit the EA nexus. This paper is therefore an attempt to answer the following research questions: what has been done? How has it been done? What are the opportunities and major challenges that needs more attention in this regard, as the case may be.

2. Methodology

An intensive review of literature relevant to the applications of artificial intelligence in the energy-agriculture nexus was conducted. Published articles including journals, book chapters and conferences in this regard were searched and identified from the most reliable scientific literature collections, specifically the databases of the web of science (https://www.webofscience.com/wos/woscc/basic-search), Scopus (www.scopus.com) and google scholar (https://scholar.google.com/). The survey was conducted between 3rd-5th February 2023, using the following keyword selections to cover the general concept and the quotation sign between the individual phrases to restrict the search within the written keywords as follows:

- "energy-agriculture nexus"
- "energy in agriculture"
- "AI in energy-agriculture"
- "AI" + "energy" + "agriculture"

The methods used herein are similar to the methods of [38]. Relevant articles were then selected based on their specific relevance to the energy-agriculture nexus, especially those with both faces of energy and agriculture at the same time, and were then subjected to a systematic literature review. The literature survey was based primarily on the relationships between energy and agriculture in a simultaneous way, with summary of these relationships presented in Table 1. It focused on major applications of AI in the nexus (method-oriented style), potential opportunities it presents and challenges that needs attention. Applications of AI in a content-oriented style was further integrated into this work,

Table 1
Basic concept of the Energy-Agricultural Nexus.

Nexus relations	Energy	Agriculture
Bioenergy Production	Tapping agricultural crops & residues	Biomass production
Renewable Energy Generation	Solar panels on agricultural lands (Agrivoltaics)	Farms and agricultural lands
Farm Operations	Farm Mechanization	Food Cultivation
Input Production	Fertilizer and pesticides	Crop Protection
Controlled Environment	Energy for greenhouse	Greenhouse food cultivation
Water Management	Irrigation water pumping, distribution and scheduling	Irrigation
Food Processing	Energy-intensive food processing	Food processing
Food Preservation	Energy for food preservation	Food preservation
Storage and Distribution	Energy for food storage	Food storage
Transportation	Energy for on-farm transportation	Transportation of agricultural products
Livestock Management	Energy for feed and water supply	Livestock housing
Agroforestry Systems	Integrating energy crops into agriculture	Simultaneous energy and food production
Smart Grid Management	Optimizing energy distribution, storage, and consumption	Farm house and resource management

expanding the overview of the technicalities in the energy-agriculture nexus from external window of literatures.

3. Applications of AI in Energy-Agriculture Nexus: A Methodological Approach

Research articles that scaled up to be considered under AI use in the defined energy-agriculture nexus were sorted according the years of publication, presented as in Fig. 5. Over the years, a significant success and research progress of AI use in energy-agriculture nexus is clearly defined, with the years 2022-2023 showing the highest publication times. A lapse, on the other hand, recorded in the years 2016 and 2021, respectively, could be a factor of research terms used while conducting the literature survey and probably a limitation of search databases used. Nevertheless, the far success recorded cannot be overemphasized.

Although the AI techniques have been applied while viewing agriculture or energy as autonomous resource systems, the usage of AI approaches has been minimal in the general interactions along the energy-agricultural nexus. This section provides a thorough overview of the many AI strategies applied to the energy-agriculture nexus domain. Since prediction and optimization are the two main applications of AI identified in the literature that is relevant to the nexus, these classifications are based on generic categorizations of those applications. These AI techniques were further generalized according to the principles of AI technique's roots and branches, and their quantification based on the literature observed were given in percentages presented in Fig. 6. Moreover, the major areas of application of these AI techniques were identified from the literature survey and thus presented in Fig. 7. An extended summary of the literature and the use of hybridization techniques to solve scientific problems along the nexus were highlighted in the appendix (Table 3).

3.1. Prediction and Forecasting Applications

3.1.1. Neural Networks (NNs)

A form of machine learning algorithm called a neural network was developed to find patterns and connections in data. They take their cues from the organization and operation of the human brain, which is made up of linked neurons that exchange electrical and chemical impulses with one another. Data is fed into a network of neurons, which are arranged into layers. The data is first taken in by the input layer, processed by the hidden layer(s), and then output by the output layer. Weights are assigned to the connections between the neurons, and these weights are changed as the network is trained to more precisely anticipate the output from the input. The nature of weights assignment, processing in the hidden layers, and output generation is dependent on the vast variety of techniques defined in relevant texts [39]. Several types of neural networks are available, including Artificial Neural Networks (ANN), (though is often considered as the NNs in other words), Convolutional Neural Network (CNN), recurrent neural networks (RNN), deep neural network (DNN), Extreme Learning Machine (ELM), Radial Basic Function (RBF) and Gene Expression Programming (GEP).

3.1.1.1. Multilayer Perceptron (MLP) Neural Networks. A particular kind of neural network architecture called an MLP (Multilayer Perceptron) is frequently employed for supervised learning tasks. Several layers of interconnected nodes, or neurons, make up MLP networks, which process input data and produce predictions as an output. They are renowned for their versatility in modeling intricate interactions between input and output variables as well as their capacity to handle non-linear data.

In the context of energy-agriculture nexus, [40] used a multi-layer perceptron (MLP) ANNs for prediction of energy used in basil crop production from 26 greenhouses in Esfahan, Iran. With a dataset collected during four consecutive cultivation periods between

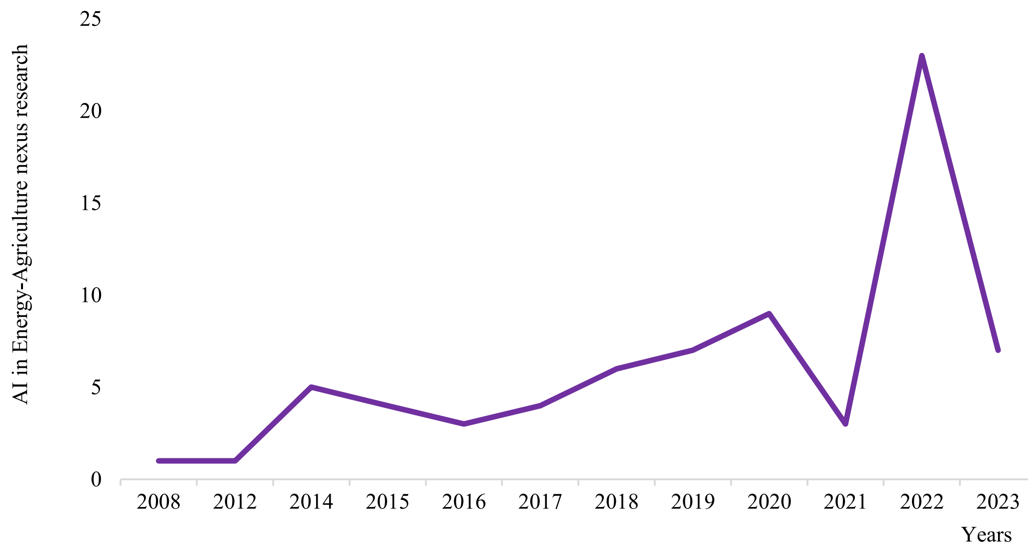

Fig. 5. AI use in energy-agriculture nexus by years of publication.

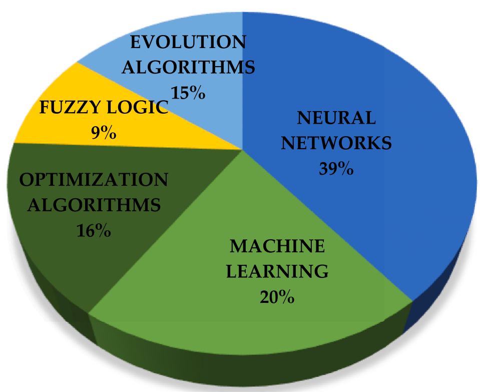

Fig. 6. General categorization of AI tools used in the literature of energy-agriculture nexus.

2009-2010 and an architecture of 7-20-20-1 (input-hidden_layer1-hidden_layer 2-output), the authors obtained the best results. At Almeria, Spain, [41]developed an ANN model to predict the energy production in an integrated PV greenhouse experimental structure. The model with a set of dataset collected from October 2009 to June 2010 and an architecture of 5-1-1 proved its suitability for application in complex and nonlinear systems. Authors of [42] developed a model using ANNs to predict the energy use in wheat cultivation at Fereydonshahr, Esfahan, Iran. Their study with a field dataset from 260 farms and a structure of 11-3-2 has the best prediction capacity.

With a combination of ANN & GEP, [43] modelled the energy dissipation of six over stepped-gabion weirs. So also in the prediction of higher heating values in the context of biofuels, authors of [44] utilized a MLP- GEP hybrid approach as the former, though the authors cited it as the first time of GEP usage in such applications. However, secondary datasets acquired from listed research articles and open databases were used to train the two hidden layer based models. As claimed by the authors of [45] who used a hybrid model of ANN-MLP to also predict higher heating values, their work possesses the novelty of its input which was based on chemical analysis and physical data for the same application with the former. Nevertheless, the success of these works iterates the applicability of AI in bioenergy applications as a component of the energy-agriculture nexus.

ANNs have further been used to predict the drawbar power of agricultural tractors in an attempt to maximize its traction efficiency while minimizing energy use [46]. In combination with GA, the authors were able to tackle the possible deficiencies of backpropagation sequel to ANNs. Authors of [47] were able to use ANNs to predict the yield and greenhouse emissions In lentil production. Their study was based on the

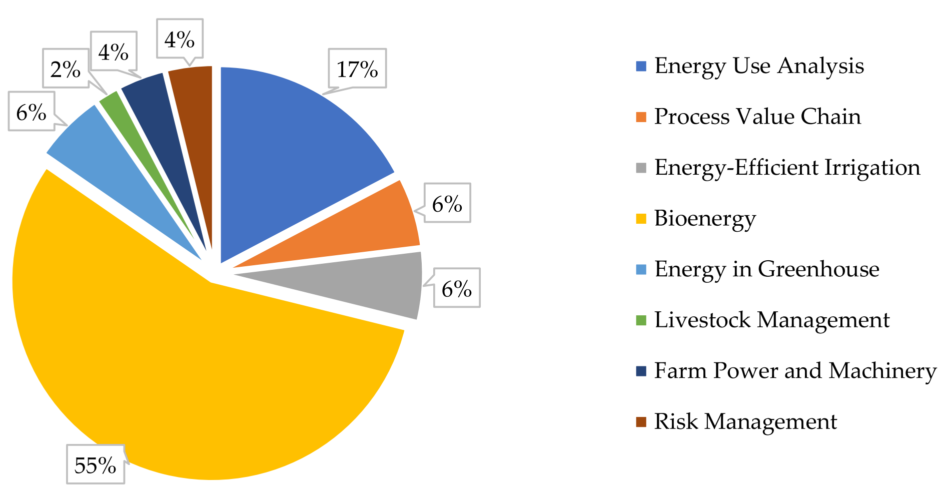

Fig. 7. Observed AI Research focus by area in the energy-agriculture nexus.

use of a field dataset tapped in the 2014-2015 season and a topology of 9-10-6-11. Furthermore, ANNs were used to predict pesticides usage based on field data from 360 rice farms for the safety of the farmers from exposure to and health hazards of such chemicals [48]. The authors even concluded that there is an over utilization of such pesticides, thus enunciating the potentials of life saving thanks to AI application in the nexus. For the purpose of estimating the amounts, distributions, production quantities, waste volumes and energy prospective of several biomass resources steadily, the authors of [49] employed the expertise of ANN based modelling.

ANN is also a significant tool for the prediction of torrefaction severity index (TSI), a measure of the extent of torrefaction and the quality of torrefied solid fuel resource, in bioenergy. Using a dataset of solid biomass properties, gasifier operating parameters and PEM fuel cell module, authors of [50] trained an ANN model and successfully predicted the fuel cell's output parameters. ANNs in a Bayesian framework with GAs, a very strong approach, have been utilized by the authors of [51] to develop a model named PREPOSOL for the photovoltaic energy prediction in irrigation pumping. While utilizing a cascade feedforward neural network (CFF), a type of NN architecture with multiple layers organized in a sequential style, among other AI tools, [52] predicted the heating energy capacity in biomass most successfully (R2=0.99.347). ANN prediction power has also witnessed application in livestock-energy context, where [53] successfully estimated energy use in a pig house (for sustainable sine production) powered by geothermal heat pump and solar system (GHPS).

3.1.2. Radial Basic Function (RBF)

A class of neural network called an RBF network is utilized for function approximation, classification, and regression. The output layer computes the output based on the weighted sum of activations from the hidden layer, and each RBF neuron measures the distance between the input data and a center point [54]. RBF networks can be sensitive to hyper parameters, yet have a number of benefits, with the capacity to handle non-linear data and quick training rates inclusive. In the energy-agriculture nexus, RBF have been utilized in comparison to other AI tools to predict energy use in agriculture and it proved to be the best predictor in the works of [55] using Gaussian activation function *(1)* in the hidden layer.

$$\phi(\mathbf{d}) = \mathbf{e}^{-\left(\frac{\mathbf{d}^2}{2\sigma^2}\right)} \tag{1}$$

where d was used as the distance of the input from the center, σ is the smoothness control coefficient.

Neural networks, in terms of Artificial Neural Networks (ANN), Extreme Learning Machine (ELM), Radial Basic Function (RBF) and Gene Expression Programming (GEP), were found to be the most used AI tools in the energy-agriculture nexus (Fig. 3). Factors contributing to such may be attributed to the nature of AI need in the nexus, its simplicity in use and widest popularity, and critical contributions of NNs in not only prediction applications but rather as a functional bridge for many other AI tools.

3.1.3. Fuzzy Logic

A logic known to allows for partial membership of items and imprecision called fuzzy logic is employed when data or the decision-making process are subject to ambiguity, uncertainty, or imprecision. With regard to conventional logic, fuzzy logic has a number of benefits, including the ability to manage complicated systems with numerous variables and the capacity to model uncertainty and ambiguity. Where conventional logic is insufficient, fuzzy logic is a significant tool for modeling and decision-making [56].

Fuzzy logic has been utilized in prediction applications along the nexus, as well, to create estimates based on missing or ambiguous facts since it allows for the representation of ambiguous or imprecise concepts. Authors of [57] predicted moisture content of a bioenergy resource (poultry litter) and identified critical parameters with fuzzy logic using a multistage methodology. It has also seen an application in agriculture based industries for performance improvement of mixers [58].

A hybrid system called adaptive neuro fuzzy systems (ANFIS) combines the strength of neural networks and fuzzy logic to enable it to adapt to various input/output pairings. It is a development of fuzzy logic that adds the ability to learn and adapt, making it more potent and adaptable for certain applications. Authors of [59] combined the both for predicting energy yield in sugarcane prediction. They defined a topology of 7-9-6-11 as the most efficient model for such application. ANFIS further recorded the superior performance record in a comparative study with ANN and SVM to predict the HHV in bioenergy as models developed in [60]. ANFIS as a significant tool for application in terms of biofuel generation has been given special consideration in the reviews of [61]. Moreover, A 4 ANFIS subnetwork based model has, in comparison with a 6-16-2 structured ANN, proved better prediction capacity in energy use analysis for calf fattening applications in Iran [62]. The authors cited nature of fuzzy rules as the main reason.

3.1.4. Applied Machine Learning Algorithms

3.1.4.1. k-Nearest Neighbors (k-NN). A common machine learning approach known as k-nearest neighbors (k-NN) is used to estimate the class or value of a new data point based on how similar it is to existing data points in a training dataset. The number of nearest neighbors, or k, must be carefully chosen since a smaller value will make the model more susceptible to local patterns, whilst a greater value would make it more resilient to noise and outliers. In the context of energy-agriculture nexus, [63] introduced an integrated machine learning and Internet of things (IoT) based system that utilizes the prediction power of k-NN for application in agricultural residues for bioenergy. However, the efficiency of such a system have not been proved in their work.

3.1.4.2. Extreme Learning Machine (ELM). As introduced by [64], the simplicity, effectiveness, and quick training times of the ELM machine-learning algorithm have made it prevalent. It has been demonstrated to perform well in terms of accuracy and generalization on a variety of datasets, and is generally used for supervised learning tasks. Its performance, however, may differ based on the particular dataset and application. In ELM, the output layer weights are determined using a linear regression method, whereas the hidden layer biases and input layer weights are created at random. The network is trained using a single iteration of the least-squares technique, which accelerates and optimizes processing. Authors of [65] used ELM to predict energy used in wheat production using an extensive input dataset of 20 years (1994-2013).

3.1.4.3. Bayesian Machine Learning. In this type of machine learning known as Bayesian machine learning, uncertainty in models is represented by using probability theory and the likelihood of a hypothesis is regularly updated when new data become available. It offers a logical approach to assess uncertainty and incorporate past data into models. In Bayesian machine learning, the parameters of the model are given a prior probability distribution that represents the previous ideas about the parameters before any data is observed. Using Bayes' theorem, the posterior probability distribution is revised as new data is gathered, updating our understanding of the parameters [24].

Bayesian machine learning was utilized by the authors [66] for complex applications, including predictions, using uncertainties from simulations of the Atikokan biomass boiler and measured data from 12 operational, model, and output parameters. The authors later developed an optimized model based on the integrated decision-making power of Bayesian decision theory [67]. Despite the complexity of these applications, the potentials of AI in the energy-agriculture nexus is perhaps highly pronounced.

3.1.5. Regression Models

When the output variable is continuous and numerical, a particular kind of prediction is used called regression. Finding the link between a continuous output variable and one or more input variables (predictors) is the aim of regression analysis (response).

3.1.5.1. Support Vector Regression (SVR). A form of machine learning model called support vector regression (SVR), as introduced in 1996 [68], is used for regression tasks to predict a continuous output variable as opposed to a categorical one. It operates by locating the hyperplane with the lowest error within which the training data fits best. The kernel function, regularization parameter, and tuning parameters that are chosen, with cross-validation, all affect SVR's performance.

In the context of energy-agriculture nexus, researchers in [49] have estimated the amount of agricultural and animal waste that can be obtained in the upcoming years using SVR method, taking into account the rate of increase in agricultural production yield.

3.1.5.2. Multivariate Adaptive Regression Splines (MARS). Jerome Friedman created the non-parametric regression analysis method known as multivariate adaptive regression splines (MARS) in the 1991 [69]. Simple linear models are fitted to each of the smaller parts created by segmenting the independent variables. Several linear models, each of which was used to analyze a certain subset of the data, are combined to create the final model. A dependent variable and a number of independent variables can be modeled using MARS, and predictions can then be made for future data. Depending on the quality of the data and the intricacy of the relationships being modeled, the accuracy of these predictions may differ.

In combination with ANN, MARS have been utilized along the energy-agriculture nexus to comparatively predict torrefaction severity index (TSI), the biomass's parameter described earlier, by the authors of [70]. With R2 value of 0.9851 and relative error of 1.49% in MARS over 0.9784 and 2.16% in ANN, respectively, the prediction power of MARS outweighs that of ANN thus presenting the larger potentials of MARS use in terms of solid biomass. However, Feedstock type, temperature, and duration taken into account as input parameters were prioritized according to significance by the two models, where MARS identified temperature as the major impact factor on TSI contrary to ANN that prioritized feedstock type. Because MARS creates a model that is simpler to understand, can be trained rapidly, and is robust to outliers in the data, it may be superior over ANN in the scenario of TSI prediction in biomass [71]. Working with biomass data, which can be noisy and challenging to model, makes use of these characteristics in particular.

3.2. Optimization Applications

3.2.1. Evolutionary Algorithms

The process of natural evolution serves as the basis for the family of metaheuristic optimization algorithms known as evolutionary algorithms (EA). EA is a family of algorithms that looks for the best solution to issues by applying the laws of genetics, mutation, and survival of the fittest. In the context of energy-agriculture nexus, the following types of EAs were observed for optimization applications:

3.2.1.1. Genetic Algorithms (GAs). Natural selection and genetics serve as the inspiration for genetic algorithms, often known as "genetic algorithms" (GAs). While attempting to identify the optimal solution to a given issue, they are employed to tackle optimization problems. A randomly generated population of potential solutions to the problem, represented as a chromosome or a genotype, is created at the beginning of the GA process. The two primary GA operators are crossover and mutation. While choosing the best solutions from the population, the fitness function is utilized to assess the quality of the population's solutions. Until a stopping criterion is satisfied, such as a certain number of generations, a time limit, or a specific degree of convergence, the GA keeps evolving the population. A type of genetic algorithm called a multi-objective genetic algorithm (MOGA) is used to resolve optimization issues involving many competing objectives.

GAs have been used in the energy-agriculture nexus to optimize energy usage in legumes cultivation [72] in an attempt to observe the sustainability indicators of the production system. The authors proved the suitability of methods used while excessive usage of diesel and fertilizers, as observed using sustainability assessment, were positively optimized using MOGA. Using the similar approach, authors of [73] have earlier optimized energy use and its environmental impacts alongside its economics using watermelon as a case study. A 28% and 33% of energy input and greenhouse gas emissions were recorded respectively thanks to MOGA. Authors of [74] even compared the power of MOGA with data envelop analysis for resource management in orange production, the results were significant.

In addition to prediction application of biogas and methane yields using a hybrid ANN-Gompertz equation model, [75] optimized the model using GA for enhanced capacity. Dataset in the study comprised of 42 secondary data obtained from specific works, however only 4 were employed as inputs for the ANN architecture. Both the prediction and optimization operations were conducted with MATLAB software. [76] employed GAs to optimize the energy, among other parameters, to develop a more advanced model suitable for use in China's greenhouse agriculture.

3.2.1.1. Particle Swam Optimization (PSO). A metaheuristic optimization approach called Particle Swarm Optimization (PSO) models the behavior of fish schools or bird flocks to locate a problem's global optimum. It operates by employing a population of particles that traverse the search space, adjusting their position and velocity in accordance with both their own and their neighbors' optimal positions. PSO is superior to conventional optimization methods in that it can handle high-dimensional and nonlinear optimization problems, is straightforward, and converges to the global optimum quickly.

In the energy-agriculture nexus, PSO have been utilized by [77] in a hybrid modelling operation with ANN to optimize the initial weights and threshold parameters of the ANN model which initially predicted the biomass pyrolysis product yields poorly. With the optimization approach, relative error of the PSO-ANN model decreased to below 10%, thus considered as effective and powerful by the authors. PSO was also used to optimize the weights of ANN model to improve its prediction capacity of the product yield in solid waste gasification process [78].

4. Applications of AI in Energy-Agriculture Nexus: A Contextual Approach

In this section, an exploration of how AI is dynamically integrated into the EA nexus is described. This thus reveals how AI technologies might revolutionize resource allocation, improve sustainability, and minimize their negative effects on the environment. With the overview of what is realized as the applications of AI along the nexus, as in Fig. 8, a further discussion with an emphasis on useful applications is presented as follows:

4.1. Sustainable Energy Generation

The incorporation of sustainable energy generation within the energy-agriculture nexus marks an essential turning point in modern agricultural techniques [79]. As global food demand rises alongside the need to cut carbon emissions, the synergy between sustainable energy and agriculture becomes increasingly important (Table 2). This

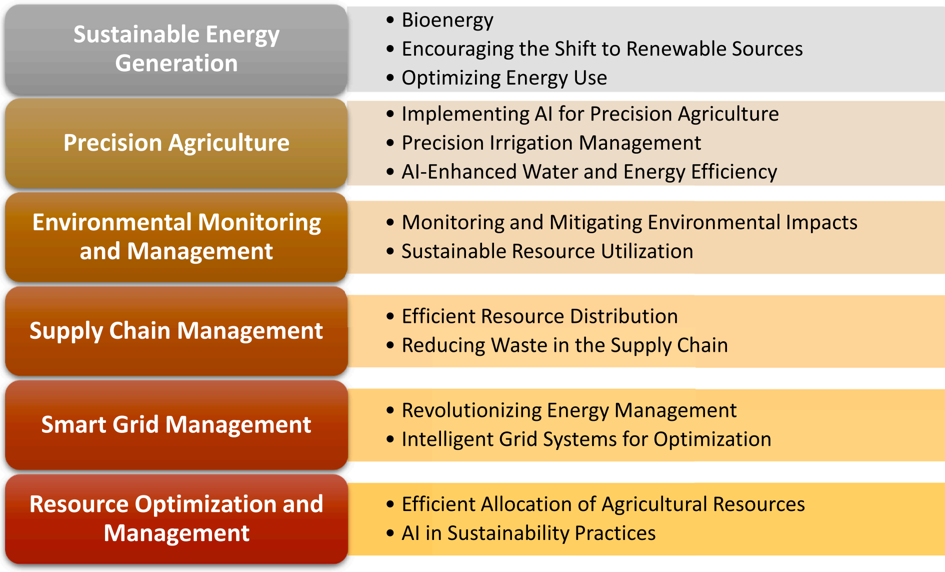

Fig. 8. General summary of AI applications along the EA nexus.

integration has the possibility of not only increasing agricultural productivity but also reducing environmental consequences, paving the way for a more resilient and environmentally conscious future [80].

Sustainable energy generation comprises a wide range of technologies and techniques that generate power from renewable resources such as solar, wind, hydro, and biofuels. The ramifications for agriculture are far-reaching, influencing various aspects of the sector, from on-farm mechanization to agro-processing [81]. This convergence necessitates a detailed examination of the complex interactions that exist between sustainable energy and agriculture, emphasizing both the potential benefits and challenges that come from their interaction.

The incorporation of artificial intelligence (AI) in the goal of sustainable energy generation is an important step forward to reconcile agricultural methods with sustainability. At the heart of the energy-agriculture nexus, this synergy has enormous promise for transforming the way energy is produced and utilized in agricultural contexts [15].

AI improves energy production by optimizing resource allocation [74], resulting in greater efficiency, lower GHG emissions and less waste. Relevant datasets, for example, have been analyzed by machine learning algorithms to fine-tune energy producing processes [82–85], ensuring that resources are spent wisely.

AI facilitates the seamless integration of renewable energy sources such as solar and wind into agricultural activities [86,87]. It also ensures a dependable and sustainable energy supply by forecasting energy output based on weather conditions [88] and trends in demand [89].

4.2. Precision Agriculture

Precision agriculture, powered by the use of artificial intelligence (AI), is an exemplary instance of innovation in modern agriculture. This innovative concept makes use of sophisticated technologies to optimize resource allocation, increase crop productivity, and cut greenhouse gas emissions [90]. Precision agriculture is critical to the efficient use of energy resources in the EA nexus, ensuring that every unit of energy invested leads to maximum yields in agriculture. Farms can reduce their energy footprint by automating processes, reducing machinery use, and utilizing data analytics, integrating agricultural practices with broader sustainability aims.

AI enables precision agriculture by analyzing a wide range of elements, from soil health to weather patterns, allowing farmers to distribute resources including water, fertilizer, and energy with remarkable accuracy [51,91,92]. This results in minimum resource usage and significant waste reduction. As stakeholders in the EA nexus, farmers and agribusinesses thus fine-tune their operations by leveraging AI-driven data which in turn enhances waste reduction while increasing efficiency [93].

Farmers may fine-tune their farming processes to meet the specific needs of each crop by employing AI. This involves customizing irrigation schedules [51], and using improved crop protection and management measures [94–96]. As a result, increase in agricultural yields is observed while ensuring sustainable energy consumption in the production process.

Precision agriculture, guided by artificial intelligence, facilitates the adoption of environmentally friendly methods. Farmers can contribute to a more sustainable and resilient agricultural sector by using data-driven decision-making to reduce chemical inputs, cut greenhouse gas emissions, and apply conservation techniques [48,97]. Moreover, precision agriculture supports energy-efficient operations by using AI-driven insights. Farms can reduce their energy footprint by automating processes, reducing machinery use, and utilizing data analytics, connecting agricultural practices with broader sustainability aims [5,98,99].

4.3. Environmental Monitoring and Management

Environmental monitoring and management, aided by the integration of new technologies and artificial intelligence (AI), is at the lead of sustainable farming practices in the energy-agriculture nexus [100]. This dynamic strategy incorporates a variety of techniques targeted at protecting natural resources, minimizing environmental consequences, and promoting the long-term viability of the EA nexus. AI-powered environmental monitoring not only provides stakeholders with real-time data but also enables proactive decision-making to reduce resource depletion and environmental damage [101,102].

Despite the fact that many industries have been reached out and expanded, AI is on the rise of usage to address the majority of regional and global environmental challenges, including energy, water, biodiversity, and transportation [103]. Since the forest area and natural resource variables, for example, negatively affect the productivity of the agricultural sector [104], utilizing the power of machine learning is one straightforward and effective solution to balance between the areas and significantly cut down the negatives [105].

AI-powered environmental monitoring gives farmers, agribusinesses, policymakers and relevant stakeholders in the EA nexus, real-time data

Table 2
Typical styles of sustainable energy utilization in agriculture.

Energy Source	Agriculture Process	Typical Forms of Usage
Solar Power	Irrigation	Solar panels capture sunlight and convert it to electricity, powering irrigation systems. This reduces the reliance on grid electricity or fossil fuels for irrigation
	Greenhouse Operations	Solar panels provide renewable energy to power environmental control systems in greenhouses. This enables precise control over temperature and humidity, optimizing crop growth
Wind Power	Crop Cooling	Wind turbines generate electricity, which can be used to power cooling systems for crops. This is especially vital in warm climates to maintain optimal growing conditions
	Machinery Operation	Wind-generated electricity can be used to power agricultural machineries, plummeting fossil fuel consumption and greenhouse gas emissions
Bioenergy	Biomass Conversion for Energy	Agricultural wastes, such as crop residues and organic matter, are converted into bioenergy through processes like anaerobic digestion or biomass combustion. This in turn can provide renewable energy source for various agricultural operations
	Greenhouse Heating	Biomass can be used to generate heat for greenhouses, maintaining optimal growing conditions. This is particularly beneficial in colder climates
Geothermal Energy	Greenhouse Heating	Geothermal systems utilize the Earth's natural heat to warm greenhouses, ensuring consistent temperatures for crops. This renewable energy source is reliable and sustainable
	Irrigation	Geothermal energy can be used to heat water for irrigation, reducing the energy demand from conventional sources
	Aquaculture	Geothermal water can be used to regulate water temperature in aquaculture systems, creating an optimal environment for fish or aquatic plant growth
Hydroelectric Power	Water Pumping for Irrigation	Hydroelectric dams generate electricity, which can be used to power water pumps for irrigation
	General Farm Operations	Hydroelectric power provides a reliable and consistent source of electricity for various on-farm operations, reducing dependence on grid electricity
Fossil Fuels	Machinery Operation	Fossil fuels like diesel or gasoline power a wide range of agricultural machinery, from tractors to harvesters. While widely used, there is a growing push for more sustainable alternatives to reduce environmental impact
	Heating	Fossil fuels are often used for space heating in agricultural buildings, especially in colder climates. Transitioning to renewable alternatives is an area of focus for sustainability efforts
Grid Electricity	General Farm Operations	Grid electricity powers various operations on farms, from lighting to machinery. Optimizing energy use and exploring renewable sources can reduce costs and environmental impact

on critical environmental indicators. This contains measures for soil health, water quality, air quality, and biodiversity, enabling for informed and timely decision-making to prevent negative consequences [59,106–109].

Environmental monitoring allows for more precise resource allocation by leveraging AI-powered insights. Targeted irrigation to conserve water [110], optimal fertilizer application to prevent nutrient runoff [16,111], yield prediction [112,113] and prudent energy use to power agricultural operations [114,115] are all examples of this. These approaches, used together, help to conserve essential natural resources.

Furthermore, AI systems excel in detecting patterns and abnormalities in large quantities of environmental data relevant to the EA nexus. This feature allows for the early detection of potential environmental hazards such as soil erosion [116,117] and air pollution [23]. Assessing the viability of on-farm solar or wind energy installations, maximizing energy storage and delivery, and ultimately minimizing reliance on fossil fuels are typical data foundations laid by AI utilization for environmental management along the EA nexus [41,84,85,118,119].

4.4. Supply Chain Management

The energy-agriculture nexus highlights the importance of supply chain management as a crucial element for smooth simultaneous functioning of the two industries. This nexus illustrates the complex interactions that occur between agriculture and the generation of energy [7], highlighting the need for sustainable practices, efficient processes, and effective resource allocation. Within the EA nexus, supply chain management comprises the organization, implementation, and enhancement of tasks related to locating, acquiring, manufacturing, and distributing energy resources and agricultural products [1,120,121]. This could cover every step of the process, from planting crops and gathering energy resources to transporting, processing, and delivering goods to final customers.

For AI utilization, the supply chain becomes fundamentally more efficient since delivery times are shortened, operating expenses are decreased, and resource use efficiency is realized. For example, AI uses sophisticated analytics to foresee malfunctions in systems, like supply chain systems, before they happen [14]. Early maintenance (proactive maintenance in other words) can minimize downtime and guarantee continuous operations by anticipating any problems and taking appropriate action. AI systems utilizes this capacity by examining data from farm machineries [122–124]. The chance of equipment failures during critical agricultural activities is hence reduced thanks to the proactive maintenance.

AI systems assess supplier performance according to several criteria, allowing stakeholders to make well-informed procurement decisions [101,125]. This guarantees a steady and dependable supply of energy inputs for farming operations.

Energy optimization is realized in transportation and on-farm operations through, for example, the selection and use of energy-efficient machineries and route planning. AI-driven systems further increase the optimization through its analytics power to a multiple or so [124,126,127]. Real-time monitoring of the environment by sensors that are AI-powered improves energy efficiency and machinery performance [128]. This may, in turn, help avoid potential breakdowns in the supply chain by enabling quick responses to any departures from ideal circumstances. Hence realizing a significant value of AI utilization for supply chain management.

4.5. Smart Grid Management

Within the EA nexus, smart grid management plays a crucial role as the glue that ties the demands of the two sectors together. Basically, the technology behind smart grids is a complex framework that combines conventional energy infrastructure with cutting-edge monitoring, control, and communication systems. This convergence facilitates an array of sophisticated features that address the specific requirements of both the energy and agriculture domains, while also enabling a smooth and uninterrupted flow of electricity.

A number of revolutionary advantages are brought about by smart grid management in the agricultural domain. It guarantees a steady and dependable energy source, which is essential for running different kinds of agricultural operations. Optimizing agricultural productivity and efficiency requires a steady flow of energy, which is essential for irrigation systems, machinery, and processing facilities [129,130].

Furthermore, smart grids help facilitate precision agriculture processes by utilizing real-time data analytics [131]. This will, in turn, allow farmers to maximize resource utilization, minimize waste, and improve total yield.

The incorporation of renewable energy is a crucial aspect of the energy-agriculture interaction, and smart grid management is essential to this process [41]. Since renewable energy sources are dynamic, including solar and wind, a complex grid infrastructure that can adjust to changing supply patterns may be required [132]. AI-powered smart grids are superior in this area because they can integrate renewable energy sources in a creative manner [18]. This fits in perfectly with the environmentally conscious philosophy of contemporary agriculture in addition to encouraging sustainable energy techniques [133].

In addition, the resilience that smart grid management provides is valuable to the energy-agriculture nexus. Smart grids can foresee and minimize interruptions in the energy supply with the use of automatic response systems and predictive analytics [134]. This is especially important in agricultural contexts where any power outage can have a significant impact on crop growth and general farm operations [135]. Smart networks strengthen agricultural systems' resistance to unforeseen obstacles by guaranteeing a steady supply of energy.

Reciprocally, the EA nexus and smart grid management collaborate. In order to run its numerous processes, the agricultural industry is significantly dependent on the efficient and reliable supply of energy. Conversely, the energy industry gains from the incorporation of renewable energy sources and the enhanced capacity to respond to demand that arises from agricultural stakeholders actively engaging in grid management. The mutually beneficial partnership highlights the significant influence that smart grid technology may have on the sustainability and efficiency of both industries [1,7,26,136].

In order to handle concerns about cybersecurity, data privacy, and grid modernization, regulatory frameworks need significant change to reflect the dynamic nature of smart grids. Furthermore, encouraging stakeholder and consumer adoption of smart grid technologies is a crucial behavioral challenge. To fully utilize smart grid management within the EA nexus and unlock a future where resilient, efficient, and sustainable energy practices drive agricultural prosperity, these challenges need to be addressed.

4.6. Resource Optimization and Management

AI has the potential to completely transform the way agriculture and energy are combined because of its capacity to handle large datasets, make choices in real time, and maximize resource utilization [137]. Large datasets are easily processed by AI algorithms, allowing them to make quick, well-informed deductions. This means that energy, water, and other essential resources will be used more effectively in the framework of resource optimization and management [13,15,51,62,78]. Using its predictive analytics and intelligent automation, AI has the capacity to maximize productivity in the EA nexus by optimally allocating resources, such as irrigation water [51,91], chemical inputs [48] and power in terms of machineries [46] where they are required.

By cutting down on waste and lessening its negative effects on the environment, AI-driven resource optimization supports sustainable practices [138]. AI-enabled precision irrigation systems, for instance, can supply water straight to plant roots in agriculture, conserving water and nutrients supply while preserving plant health [16].

Moreover, the energy and agricultural sectors, through the EA nexus, can potentially achieve large cost savings through resource optimization. AI, for example, can reduce input costs in agriculture by precisely distributing water, herbicides, and fertilizers. Demand-response systems powered by AI in the energy sector can reduce operating costs by effectively controlling energy use [22,27,126,139].

Predictive analytics-enabled AI systems can aid in the EA nexus' adaptation to changing climatic circumstances. AI, for example, can alert help farmers to weather-related threats early on, allowing them to modify irrigation and planting schedules, and may even further help by predicting changes in the energy supply and demand patterns brought on by these climate-related phenomena [28,138].

AI-driven solutions enhance the well-being of society at large by optimizing resource utilization, especially in resource-intensive interactions like the EA nexus [12]. By reducing waste and maximizing productivity, they promote economic viability, which can benefit communities that depend on these industries by improving their standard of living and fostering economic stability [32,140].

Research and development are aided by the integration of AI in the EA nexus. This passion for innovation has the potential to provide cutting-edge methods, tools, and techniques that improve resource management and optimization even further [85,141,142]. It encourages technological innovation and a culture of constant improvement.

5. Opportunities of AI utilization in energy-agriculture nexus

By fostering opportunities for the production and use of renewable energy sources, encouraging sustainable land use strategies, and enhancing energy efficiency in agricultural activities, the energy-agriculture (EA) nexus can promote sustainable energy. Agroforestry systems, energy crop integration into agricultural systems, and bioenergy from agricultural waste, for instance, all have the potential to be socially and environmentally valuable sources of renewable energy. Further opportunities derived from the utilization of AI in the EA nexus are presented in this section as follows:

5.1. Sustainable Development

The EA nexus could comparatively maximize sustainable development goals even more than the Integrated Energy-Food Systems (described by [1]), as it enhances the encouragement of resource efficiency, lowering of waste and emissions, and boosting of the agro-ecosystems ability to withstand climate change set by the SDGs (https://sdgs.un.org/goals). From their contexts, EA nexus intersects with the former in SDG2 and SDG7, while the former could achieve SDG 12, energy-agriculture nexus could achieve SDG13, which is said to be more complex. Further description of these goals could be reflected as in Fig. 9. The most efficient technologies and interventions for accomplishing sustainable development goals can be found using hybrid AI models (detailed in Table 3), which can also give decision-makers the data they need to put those interventions into practice [1,51,143].

5.2. Entrepreneurship and innovation

The EA nexus offers chances for innovation and entrepreneurship in industries like agroforestry, precision agriculture, and renewable energy. The most promising technologies and business models in various fields can also be found with the use of hybrid AI models [65], which can even offer advice on how to scale up and duplicate successful efforts.

5.3. Balancing the economics of energy-agriculture markets

The energy-agriculture nexus from its concepts indicates some implications for the global economy and energy markets. The demand for energy in agriculture may increase as the world's population bounces up and consequently the demand for food soars. At the same time, the production of bioenergy from agricultural crops and residues has the potential to significantly increase the global energy supply. With AI [144], a wheel balance can be easily made from optimization means and proper decisions could be made appropriately.

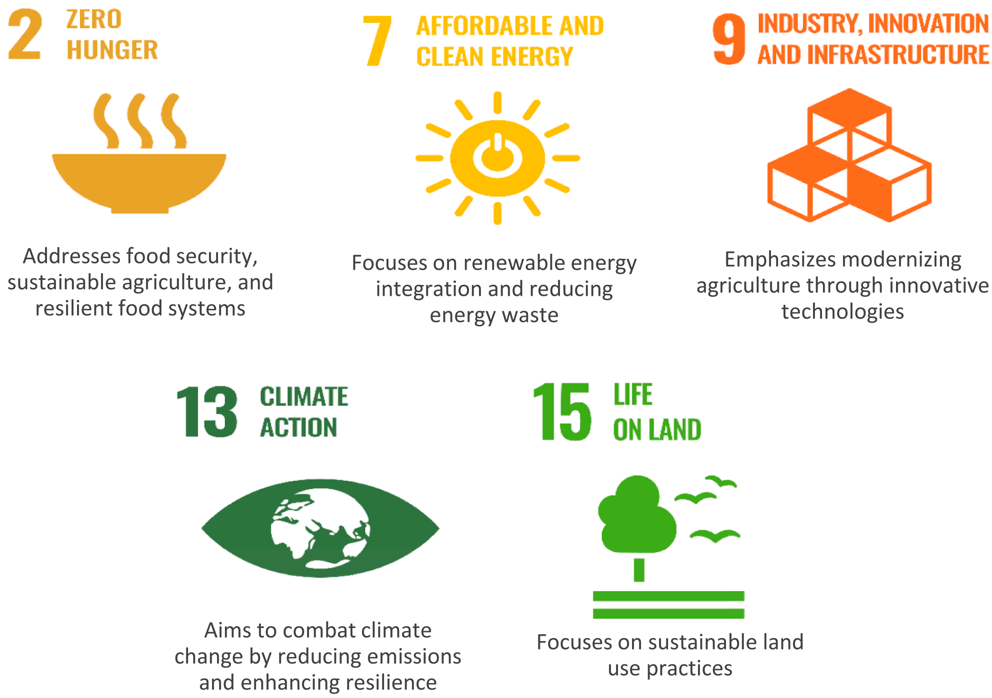

Fig. 9. Supposed SDG goals aligning within the energy-agriculture nexus.

5.4. *Efficient and Responsible Utilization of Energy Resources*

Artificial intelligence (AI) technologies have the potential to completely transform how agricultural operations manage energy. AI systems can optimize patterns of energy consumption by implementing automation and predictive analytics. For example, AI-driven models are able to deliver customized suggestions for energy-efficient practices by analyzing historical data on energy usage along with real-time inputs such as crop development phases and weather. This can entail controlling the operation of machines, scheduling irrigation more effectively, or even incorporating renewable energy sources [49,60]. Farmers may save costs and adopt a more sustainable energy use strategy by utilizing AI's data-driven skills to drastically cut energy waste.

5.5. *Lowering Emissions of Greenhouse Gases*

It is crucial to address how agriculture affects the environment, especially in terms of greenhouse gas emissions. AI technologies provide strong instruments to reduce these emissions. For example, farmers can use strategies that maximize fertilizer application, decrease the usage of chemical inputs, and minimize tillage with the help of AI-powered precision agriculture techniques [74,145]. AI-driven monitoring systems can also measure emissions from livestock and assist in putting emission reduction plans into action [62]. Agriculture may move toward more environmentally friendly methods by utilizing these AI-driven strategies, which will ultimately result in a significant decrease in the industry's overall environmental impact.

5.6. *Increased Productivity through Precision Agriculture*

Precision farming, supported by AI technologies, is a revolutionary method of farming. Farmers obtain previously unattainable insights into their fields by incorporating AI-driven data analytics. Real-time monitoring is possible for crop health, pest and disease occurrence, moisture content, and soil quality [146,147]. Customized fertilization plans and precision irrigation are only two examples of the highly targeted interventions made possible by this abundance of data. Crop yields are therefore increased while resource utilization is optimized. AI systems can help with holistic farm management in addition to individual crop management by coordinating efforts across several fields for a cohesive and effective strategy. Precision farming ensures that resources are used wisely, which not only increases productivity but further promotes long-term sustainability.

6. Challenges of AI use in energy-agriculture nexus

The capabilities of AI in the EA nexus thus represents its transformative potentials. However, this paradigm change brings with it a number of issues including technical challenges [18], ethical concerns in terms of data privacy, algorithmic bias, and transparency [17], and long-term sustainability concerns, that needs to be addressed for its successful integration. This could be further enunciated as follows:

6.1. *Data availability*

The engine of AI's success is quantity and quality of datasets. Data availability in the energy-agriculture nexus are scarce and fragmented, thus posing a serious challenge in developing highly efficient and reliable models. Similar observations were documented by [28] relative to machine learning usage along the energy-water usage.

6.2. *Data complexity and heterogeneity*

Nature of the energy-agriculture nexus involving a dynamic set of interacting factors including energy usage, productivity, and other resource utilization, among others, presents a multidimensional and interdependent data types. Consequently, handing such data with a single AI technique could be much more challenging, thus the need for a hybridization approach. A variety of data types can be integrated using hybrid AI models consequently increasing the accuracy of both the predictions and optimization applications observed.

6.3. *Computing Power*

The application of AI in the energy-agriculture nexus necessitates a large amount of computing power, which may be scarce in some areas.

This could be the reason why significant research works relevant to AI use in the energy-agriculture nexus couldn't be found from states in Africa, particularly, and major developing countries. Even though some researches were conducted by authors from these regions, such as [60, 148], the difference is still clear. Development of new computing platforms and the deployment of AI-enabled systems in rural and remote areas is good solution.

6.4. Accountability and Transparency in AI decision-making

The incorporation of AI into the energy-agriculture nexus raises concerns regarding the accountability and transparency of AI decision-making [66,67]. This is crucial given the potential negative effects that AI-driven decisions may have on energy use and food security among others. Involving stakeholders in the development and implementation of AI in the energy-agriculture nexus, including farmers, energy providers, researchers, policymakers, etc., could help ensure that AI solutions are tailored to the specific needs and contexts of the energy-agriculture nexus through their contributions and collaboration, and that they are adopted and used in a way that is beneficial to all stakeholders involved.

6.5. Research Focus

The energy-agriculture nexus has significant social and economic ramifications, which makes it crucial to consider these in order to spread the positives and reduce possible negative effects. Almost all the works observed in this study has little to do with the direct social and economic values of AI in the energy-agriculture nexus, thus indicating a serious challenge and need for much more multifaceted utilization of AI.

7. Conclusion

Artificial intelligence in the energy-agriculture nexus as an entity that needs specific attention for the betterment of the multidisciplinary field of research was observed in this study. An intensive review of literature was successfully conducted with the aim of highlighting the usage, challenges and opportunities provided along the nexus. AI applications in EA nexus provides several challenges and opportunities, which requires a more sophisticated and well defined multidisciplinary approach to modeling and analysis. It will be crucial to enhance research, development, and investment in AI technologies in order to address the gaps and difficulties outlined. By doing this, the development of this area could be encouraged and new possibilities for efficient and sustainable agricultural and energy systems could be further realized.

Future Work

Owing to the rigorous study conducted in this research, some important gaps for further research to address were observed and outlined in the following bullets:

- ***Nexus Definition:*** In recent academic literature, there isn't a logical or widely acknowledged explanation of the energy-agriculture nexus itself. Nevertheless, the available literature on ground acknowledges the relevance of this concept, but there is no agreed-upon definition, which results in differing interpretations and a blurred understanding of the nexus' concept. The creation of a thorough framework that captures the complex interactions, interdependencies, and feedback loops between energy and agriculture ought to be the top priority for future research. Furthermore, a multidisciplinary viewpoint need to be integrated into this framework in order to present a more comprehensive picture of the nexus that takes into account various socioeconomic, environmental, and geographic circumstances. A more specific description will enable a better resource allocation, policy formation, and sustainable development initiatives by facilitating clearer communication.
- ***AI for Agrivoltaics***: Although AI is a relatively new field, its application in agrivoltaics, a crucial component that well defines the energy-agriculture nexus, is noticeably understudied. An interesting area for AI application is agrivoltaics, which entails the co-utilization of agricultural lands for simultaneous crop and solar energy production [149]. The creation and implementation of AI-driven algorithms should be included as a significant focus of future research in order to maximize crop yield, solar energy output, and land use efficiency. Through the utilization of artificial intelligence (AI) methods like machine learning, remote sensing, and predictive analytics, scientists can investigate cooperative strategies that optimize crop yield and renewable energy generation in photovoltaic systems.
- ***Enhancing AI Utilization in Bioenergy***: Although AI is being used extensively in bioenergy, most of the attention is presently directed toward optimizing agriculture for energy generation, ignoring the mutually beneficial correlation wherein agriculture gains from energy generation. Subsequent investigations ought to surpass this unidirectional methodology and examine the bidirectional consequences of artificial intelligence in bioenergy systems. Research should specifically focus on utilizing AI techniques to improve biomass conversion, energy crop selection, and biofuel production efficiency. Adopting AI-driven precision agriculture methods, such as modeling, data analytics, and sensor networks, may maximize bioenergy production while maintaining sustainable farming methods.
- ***Deep Learning Exploration:*** Although AI has come a long way, there is still a lack of academic discourse on its significant application in the EA nexus. The underrepresentation of deep learning approaches makes it more difficult to thoroughly investigate future developments and applications in this field. Future studies should focus on examining the unexplored potential and difficulties related to using deep learning methods. Through investigating neural networks, including convolutional neural networks (CNNs), recurrent neural networks (RNNs), and reinforcement learning, researchers can gain understanding of intricate relationships between agriculture and energy. There is great potential for the sustainable development of the nexus if deep learning is applied to forecast energy consumption, optimize resource allocation, and improve decision-making processes.
- ***Robust AI Algorithms:*** Advanced AI algorithms that can comprehend and integrate a variety of variables, including meteorological patterns, soil composition, crop health indices, and market dynamics, are necessary to address the energy-agriculture nexus. For these algorithms to handle the nexus's challenging complexities, they need to be dynamically adaptive. Computational intelligence approaches (CIA) such as machine learning, optimization, and computational modeling fall under this larger category. As sophisticated tools, CIA systems will be particularly useful for the EA nexus since they can be very effective in comprehending the intricate relationships between agricultural practices and energy systems and optimizing outcomes [150]. Employing these for future research will be a milestone for building stronger EA nexus-based AI systems. Additionally, it will help facilitate thorough analysis and decision-making, offering sophisticated perspectives on better environmentally friendly methods, resource management, and operational effectiveness in the energy and agricultural industries. Models that are dynamically adaptable, as such, are certain to be current and useful in the face of changing market, technological, and environmental conditions [151,152].
- ***Field-Level Implementation Studies:*** To validate AI solutions in actual agricultural and energy environments, field-level implementation studies are essential. The research needs to encompass a range of geographical locations in order to evaluate the scalability and relevance of AI-driven approaches. The identification of implementation barriers, technological challenges, and socio-economic

restrictions is made possible by real-world validation, which in turn facilitates the development of AI applications to achieve optimal performance and smooth integration into a variety of situations.
- ***Longitudinal Studies and Impact Assessment:*** Understanding the effects of AI interventions on the economy, environment, and society requires longitudinal research. These evaluations shed light on the robustness, scalability, and sustainability of AI-driven processes. They provide insight for flexible techniques that allow stakeholders to maximize gains while minimizing unintended consequences. These evaluations also help to enhance AI tactics for longer-lasting benefits and better performance [153].
- ***Ethics from Policy Frameworks:*** To ensure data privacy, algorithmic transparency, and equitable benefit distribution, the energy-agriculture nexus demands particular norms and legal frameworks for the ethical application of AI. Integrating AI technologies seamlessly requires alignment with current policies in both areas. In order to enable responsible use of AI technologies and to ensure that they comply with environmental and sustainability norms, ethical principles and regulatory frameworks should be developed. This will pave the way for the advancement of AI in a way that is open to all, open, and sustainable.

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CRediT authorship contribution statement

Masud Kabir: Conceptualization, Methodology, Writing – original draft. **Sami Ekici:** Methodology, Writing – review & editing.

Declaration of competing interest

The authors declare no conflict of interest.

Data availability

Data sharing not applicable.

Appendix

Table 3

Table 3
General use of literature of AI use along the energy-agriculture nexus.

References	Year	Location	Hybrid methods used	Problems Addressed
Artificial Neural Network (ANN)				
[47]	2017		-	Energy use in lentil crop production and yield modeling
[41]	2012	Spain		Energy prediction modelling for greenhouse integrated PV system
[75]	2021	Algeria	GA	Methane and biogas prediction model from anaerobic digestion
[44]	2014	India	GP	Estimation of higher solid biomass heating values
[77]	2022	China	PSO	Prediction of products for oxidative pyrolysis of biomass
[60]	2022	-	MLR-ANFIS-SVR	Prediction of biomass higher heating value
[50]	2022	Turkiye	-	Forecasting of proton exchange membrane output parameters in torrefied biomass system
[154]	2023	China	SVM-RF-TS	Prediction of cassava's green and blueprint
[52]	2022	-	CFFNN- SVM	Biomass heat capacity prediction
	2023	Brazil	-	Agroeconomic-based process optimization of renewable energy use on farms
[78]	2022	China	PSO	Prediction of energy yield from pinewood dust gasification process
[155]	2016	Thailand	MLP and BP Neural Networks	Energy (steam) prediction from biomass boiler
[156]	2018	Iran	ANFIS	Prediction of agricultural energy use
[157]	2018	India	GA	Forecasting the optimum processing conditions of biomass from green microalga in an integrated system
[158]	2019	Algeria	MLP Neural Network	Prediction of higher heating value of date palm biofuel
[59]	2019	Iran	ANFIS	Output energy prediction for sugarcane production
[46]	2015	Iran	GA	Prediction of power in farm tractors
[62]	2017	Iran	ANFIS	Prediction of energy use in cattle fattening farm
[48]	2019	Pakistan	CD-RA	Optimization of pesticides use and its health hazard prediction for rice farming
[46]	2015	-	GA-LMA	Prediction of energy efficiency in driven wheels of agricultural tractor's based on specific tire parameters
[43]	2014	-	GEP-RA	Energy dissipation modelling in irrigation structures
[51]	2022	Spain	GA	Solar energy prediction for irrigation system
[159]	2020	Iran	CD-RA-SVM-RBF	Comparative analysis of energy use in agriculture
[74]	2016	Iran	GA	Energy use optimization in orange plantation
[70]	2022	China	MARS	Estimation of torrefaction severity index in biomass
Fuzzy Logic				
[143]	2019	Iran	ANFIS	Predicting energy output, environmental and economic indicators for rice processing mill
[59]	2019	Iran	ANN	Output energy prediction for sugarcane production
[60]	2022	-	MLR-ANN-SVR	Prediction of biomass higher heating value
[156]	2018	Iran	ANFIS	Prediction of agricultural energy use
[57]	2017	Mexico	-	Prediction of moisture content in poultry litter and identification of highly significant variables
[62]	2017	Iran	ANN	Prediction of energy use in cattle fattening farm

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Table 3 (*continued*)

References	Year	Location	Hybrid methods used	Problems Addressed
[58]	2022	Turkiye	-	Energy use optimization in chaotic mixing system for humic acid production
Genetic Algorithms				
[75]	2021	Algeria	ANN	Methane and biogas prediction model from anaerobic digestion
[72]	2021	Iran	Multi Objective GA only	Optimization of energy use for sustainable legumes production
[74]	2016	Iran	ANN	Energy use optimization in orange plantation
[51]	2022	Spain	ANN	Solar energy prediction for irrigation system
[46]	2015	Iran	GA	Prediction of power in farm tractors
[73]	2015	Iran	MOGA only	Optimization of energy flow in watermelon production
[44]	2014	India	MLP NN	Estimation of higher solid biomass heating values
[157]	2018	India	ANN	Forecasting the optimum processing conditions of biomass from green microalga in an integrated system
[160]	2008		PSO	Optimization of bioenergy plant's location
[76]	2022	China	Multi Adaptive Improved GA only	AI-based agricultural greenhouse's energy control system
[161]	2022	India	MOGA-PSO	Complex agricultural resource optimization and management model
Machine Learning				
[66,67]	20222023	Canada	Bayesian ML & Gaussian Process Regression	Prediction of operating variable set points for biomass boiler optimization
[45]	2020	-	Linear RA	Estimation of higher heating value in biomass
[148]	2023	-		Biomass growth monitoring in semi-batch cultivation of Chlorella vulgaris
[162]	2022		CNN, Long Short-Term Memory (LSTM) & Gated Recurrent Unit (GRU)	Classification of biomass energy
Support Vector Machine (SVM)				
[154]	2023	China	ANN-RF-TS	Prediction of cassava's green and blueprint
[52]	2022	-	ANN-CFFNN	Biomass heat capacity prediction
[163]	2018	Turkiye	RF	Prediction of biomass gasification products
[159]	2020	Iran	ANN-CD-RA-RBF	Comparative analysis of energy use in agriculture
Support Vector Regression (SVR)				
[49]	2022	Turkiye	SVR only	Prediction of bioenergy potential of several biomass resources
[60]	2022	-	ANN- MLR-ANFIS	Prediction of biomass higher heating value
[65]	2020	Iran	ELM	Estimation of energy use in wheat production
Regression Analysis				
[48]	2019	Pakistan	ANN-CD	Optimization of pesticides use and its health hazard prediction for rice farming
[43]	2014	-	ANN-GEP	Energy dissipation modelling in irrigation structures
[159]	2020	Iran	ANN-CD-SVM-RBF	Comparative analysis of energy use in agriculture
[13]	2020	-	SGD	Estimation of higher heating value in biomass
[60]	2022	-	ANN- SVR-ANFIS	Prediction of biomass higher heating value
[76]	2022	China	ANN	Estimation of torrefaction severity index in biomass
Cobb-Douglas (CD)				
[159]	2020	Iran	ANN-RA-SVM-RBF	Comparative analysis of energy use in agriculture
[48]	2019	Pakistan	ANN	Optimization of pesticides use and its health hazard prediction for rice farming
Gene Expression Programming (GEP)				
[43]	2014	-	ANN-RA	Energy dissipation modelling in irrigation structures
[53]	2022	Korea	-	Energy use prediction in Pig House
Random Forests (RF)				
[154]	2023	China	ANN-SVM-TS	Prediction of cassava's green and blueprint
[163]	2018	Turkiye	SVM	Prediction of biomass gasification products
Particle Swam Optimizer (PSO)				
[78]	2022	China	ANN	Prediction of energy yield from pinewood dust gasification process
[161]	2022	India	MOGA	Complex agricultural resource optimization and management model
[160]	2008		GA	Optimization of bioenergy plant's location
[77]	2022	China	ANN	Prediction of products for oxidative pyrolysis of biomass
Time Series Algorithms (TSA)				
[154]	2023	China	SVM-RF-ANN	Prediction of cassava's green and blueprint
Extreme Learning Machine (ELM)				
[65]	2020	Iran	SVR	Estimation of energy use in wheat production
Radial Basic Function (RBF)				
[159]	2020	Iran	ANN-RA-SVM-CD	Comparative analysis of energy use in agriculture

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