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REVIEW ARTICLE

Artificial intelligence-based solutions for climate change: a review

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Abstract

Climate change is a major threat already causing system damage to urban and natural systems, and inducing global economic losses of over $500 billion. These issues may be partly solved by artificial intelligence because artificial intelligence integrates internet resources to make prompt suggestions based on accurate climate change predictions. Here we review recent research and applications of artificial intelligence in mitigating the adverse effects of climate change, with a focus on energy efficiency, carbon sequestration and storage, weather and renewable energy forecasting, grid management, building design, transportation, precision agriculture, industrial processes, reducing deforestation, and resilient cities. We found that enhancing energy efficiency can significantly contribute to reducing the impact of climate change. Smart manufacturing can reduce energy consumption, waste, and carbon emissions by 30–50% and, in particular, can reduce energy consumption in buildings by 30–50%. About 70% of the global natural gas industry utilizes artificial intelligence technologies to enhance the accuracy and reliability of weather forecasts. Combining smart grids with artificial intelligence can optimize the efficiency of power systems, thereby reducing electricity bills by 10–20%. Intelligent transportation systems can reduce carbon dioxide emissions by approximately 60%. Moreover, the management of natural resources and the design of resilient cities through the application of artificial intelligence can further promote sustainability.

Keywords Artificial intelligence · Climate change · Energy efficiency · Sustainability · Resource management

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Introduction

The carbon dioxide emissions caused by industrial production are leading to climate change, which is currently one of humanity's most severe climate problems. Sea level rise, the increasing frequency of natural disasters, the reduction of crop production capacity, and the loss of biodiversity are closely related to climate change (Shivanna 2022). The widespread use of fossil fuels in manufacturing processes is primarily responsible for the extensive carbon dioxide emissions (Yue and Gao 2018). Therefore, improving energy efficiency, developing green energy, and conserving energy are essential to address climate change. The transition from a society based on fossil fuels to one based on electricity can positively affect ecological protection (Fang et al. 2023; Farghali et al. 2022).

Artificial intelligence can achieve automated discovery, distribution, and transmission operations through deep neural networks, significantly reducing energy consumption (Farghali et al. 2023). As the severity of climate change issues continues to increase, artificial intelligence is often touted as a potential solution for addressing the challenges of climate change. Artificial intelligence technology has the potential to seamlessly integrate the expanding opportunities offered by the internet of things (IoT) and renewable energy within the energy industry. It can play a crucial role in energy supply, optimizing decision-making processes, and autonomous software control, thus serving as a significant driving force in the energy sector. In addition, artificial intelligence has also played an indispensable role in solar radiation modeling, simulation and optimization of renewable energy systems, urban power load forecasting, and urban building heat load forecasting (Al-Othman et al. 2022; Jha et al. 2017; Khosravi et al. 2018; Lyu and Liu 2021; Wang and Srinivasan 2017). Artificial intelligence can aid in mitigating climate change in multiple ways, such as improving the prediction of extreme weather events (McGovern et al. 2017), constructing energy-efficient and green intelligent buildings that collect and sense data while predicting thermal comfort (Ngarambe et al. 2020; Yan et al. 2021), establishing nutrient cycling and crop productivity models to reduce fertilizer usage (Elahi et al. 2019b; Zhang et al. 2021), implementing sustainable forest management practices that are efficient and precise to decrease deforestation (Liu et al. 2021), providing smart waste management systems (Fang et al. 2023), and developing resilient cities (Allam and Dhunny 2019).

Currently, the review of artificial intelligence and climate change primarily focuses on the technical aspects of artificial intelligence, omitting a perspective on how artificial intelligence can be applied in various fields that are impacted by climate change. As illustrated in Fig. 1, this review divides the impact of climate change on human social production and life into eight sections, each of which investigates the use of artificial intelligence in resource management, green energy efficiency, and sustainable development. Furthermore, the future of artificial intelligence's sustainable development in the context of climate change was investigated. In short, artificial intelligence has the potential to transform how we respond to climate change mitigation by providing new tools and insights to assist us in achieving a more sustainable future.

Using artificial intelligence in energy efficiency, carbon sequestration, and storage

Energy efficiency

In contemporary society, energy concerns have emerged as one of the major global issues. As the global economy steadily expands and the population continues to burgeon, there has been an exponential surge in energy demand (Chen et al. 2022b; Osman et al. 2022; Yang et al. 2023). Concurrently, the judicious utilization of energy and the attainment of sustainable development has posed an increasingly momentous challenge (Chen et al. 2023a). In order to meet the mounting energy demand and curb deleterious environmental impact, efficacious measures must be implemented to enhance energy efficiency and abate energy wastage (Cai et al. 2019; Nižetić et al. 2019). Artificial intelligence technology has progressively emerged as a new technological tool in the energy sector, offering novel prospects and challenges for ameliorating energy efficiency and realizing sustainable development (Baysan et al. 2019; Farghali et al. 2023).

In the energy sector, the implementation of artificial intelligence can heighten the efficiency of energy utilization by predicting energy demand, optimizing energy production and consumption, and realizing intelligent control, thus curtailing energy costs, lessening environmental pollution, and fostering sustainable development (Khalilpourazari et al. 2021; Lee and Yoo 2021). As a result, the relationship between artificial intelligence and energy efficiency has emerged as a highly discussed topic in the research community, garnering the interest of numerous scholars and corporations alike (Ahmad et al. 2021; Kumari et al. 2020). Moreover, it is contended that judiciously applying artificial intelligence technology can result in a tangible enhancement of energy efficiency, foster sustainable development, and pave the way for a more promising future for human society. Accordingly, Table 1 presents an analysis of the utilization of artificial intelligence technology in augmenting energy

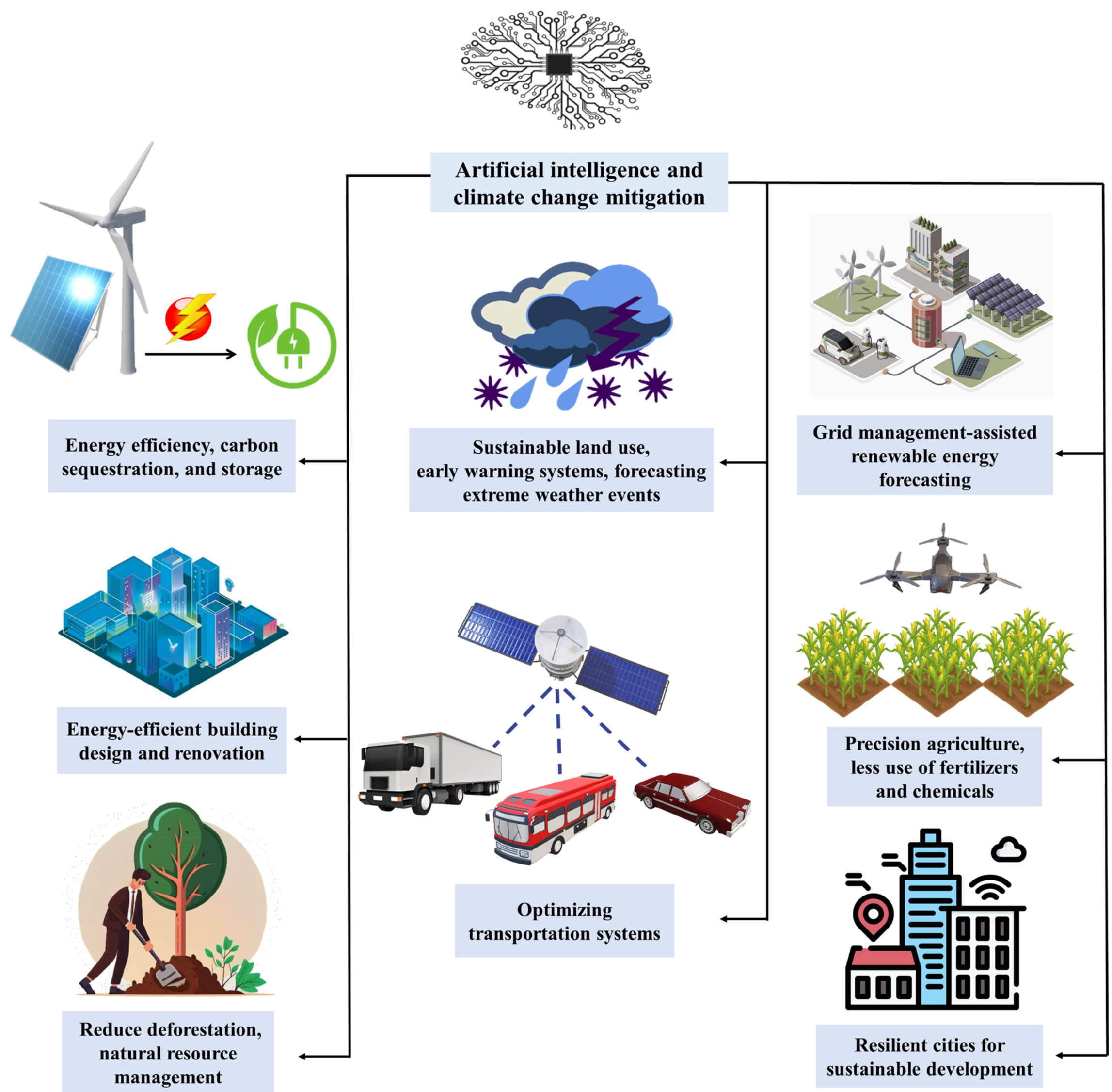

Fig. 1 Utilization of artificial intelligence in reducing the impact of climate change. This figure outlines various artificial intelligence applications in energy efficiency, including carbon sequencing, storage, and renewable energy forecasting. Furthermore, artificial intelligence optimizes transportation systems, precision agriculture, and natural resource management. The technology is also employed in energy-efficient building design and retrofitting, weather forecasting, and industrial process optimization. Consideration is given to the discourse surrounding the implementation of sustainable and resilient urban centers and their potential implications in the upcoming era. The discussion focuses on implementing sustainable and resilient urban development

efficiency, outlining the present status and efficacy of its deployment in the energy sector.

Artificial intelligence has recently revolutionized the energy sector, which has emerged as a revolutionary technological tool offering novel opportunities and challenges for enhancing energy efficiency and accomplishing sustainable development (Ahmed et al. 2022a; Farghali et al. 2023; Yang et al. 2022). A thorough examination outlined in Table 1 has revealed that artificial intelligence has been proficiently employed in various domains of energy efficiency, such as fault detection and diagnosis, thermal comfort prediction and control, demand response, and energy storage optimization. The application of artificial intelligence in these domains has demonstrated promising results in augmenting energy efficiency, reducing energy waste, and fostering sustainable development (Chopra et al. 2022; Fang et al. 2023). However, implementing artificial intelligence in energy efficiency is an ongoing process. Its effectiveness is heavily contingent upon the accuracy of input data and the proper selection of artificial intelligence algorithms (Arumugam et al. 2022; Ouadah et al. 2022).

Table 1 Utilization of artificial intelligence technologies to improve energy efficiency at present

Research project description	Country	Application area	Current status	Effectiveness	Critical findings	References
The convergence of the internet of things and artificial intelligence facilitates energy efficiency	Italy	Energy management systems	Widely used	Highly effective	The investigation exhibits the advantageous potential of the internet of things (IoT) paradigms and machine learning techniques in pursuing self-sufficient energy efficiency. However, it is noteworthy that the outcomes pertain to comparably uncomplicated settings, and further exploration is essential for energy-intensive operations, sizable offices, and other vast infrastructures	Tomazzoli et al. (2020)
The development of artificial intelligence in smart buildings has progressed to enhance energy efficiency	Japan	Energy management systems	Widely used	Highly effective	The paper explores using artificial intelligence technology to optimize building energy systems and minimize energy consumption. Nevertheless, there is a need to enhance the robustness, precision, and dependability of the judicious deployment of artificial intelligence systems in smart buildings	Farzaneh et al. (2021)
Using artificial intelligence to assist with predicting maintenance needs for renewable energy systems	UK	Predictive maintenance	Emerging	Effective	This study highlights the efficacy of artificial intelligence techniques in the predictive maintenance of renewable energy systems and suggests that further experimentation in diverse operational modes is warranted for improvement	Shin et al. (2021)
Artificial intelligence-driven methods for detecting and diagnosing faults in building energy systems	China	Fault detection and diagnosis	Emerging	Effective	This research thoroughly examines fault detection and diagnosis techniques for building energy systems that rely on artificial intelligence. However, further investigation is still needed into these systems' efficacy, efficiency, scalability, and dependability in real-world scenarios	Zhao et al. (2019)

Table 1 (continued)

Research project description	Country	Application area	Current status	Effectiveness	Critical findings	References
The convergence of artificial intelligence and building energy efficiency	China	Building automation and control	Emerging	Effective	The present study explores using artificial intelligence-based technology to enhance building energy efficiency. Artificial intelligence constitutes a practical approach toward achieving zero energy in buildings, and further research in this domain is imperative	Yan et al. (2021)
The employment of artificial intelligence techniques in forecasting indoor thermal comfort in buildings	South Korea	Occupancy and comfort control	Emerging	Effective	The present study demonstrates the potential effectiveness of artificial intelligence-based technology in regulating thermal comfort in buildings, but its economic viability warrants further investigation	Ngarambe et al. (2020)
The application of artificial intelligence in the economic evaluation of energy efficiency and renewable energy technologies	India	Renewable energy integration	Emerging	Promising	The study introduces an effective evaluation model based on artificial intelligence that can be utilized for predicting energy efficiency and conservation. The proposed model exhibits a significant energy efficiency rate of around 97.32%	Chen et al. (2021)
A system for residential demand response that utilizes artificial intelligence technology is discussed in this study	Spain	Demand response	Emerging	Promising	The study highlights the potential of artificial intelligence-based demand response systems in residential buildings but suggests further investigating its applicability in other building types	Esnaola-Gonzalez et al. (2021)
Artificial intelligence is used to anticipate, enhance, and manage thermal energy storage systems	United Arab Emirates	Energy storage management	Emerging	Promising	According to research, using artificial intelligence methods in thermal energy storage systems is an ongoing process. However, the accuracy of artificial intelligence largely depends on the quality of input data, which remains a major limitation	Olabi et al. (2023)

The table examines research conducted in various nations on the role of technologies driven by artificial intelligence in enhancing energy efficiency. According to the data in the table, artificial intelligence has been utilized effectively in various ways to improve energy efficiency. This includes fault detection and diagnosis, thermal comfort prediction and control, demand response, and energy storage optimization. The table also illustrates the barriers to adopting artificial intelligence technologies in the energy sector

According to the findings presented in Table 1, research conducted in Italy and Japan suggests that using artificial intelligence technologies in energy management systems has been widespread and has resulted in favorable outcomes. Similarly, the research conducted in the UK suggests that while the use of artificial intelligence in predictive maintenance is still in its early stages, it has demonstrated good effectiveness. Moreover, in other countries, such as China and India, artificial intelligence is used for fault detection and diagnosis and in integrating renewable energy and demand response. Overall, the analysis presented in Table 1 suggests that most of the applications of artificial intelligence in various aspects of energy efficiency are still in their nascent stages, and their effectiveness needs further investigation. Thus, there is a need to conduct further research to assess the efficacy of these applications.

Some scholars contend that the exorbitant cost of artificial intelligence technology is a major obstacle to its application in energy efficiency (Enholm et al. 2022; Yang 2022; Zhao et al. 2022). This is because the creation and implementation of artificial intelligence-based systems necessitate significant investment, which may exceed the financial capacity of specific organizations (Ahmed et al. 2022b). Additionally, the scarcity of data and proficient experts in artificial intelligence presents a significant challenge to its widespread implementation in energy efficiency (Chai et al. 2022). Nonetheless, despite these obstacles, it is expected that the utilization of artificial intelligence technologies in energy efficiency will increase, driven by the burgeoning need to reduce energy consumption, mitigate environmental impact, and achieve sustainable development.

This section thoroughly examines using artificial intelligence-based technologies to enhance energy efficiency. The findings demonstrate that artificial intelligence is a powerful tool that enhances energy efficiency and promotes sustainable development. Artificial intelligence has demonstrated efficacy in numerous areas, although its potential requires further evaluation. The scarcity of expertise and financial constraints hinder its widespread adoption. Nonetheless, the future holds promise for increased utilization of artificial intelligence in energy efficiency.

Carbon sequestration and storage

Carbon sequestration and storage are pivotal elements of climate change mitigation strategies (Liu et al. 2022b; Osman et al. 2022; Yang et al. 2022, 2023). The application of artificial intelligence in this field can significantly augment the efficiency and effectiveness of these processes (Cheong et al. 2022; Kaack et al. 2022). Artificial intelligence-based technologies can be harnessed to discern appropriate geological formations for carbon storage and prognosticate the behavior of carbon dioxide after it is introduced into storage sites (Abdalla et al. 2021). Furthermore, artificial intelligence can optimize the injection procedure and monitor storage sites to ensure carbon dioxide is securely trapped underground (Li et al. 2021). Artificial intelligence can also expedite the development of novel and ingenious carbon sequestration approaches, such as mineral carbonation, which converts carbon dioxide into stable minerals (Ding et al. 2022).

In summary, incorporating artificial intelligence in carbon sequestration and storage can promote climate objectives and sustainable development. Figure 2 depicts the sequential phases of incorporating artificial intelligence technology in carbon sequestration and storage and its capacity to facilitate the realization of climate goals and sustainable development. By leveraging artificial intelligence, it is feasible to reduce greenhouse gas emissions and alleviate the impacts of climate change, expediting the attainment of carbon neutrality.

In recent years, the utilization of artificial intelligence in carbon sequestration and storage has increased significantly (Qerimi and Sergi 2022). As depicted in Fig. 2, artificial intelligence has the potential to enhance the efficiency and efficacy of these processes by identifying appropriate geological formations for carbon storage (Jin et al. 2022), predicting the behavior of carbon dioxide once it is introduced into the storage sites (Chinh Nguyen et al. 2022), optimizing the injection process (Elsheikh et al. 2022), monitoring storage sites (Kishor and Chakraborty 2022), and devising new and innovative carbon sequestration methods (Gupta and Li 2022). Moreover, artificial intelligence can aid in accomplishing sustainability objectives and achieving carbon neutrality by reducing greenhouse gas emissions and mitigating climate change (Jahanger et al. 2023; Sahil et al. 2023). Therefore, one of the advantages of artificial intelligence technology in carbon sequestration and storage is its capacity to analyze vast amounts of geological and engineering data to locate appropriate storage sites and optimize the injection process (Yao et al. 2023). Additionally, artificial intelligence can anticipate the behavior of carbon dioxide in storage sites and monitor the site to ensure the permanent trapping of the gas underground (Kushwaha et al. 2023). Another strength is its ability to develop new and innovative carbon storage methods, such as driving the development of promising materials for sustainable carbon dioxide management (Zhang et al. 2022).

Integrating artificial intelligence in carbon sequestration and storage encounters various impediments (Hasan et al. 2022). Among them, the financial expenses required for implementation (Heo et al. 2022) and a lack of expertise in the field (Ahmad et al. 2022) pose significant obstacles. Moreover, ethical and regulatory concerns may arise in monitoring and managing carbon storage sites through the use of artificial intelligence (Swennenhuis et al. 2022), and careful attention must be given to ensure that the technology does not cause any detrimental environmental impacts or

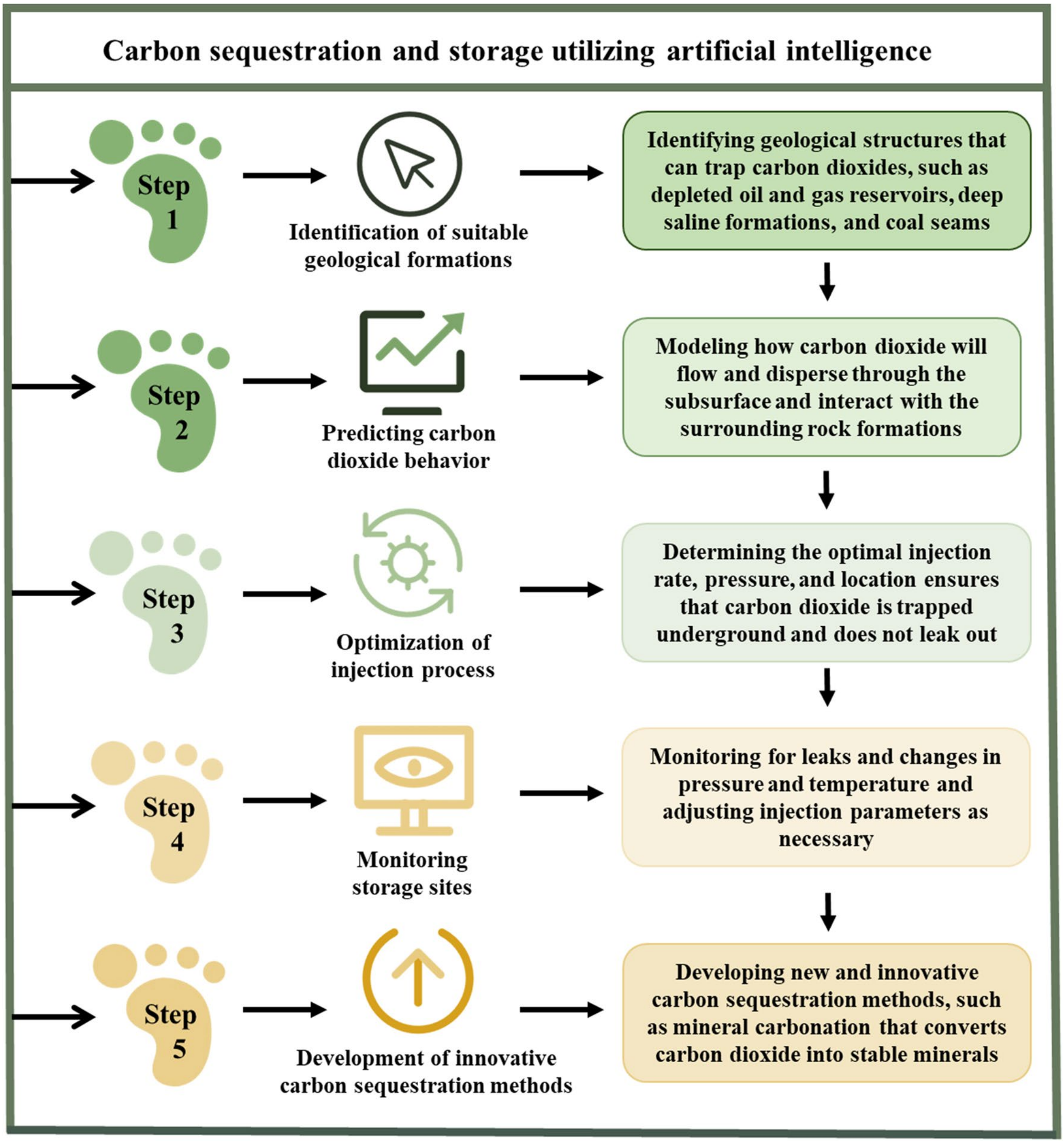

Fig. 2 Carbon sequestration and storage utilizing artificial intelligence. Five distinct phases are depicted in the figure above for incorporating artificial intelligence into carbon sequestration and storage. It also highlights artificial intelligence's critical role in achieving climate goals and promoting sustainable development. The illustration depicts the use of artificial intelligence in the analysis of geological data to identify suitable formations for carbon storage and in predicting the behavior of carbon dioxide upon injection at storage sites. In addition, it demonstrates how artificial intelligence can improve the efficiency of the injection process to maximize carbon storage while ensuring the security of underground carbon dioxide sequestration through site monitoring. Moreover, artificial intelligence can accelerate the development of pioneering carbon storage techniques

unintended consequences (Delanoë et al. 2023). However, as technology advances and becomes more accessible in the future (Liu et al. 2022c), the usage of artificial intelligence in carbon sequestration and storage is anticipated to increase. Therefore, ensuring that artificial intelligence technology is implemented ethically and responsibly is crucial, aiming to achieve sustainability goals and carbon neutrality. Moreover, further research and development must address the challenges of using artificial intelligence in carbon sequestration and storage and capitalize on the technology's potential benefits.

To sum up, integrating artificial intelligence in carbon sequestration and storage can significantly augment the efficacy and potency of these processes, facilitate the attainment of climate objectives, and promote sustainable growth. This technology can be employed to discern appropriate geological formations for carbon storage, anticipate the behavior of carbon dioxide, optimize the injection process, oversee storage sites, and generate fresh and inventive carbon sequestration techniques. Nevertheless, the application of artificial intelligence in this realm also encounters obstacles such as financial expenditure, dearth of expertise, ethical and regulatory quandaries, and plausible adverse environmental effects.

Using artificial intelligence in weather forecasting

Severe weather occurrences such as tornadoes, hail, and thunderstorms can cause significant damage to infrastructure and human settlements, resulting in financial losses and posing a severe threat to public safety. Improved observational and calculation techniques have contributed to a reduced risk of loss of life and damage from the effects of climate change. Despite a scientific consensus on the fundamental aspects of climate change, accurately predicting results remains challenging due to the intricate nature of earth system models and the inherent uncertainty surrounding climate change (Bonan and Doney 2018). Artificial intelligence's data processing and collection capabilities significantly improve the gap between digital model predictions and real situations, achieving more accurate predictions of future results (McGovern et al. 2017).

The large amount of data provided by observation satellites and the complexity of climate models have made artificial intelligence increasingly crucial in weather forecasting. Artificial intelligence is widely used to search for all information and discover new climate models, thereby reducing prediction bias and improving accuracy (Jones 2017). Gradually more professionals are paying attention to the potential of artificial intelligence in weather forecasting. Hsiang et al. (2017) predicted the effects of climate change on the economy in the USA using data from six economic sectors on short-term weather changes. Introducing artificial intelligence will better assist relevant departments in modeling data and predicting the effects of weather change on the economy. In short, combining artificial intelligence and numerical climate simulation data can effectively fill the data gaps in observations, reducing uncertainty and bias in climate prediction (Kadow et al. 2020). Table 2 demonstrates the application of artificial intelligence in weather forecasting.

More precise meteorological models can be created by analyzing many historical and present weather data using machine learning algorithms. These models can help predict several climatic characteristics, such as temperature, precipitation, and wind speed. By contrasting three models—deep neural network, time convolution neural network, and short-term memory neural network—with support vector machine, random model, and empirical equation, Chen et al. (2020b) calculated daily evapotranspiration in the Northeast China Plain of China. Zhang et al. (2019a) found that distributed lagged nonlinear models outperform cross-correlation functions in predicting variable selection and determining lag effects. In contrast, machine learning methods predict standardized precipitation evapotranspiration indices more accurately than nonlinear models using artificial neural networks.

The impact of solar activity on climate change, particularly concerning droughts and floods, is significant. To improve solar activity's early detection and warning capabilities, researchers such as Jiang et al. (2023) have turned to artificial intelligence. Specifically, they have employed three-dimensional recognition techniques to identify meteorological and ecological drought events, followed by the extraction of propagating drought events using spatiotemporal overlap rules. Machine learning models and the C-vine copula are combined to compute the propagation probability. Artificial intelligence-based solar energy forecast models were the subject of classification research by Wang et al. (2020). Pham et al. (2020) gathered the highest temperature, lowest temperature, wind speed, relative humidity, solar radiation, and other meteorological characteristics. The fuzzy reasoning system based on an adaptive network forecasts rainfall using support vector machines, artificial neural networks, and particle swarm optimization.

The use of artificial intelligence contributes to reducing forecast uncertainty and speeding up prediction execution. Artificial intelligence can detect geographic variables complex for humans, establishing more accurate climate models. Mostajabi et al. (2019) used station-level air pressure, temperature, relative humidity, and temperature to construct a machine learning model to forecast the occurrence of lightning. Convolutional neural networks were used by Duan et al. (2021) to propose a data-driven model that reconstructs radar reflectivity using deep learning and RR using Himawari-8 radiation data. Deep learning is used by Pullman et al. (2019) to identify infrared brightness temperature and other hail-related parameters for hail detection. In a study published in 2021, Adikari et al. (2021) compared the predictive abilities of wavelet decomposition function, convolutional neural network, short-term memory network, and adaptive neuro-fuzzy inference system in flood and drought.

Satellites can obtain massive amounts of land resource information at different periods through artificial intelligence to compare these data can improve the efficiency of spatial land planning and enhance the rationality and feasibility of planning schemes. López Santos et al. (2019) studied the critical variables of artificial neural case studies in sustainable land management. They found through random abstraction of orchards that the yield of orchards depends

Table 2 Weather forecasting incorporating artificial intelligence

Regional scope	Particular year	Data time	Prediction content	Method	References
The whole world	2019	1901–2016	Average temperature	Using deep neural networks for top-down climate prediction	Ise and Oba (2019)
The whole world	2019	1984–2017	El niño-southern oscillation	Establishing a statistical prediction model using deep learning methods to predict el niño-southern oscillation with a lead time exceeding one and a half years	Ham et al. (2019)
The whole world	2020	2010–2019	Tropical instability wave	Using a data-driven model based on deep learning to predict the spatiotemporal changes in sea level temperature related to unstable tropical waves	Zheng et al. (2020)
Malaysia, Terengganu	2021	1985–2019	Rainfall	constructing and contrasting regression models using neural networks, decision trees, Bayesian linear models, and decision forests to predict rainfall	Ridwan et al. (2021)
Seoul, South Korea	2018	1994–2015	Torrential rain	Use machine learning with prediction performance higher than the regression model to open the function of predicting rainstorm damage in advance	Choi et al. (2018)
Shaanxi, China	2020	1961–2016	Drought	Compare the cross-correlation function with the distributed lag nonlinear model to determine the optimum prediction variable and the lag period. Create a distributed lag nonlinear model, an artificial neural network model, and machine learning software to estimate the standardized water evaporation index	Zhang et al. (2019a)
Switzerland	2019	2006–2017	Lightning	A four-parameter model was created based on four frequently used surface meteorological variables—station-level air pressure, temperature, relative humidity, and wind speed. Use data validation from the lightning location system to confirm the generated alert	Mostajabi et al. (2019)
Taiwan, China	2020	1965–2019	Typhoon	Digitize the path of typhoons before and after landfall using artificial intelligence methods and combine it with hydrological and geographic features for prediction	Chang et al. (2020)
Poland	2019	2008–2017	Hail	Building a machine learning model driven by radar reflectivity, remote sensing data, and environmental variables to predict hail	Czernecki et al. (2019)
Shaanxi, China	2023	1982–2020	Drought	Employing three-dimensional identification approaches to recognize biological and meteorological drought events, extracting the propagating drought events based on certain spatiotemporal overlap rules, and computing the propagation probability by fusing machine learning models and C-vine copula	Jiang et al. (2023); Pham et al. (2020)

Using artificial intelligence, meteorological models can be developed for temperature fluctuations, drought, hail, and typhoons. Predicting and forewarning extreme weather conditions can aid in establishing adaptation and mitigation procedures to reduce the resulting damage. The application of artificial intelligence reduces the execution time of predictions and the uncertainty associated with them. As more data is analyzed, the accuracy of artificial intelligence in weather forecasting will increase on the physical planting conditions, the ability to utilize climate, and the level of understanding of crops of fruit farmers. Using the cellular automata model of an artificial neural network, Saputra and Lee (2019) selected the height, slope, aspect, distance, and soil type as parameters to simulate and predict the change in land use and land cover in Sumatra.

Artificial intelligence is more intelligent and automated in land classification, allowing for global zoning and decision-making. Besides, artificial intelligence has improved soil functionality and land use sustainability. AlDousari et al. (2022) employed support vector machines and artificial neural networks to assess and forecast changes in Kuwait's land usage and cover. Combining a linear regression technique and an artificial neural network, Ebrahimi et al. (2019) assessed various subsurface soil parameters from diverse land use efficiencies and projected soil respiration using detailed soil data. Nguyen et al. (2021) investigated a technique for openly accessing existing data and Sentinel-2 satellite photos through machine learning algorithms. Then they utilized land use maps to examine how changes in land use affect sustainable development using local and global indicators.

In summary, weather forecasting is a data issue. The accuracy of artificial intelligence in weather forecasting will continue to improve as the amount of analyzed data increases. The increase in accuracy and timeliness of weather forecasting can help reduce the occurrence of weather disasters and improve land use efficiency.

Potential of artificial intelligence-assisted renewable energy forecasting and grid management

The expansion of the global population and economy has led to an increase in energy use. Although with technological advances and energy efficiency legislation, the efficiency of energy end-use services has gradually increased. However, this improvement is not always enough to offset increased demand for energy services, such as commodity production and consumption. Farghali et al. (2023) mentioned that global energy-related carbon emissions reached alarming levels in 2021 and rebounded to the second-highest annual growth rate in history. Chatterjee and Dethlefs (2022) applied that traditional energy sources affected the environment, leading to difficulties such as acid rain, greenhouse effects, and ozone depletion. Sustainable green energy, such as wind and solar, can replace traditional energy to reduce carbon emissions. As a result, the share of renewable energy in global power generation jumped from 27% in 2019 to 29% in 2020. Renewable energy generation grow by more than 8% in 2021, the fastest year-on-year increase since the 1970s. Solar and wind contribute two-thirds of the growth in renewable energy. Hannan et al. (2021) found that overall renewable energy production should increase the share of renewable energy in electricity generation structures to a record 30% in 2021.

There are many challenges to renewable energy production, such as land and human resource waste due to inappropriate site selection, security risks due to poor layout, and the intermittent impact of renewable energy production on the grid. Intermittent production is the primary issue of renewable energy. The time and extent of electricity generated by commonly used renewable sources are not controlled. The power generated by tradition can be manually adjusted by the power required for the load, while the output power of green energy is uncontrollable. The power generated by renewable energy sources usually depends on solar radiation, wind, and other factors. Alassery et al. (2022) applied the difference between the output power of green energy and the power required for the load can lead to power outages or excessive energy output, resulting in a waste of energy.

Artificial intelligence can help promote the broader adoption of renewable energy worldwide. Artificial intelligence is a powerful tool for solving the complexity of global energy transformation, improving system efficiency, and reducing costs. Bahaloo et al. (2022) mentioned that the digitization of oil and gas was well documented, with almost all energy majors adopting artificial intelligence, machine learning, and other innovative technologies to improve operations. Artificial intelligence can also be used in wind, solar, and other green energy projects to increase efficiency through greater automation. Liu et al. (2022c) applied that as energy companies looked to digitize operations to a greater extent, artificial intelligence play a leading role in energy transformation in the future. Because solar and wind have high randomness, low predictability, and intermittent characteristics, using intelligent technology for renewable energy scheduling, management, and optimization can stabilize the grid power and ensure the grid supply security, as shown in Fig. 3.

In the early planning phase, artificial intelligence can better generate renewable energy locally by planning and siting. Artificial intelligence uses geographic information systems to select suitable places to produce renewable energy. Artificial intelligence determines the most convenient address based on a comprehensive topography analysis, climate, land use, and other factors. In site selection, there is no need for renewable energy leaders to visit the local area. Artificial intelligence can assist investors in determining the risk level of new green energy projects, predicting the energy production of various renewable energy sources under different conditions, and anticipating energy demand in different locations at different times of the day through neural modeling analysis. An et al. (2023) demonstrated the use of artificial intelligence in determining the optimal location for a solar

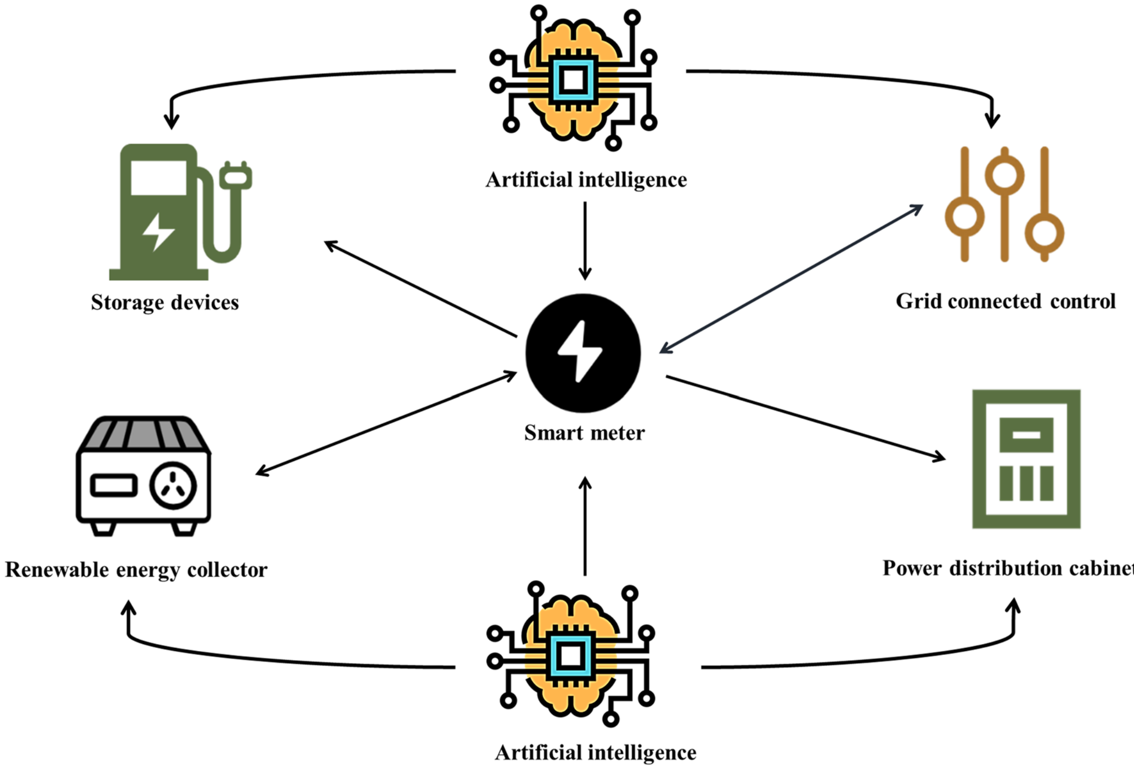

Fig. 3 Technology's role in managing renewable energy sources and the power grid using artificial intelligence. This figure shows how artificial intelligence connects the power grid, renewable energy collectors, and power distribution cabinets used by residents. The figure shows that artificial intelligence can timely adjust and control each part's input and output power by controlling the smart meter. This figure illustrates how artificial intelligence is used in today's energy networks. In addition, this figure shows how artificial intelligence can better ensure normal electricity use by using smart meters to take information to control the charging and discharging of electrical storage devices

farm based on the time and intensity of the sun, assisting operators in site layout planning, and controlling solar panels to rotate toward the sun throughout the day for maximum sunlight capture when generating electricity through solar energy.

Artificial intelligence minimizes operational costs by identifying faults at an early stage. Shin et al. (2021) applied that the impact of a failure in the renewable energy industry may be disproportionate compared to other machinery industries. For example, when a wind power plant's main components are damaged late, significant elements must be manufactured and transported. High requirements for customization and complicated installation will make the wind turbine shut down for several months, so in addition to maintenance costs, there will be a considerable loss of revenue. Bode et al. (2020) mentioned that artificial intelligence-assisted methods had attracted attention. Artificial intelligence uses neural network learning methods to input historical and real-time data into artificial intelligence models for comparison. Heo et al. (2022) mentioned that if data is abnormal, artificial intelligence will provide diagnostic advice to the human inspector to help the artificial intelligence make the final decision. This help is expected to lead to better predictive maintenance by overcoming several limitations of manual inspection, such as the fatigue and variability of inspectors.

Artificial intelligence's prediction and management of power characteristics can often be divided into power generation and demand forecasting. Bendaoud et al. (2022) stated that when people need power generation forecasting, artificial intelligence is often used to combine multiple meteorological models to improve the accuracy of sustainable energy forecasts. For example, the Thomas Institute, in conjunction with the National Renewable Energy Laboratory of the USA, has developed a model that includes a variety of weather parameters and imports a large amount of historical data for artificial intelligence learning. Boza and Evgeniou (2021) compared with a meteorological model with only one parameter, the prediction accuracy of solar energy is more than 30% higher. The UK's national grid power system operators also use artificial intelligence to improve renewable generation forecasts. The carrier provides a system based on about 80 input variables and improved solar forecasting by 33%. Wind power can also create models for learning the information used in weather forecasting. This model increases the value of wind power and reduces the risk and loss of machines from storms through intelligent regulation.

As with power generation forecasting, demand forecasting is essential to balance the grid. Wang et al. (2019) mentioned that the global deployment of smart meters has significantly increased available data related to power consumption, providing a database for artificial intelligence to build predictive models. Artificial intelligence makes an overall linear and nonlinear energy demand prediction model through artificial neural networks. General linear models are more effective than nonlinear energy demand forecasting models for large, geographically divided environments. Saxena et al. (2019) mentioned that nonlinear energy demand forecasting models perform better in smart cities, especially in complex environments with increasingly small geographic/market-scale forecasts. In the study, the nonlinear energy demand prediction model accurately predicted 40 days of 57 peak load days at a university in the USA, with predictions of up to one percent accuracy, and estimated that a university in the USA could save about 80,000 dollars over a 1-year test period. It also demonstrates the potential of artificial intelligence to deliver economic benefits in demand forecasting.

Guo et al. (2023) analyzed that grid frequencies play a central role in grid control because they reflect the power generation and demand balance. The excess power supply can increase frequencies, while shortages lead to lower frequencies. Large frequency deviations correspond to large power imbalances, threatening system stability and leading to large-scale power outages. Artificial intelligence system significantly affects the temporary problem of the intelligent grid, combined with information, digitization, innovative operation mechanism, operation mode, and realizing practical analysis. Nawaz et al. (2021) mentioned that artificial intelligence relies on the analogy and learning of many training samples to form the knowledge of grid stability evaluation to make online discrimination of grid safety level. People analyzed the complex mechanism of the power system involves many factors affecting electromagnetic and electromechanical transient processes, reaching hundreds of nodes in the test system alone. Artificial intelligence has advantages over traditional machine learning in solving complex problems with multiple factors and unknown mechanisms.

Kruse et al. (2021) stated that artificial intelligence helps people generate renewable energy and reduce carbon emissions, but it still has significant challenges as a new technology. To efficiently manage new sample data that is constantly generated in the power system's operation, strengthen the power system's stability analysis based on artificial intelligence. There is a need for timely disaggregation of the latest data. It takes much time and can cause learning to lag behind data updates. Artificial intelligence requires more historical data than traditional time domain simulation and reverse trajectory techniques. Xu and Yin (2015) built a learning model that selects/extracts critical features in the grid, reduces spatial input dimensions, eliminates redundant components, and improves predictive efficiency.

In conclusion, artificial intelligence's potential for renewable energy has been proved, and artificial intelligence helps people to locate renewable energy sources and prevent facilities from failing. Because of the uncontrollability of renewable energy production, too much electricity will be wasted, and too little electricity will affect people's regular use. Artificial intelligence coordinates grids by predicting renewable energy production to reduce energy waste. The initiative of artificial intelligence to help power grid operators has been recognized in many regions and has created some resource benefits.

Feasibility of artificial intelligence in energy-efficient building design and retrofitting

Integrating artificial intelligence in building energy-efficient design and retrofitting is a rapidly developing field with tremendous promise for reducing energy consumption and carbon emissions in the built environment (Moraliyage et al. 2022; Tian et al. 2021). By leveraging the power of advanced algorithms, artificial intelligence can analyze copious amounts of data, including energy usage patterns, building occupancy, weather conditions, and other relevant factors that impact building energy consumption (Kim et al. 2020). Subsequently, this analysis can inform the development of predictive models that optimize building performance by adjusting heating and cooling systems, lighting, and other building systems, thereby minimizing energy waste (Chen et al. 2023b; Dong et al. 2021). Furthermore, artificial intelligence can also be utilized to design new buildings that are inherently more energy-efficient by leveraging advanced modeling and simulation tools (Baduge et al. 2022). By optimizing building orientation, window placement, insulation, and other design elements, architects and engineers can create energy-efficient and comfortable buildings for occupants (Debrah et al. 2022).

In addition to optimizing new buildings, artificial intelligence can be leveraged to retrofit existing buildings and improve their energy efficiency (Konhäuser et al. 2022). Artificial intelligence-powered retrofitting involves analyzing building data and identifying areas where energy efficiency can be improved, such as upgrading insulation, installing efficient lighting, or replacing outdated heating, ventilation, and air conditioning systems (Chan et al. 2022). Therefore, artificial intelligence-powered energy-efficient building design and retrofitting have the potential to significantly reduce energy consumption and carbon emissions in the built environment. Although there are challenges to implementing these technologies, such as the need for accurate data and the cost of implementing new systems, the benefits are evident, making this a promising area for future research and development.

The integration of artificial intelligence in energy-efficient building design and retrofitting has the potential to revolutionize the construction and operation of buildings, leading to substantial reductions in energy consumption and greenhouse gas emissions (Zhang et al. 2023). By analyzing data on occupancy, weather conditions, and other factors, buildings can be optimized to minimize energy waste while ensuring occupant comfort, resulting in significant cost savings for building owners and operators and a more sustainable built environment. Figure 4 demonstrates how artificial intelligence can be utilized to analyze massive amounts of data and optimize various aspects of buildings, including heating, ventilation, air conditioning, lighting control, building envelope optimization, renewable energy integration, energy modeling, and predictive maintenance. For instance, artificial intelligence algorithms can adjust heating, ventilation, air conditioning, and lighting systems to reduce energy waste based on data analysis of occupancy rates and weather conditions (Chen et al. 2022a). Additionally, artificial intelligence technology can assist in designing building maintenance structures by analyzing data on building orientation and weather conditions, among other factors (Huseien and Shah 2022). Artificial intelligence technology can also aid in integrating renewable energy sources into buildings to reduce reliance on non-renewable resources (Al-Othman et al. 2022). Moreover, by detecting maintenance

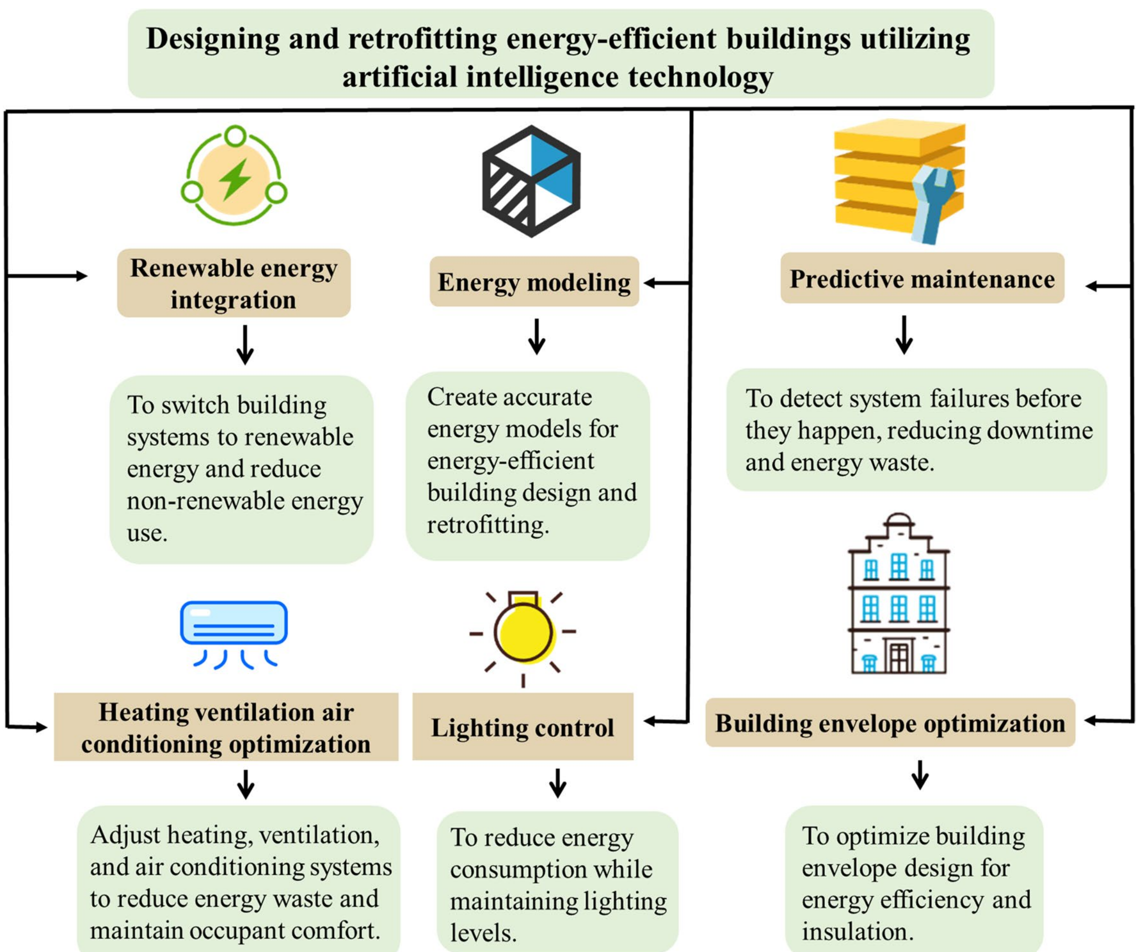

Fig. 4 Designing and retrofitting energy-efficient buildings utilizing artificial intelligence technology. The illustration shows the use of artificial intelligence technologies to increase the efficiency of heating, ventilation, and air conditioning systems, regulate lighting, optimize building envelopes, incorporate renewable energy sources, simulate energy consumption, and predict maintenance needs within buildings. The figure also effectively illustrates the potential for artificial intelligence technology to offer pragmatic optimization solutions by analyzing building data, reducing energy consumption, and improving occupant comfort. In addition, the figure illustrates the potential for artificial intelligence technology to predict building system maintenance requirements

needs before the building's operational systems fail, artificial intelligence technology can prevent downtime and ensure the continuous operation of buildings (Javaid et al. 2022).

Moreover, studies indicate that utilizing artificial intelligence in energy-efficient building design and retrofitting offers many advantages, including rapidly and precisely analyzing vast quantities of data (Ma et al. 2023). This enables artificial intelligence algorithms to identify energy optimization opportunities that might elude human analysts. For instance, artificial intelligence can pinpoint energy usage patterns imperceptible to the human eye, enabling building operators to make modifications that can result in significant energy savings (Mhlanga 2023). In addition, artificial intelligence's capacity to generate more accurate energy models of buildings can inform decisions regarding design and retrofitting (Saheb et al. 2022). Another benefit of incorporating artificial intelligence in energy-efficient building design and retrofitting is the ability to continuously monitor and adjust building systems in real time (Felius et al. 2020). This can result in enhanced energy performance over the building's lifespan. Artificial intelligence algorithms can tweak building systems to adapt to occupancy patterns, weather conditions, and other factors. It also allows for predictive maintenance of building systems, mitigating downtime and preventing energy waste caused by poorly functioning systems (Lee et al. 2019).

To conclude, the section mentioned above highlights that using artificial intelligence-powered energy-efficient building design and retrofitting presents a tremendous opportunity for mitigating energy consumption and carbon emissions in the built environment. Using artificial intelligence algorithms to optimize building systems and design, buildings can be more energy-efficient while ensuring occupants' comfort. The continued research and development in this domain are expected to give rise to novel and pioneering applications, further amplifying the potential for energy conservation and sustainability in the built environment.

Role of artificial intelligence in optimizing transportation systems for reducing greenhouse gas emissions

The transport sector contributes to greenhouse gas emissions, constituting almost one-third of worldwide emissions (Solaymani 2019). As the globe confronts climate change challenges, decreasing transportation emissions has become a top priority (Li and Yu 2019). Using artificial intelligence to enhance transportation systems and diminish carbon footprint presents a promising solution (Fatemidokht et al. 2021). Artificial intelligence can revamp transportation systems by refining routes, managing fleets, developing self-governing vehicles, optimizing public transit, and regulating demand (Abduljabbar et al. 2019). Using extensive data on traffic patterns, passenger demand, and weather conditions, artificial intelligence algorithms can identify opportunities to curtail emissions and augment efficiency in transportation systems. This can result in substantial cost savings, as well as a decline in greenhouse gas emissions and a more sustainable transportation sector. Hence, Fig. 5 displays the various ways in which artificial intelligence can be employed to optimize transportation systems and decrease their carbon footprint, along with the potential benefits and challenges of implementing these solutions.

Artificial intelligence technology is extensively utilized in transport systems. As per Fig. 5, artificial intelligence can be applied to refine transportation routes based on various factors, such as traffic patterns, road conditions, and weather (Chavhan et al. 2020). This can lead to reduced travel times, improved fuel efficiency, and reduced emissions. Furthermore, artificial intelligence can also be employed to manage vehicle fleets more efficiently, which includes optimizing maintenance schedules and fueling (Alexandru et al. 2022). Using predictive analytics to anticipate maintenance needs and plan refueling stops, transportation systems can minimize downtime and lessen fuel consumption. Developing self-governing vehicles presents the potential to significantly reduce emissions by refining fuel efficiency and decreasing traffic congestion (Tyagi and Aswathy 2021). Artificial intelligence algorithms can be utilized to control autonomous vehicles, refining their performance and decreasing energy consumption.

Furthermore, artificial intelligence can also be utilized to refine public transit systems, which includes scheduling and route planning (Nikitas et al. 2020). By utilizing data on passenger demand and traffic patterns, transit systems can refine efficiency and reduce emissions by diminishing empty buses or trains and optimizing routes. Ultimately, artificial intelligence can also be utilized in public transit systems, including incentivizing users to transition to lower-emission modes of transportation, such as public transit or electric vehicles (Olayode et al. 2020). Using data on user behavior and preferences, transportation systems can promote the adoption of more sustainable transportation modes.

Despite the potential benefits of artificial intelligence technologies in optimizing transport systems to reduce carbon emissions and advance early carbon neutrality in the transport industry, some challenges are still associated with these technologies. The utilization of artificial intelligence technologies in transportation systems hinges on the aggregation and interpretation of vast amounts of data, including personal data about users. Ensuring the confidentiality and security of this data is crucial to establish trust in these systems and forestall any potential misuse or exploitation. Moreover, implementing artificial intelligence technologies necessitates considerable investment in infrastructure and

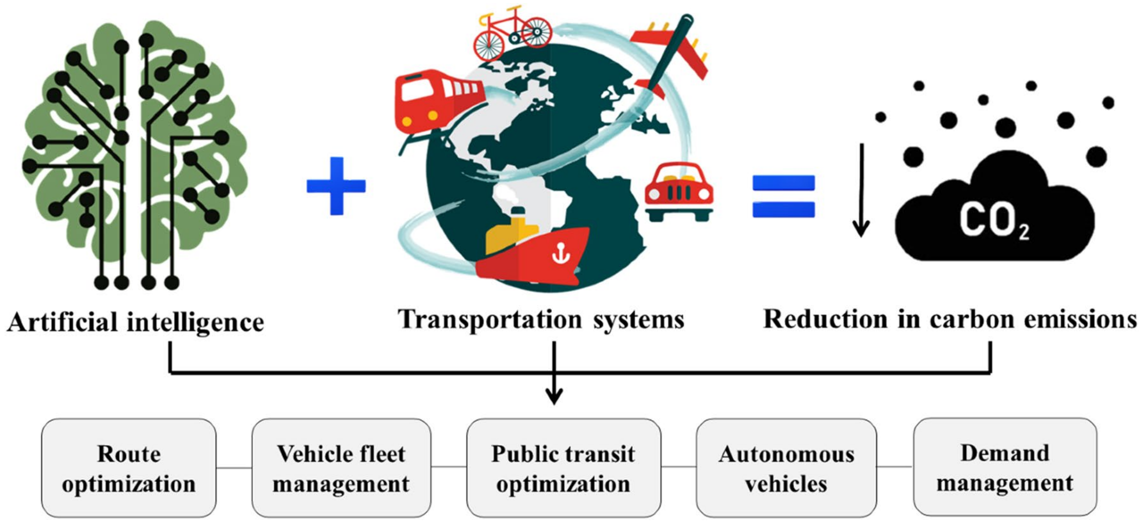

Fig. 5 Importance of artificial intelligence in reducing greenhouse gas emissions by optimizing transportation systems. The illustration depicts the application of artificial intelligence technology to improve transportation systems and reduce carbon emissions. The statement emphasizes the potential for artificial intelligence to optimize transportation routes based on various factors. Furthermore, it demonstrates the capability of artificial intelligence to improve fleet management efficiency. In addition, the diagram depicts the potential application of artificial intelligence to the regulation of autonomous vehicles. Ultimately, the diagram demonstrates that artificial intelligence can potentially optimize public transportation systems and control transportation service demand. CO_2 refers to carbon dioxide

technology, including sensors, cameras, and data processing capabilities. This can present a significant obstacle, primarily for smaller transportation systems or those in developing countries (Abduljabbar et al. 2019).

Furthermore, with the growing prevalence of artificial intelligence technologies in transportation systems, a pressing need arises for clear and effective governance and regulation to ensure ethical and responsible use. This involves addressing critical issues such as determining liability for accidents involving autonomous vehicles and mitigating the exacerbation of existing inequalities or biases. Additionally, the potential for autonomous vehicles and other artificial intelligence-powered transportation technologies to displace many workers in trucking and delivery must be acknowledged. A just transition for affected workers should be a top priority. Finally, the acceptance and adoption of artificial intelligence-powered transportation technologies hinge on various factors, including cultural attitudes, user preferences, and trust in these systems. Thus, developing these technologies should be user-centric and involve consistent consultation with users to ensure their success (Hahn et al. 2021).

This section elaborates on how artificial intelligence algorithms can be utilized to enhance transportation systems, such as optimizing transportation routes, managing vehicle fleets, controlling autonomous vehicles, optimizing public transit systems, and managing the demand for transportation services. Nonetheless, implementing these technologies necessitates substantial investment in infrastructure and technology and clear governance and regulation while ensuring data privacy and security. Tackling these critical issues ensures that artificial intelligence-powered transportation technologies are developed and deployed responsibly and ethically.

Using artificial intelligence for precision agriculture to reduce fertilizer and chemical use emissions

As demand for food production steadily expands, chemical treatments (pesticides) are widely used to increase crop market penetration, thus significantly impacting pollinators and the earth's environment. Precision farming uses cutting-edge sensors for predictive analytics to gather real-time information on soil, crop maturity, air quality, weather, equipment and labor prices, and availability to increase agricultural yields and improve decision-making (Raj et al. 2021). Precision agriculture aims to increase agricultural output and minimize environmental effects (Das et al. 2018). It is making modern agriculture more profitable and sustainable by applying artificial intelligence (Ampatzidis et al. 2020; Wei et al. 2020). Precision agriculture benefits from artificial intelligence, which identifies pests, detect diseases, predicts yields, and plans fertilizer and pesticide use. The technology enables models incorporating data inputs to measure farm organization and directly impact efficiency, resulting in improved outcomes (Bacco et al. 2018; Reddy et al. 2020). Advances in computer vision, machine learning, and deep learning technologies may be used to identify crop illnesses from various current crop diseases accurately, quickly, and more swiftly. Robotics and artificial intelligence are developing cognitive capacities similar to those of humans, increasing productivity and enhancing and amplifying human potential (Barile et al. 2019).

Herbicides or other chemical residues are left on plant products due to chemical spray transfer, often when the wind blows tiny droplets of spray solution to nearby crops or fields (Creech et al. 2015). The use of unneeded herbicide applications to redundant regions can result from precision spraying technology, which can drastically reduce the quantity of herbicide required. Applying herbicides where weeds are present might lessen the environmental impact while lowering the risk of expense, crop damage, and excessive chemical residues (Balafoutis et al. 2017). Applications for agricultural remote sensing are increasingly using deep learning and convolutional neural networks (Kussul et al. 2017). According to Swaminathan et al. (2023), robots that monitor and spray weeds using computer vision and artificial intelligence might eliminate 80% of the chemicals now sprayed on crops and lower the price of herbicides by 90%. A fertilizer application model is used in precision fertilization to calculate the necessary fertilizer input and apply fertilizer using a variable rate applicator after checking the soil's nutrient levels and segmenting the field into a grid (Elbeltagi et al. 2022). Precision fertilizer application can minimize fertilizer use, increase crop yields, balance soil nutrients, and reduce atmospheric emissions. Table 3 demonstrates the use of artificial intelligence technology to improve the use of fertilizers and pesticides in precision agriculture.

Using genome analysis and editing techniques, precision agriculture and artificial intelligence technologies may generate successful crops that are fit for the land and maximize plant production (Joseph et al. 2021). Lessening the effect of chemicals on the soil will help minimize the usage of chemical fertilizers in agriculture and make farming more ecologically friendly. In Hafizabad and Sheikhupura districts, Elahi et al. (2019a) estimated target values of agrochemicals used on rice farms by maintaining rice yields at current levels and found that 52.6% of pesticide and 43.6% of pure nitrogen fertilizer inputs could be reduced to have a favorable and significant impact. Putra et al. (2020) modeled the amount of nutrient data stored and released by fertilizer application to simulate the availability and loss of oil palm nutrients so that the nutrient balance can be effectively determined to be maintained by fertilizer application to a specific site. Du et al. (2021) developed a water and fertilizer control system based on soil conductivity thresholds to improve the utilization of water and fertilizer for cotton cultivation from soil conductivity and moisture content, resulting in a 10.89% reduction.

Chen et al. (2020a) enhanced image recognition of pests by using the "You Only Look Once" neural algorithm and acquired images using an uncrewed aerial vehicle with a 90% recognition rate. High-resolution pest images are acquired by stabilized flight unmanned aerial vehicles to solve the disturbance of leaves by propeller wind. Enhance the speed of picture identification to locate pests and diseases more effectively and use fewer pesticides on farms. The smart sprayer is a piece of technology that combines weed recognition, a mapping system, and a unique rapid and precise spraying mechanism. It also uses a newly created algorithm to generate visual maps. Partel et al. (2019) used an embedded graphics processing unit in a smart sprayer for precision weed control of artificial and amaranth weeds with 59–71% accuracy, which can significantly reduce pesticide costs, crop damage, and the risk of excessive herbicide residues, and potentially reduce environmental impacts. Facchinetti et al. (2021) used a "Rover" sprayer vehicle to accurately detect color differences between salad and ground and reduce pesticide spraying by 55%. The I^2PDM system is composed of an intelligent integrated pest management wireless sensor network that collects images, pest numbers, and species through sensor nodes and stores them in a database for analysis, thus generating models that can be visually translated into numerical information (Rustia et al. 2020). The technique was applied to a tomato field, and the pesticide dose was reduced from 235 to 204 L/time (16%), indicating that insecticide spraying effectively reduced pests (Rustia et al. 2022).

In conclusion, artificial intelligence provides systems that are proved to be scalable, stable, and accurate to provide real-time data for precision agriculture. Artificial intelligence-supported precision agriculture eliminates randomness, provides precise and required amounts of fertilizers and pesticides, and can increase food productivity by utilizing the limited available arable land for farming.

Use of artificial intelligence in optimizing industrial processes for more energy-efficient and lower-emission operations

In recent years, various companies have also recognized the idea of energy conservation and emission reduction efficiency by developing a green energy strategy. In the process of energy transformation, many industrial enterprises are in the process of developing many challenges. However, the use of artificial intelligence can provide new ideas for the transformation of these companies. Lei et al. (2023) mentioned that traditional enterprises had used many excellent management methods, such as comprehensive quality management, ISO 9000 quality management system, and

Table 3 Artificial intelligence interventions to improve fertilizer and chemical use in precision agriculture

Agricultural products	Artificial intelligence	Descriptions	Impact	References
Paddy in Sheikhupura and Gujranwala districts	Artificial neural networks	Evaluated the actual usage of agrochemicals	Reduce pesticides: 52.6%; nitrogen fertilizer: 43.6%	Elahi et al. (2019a)
Longan	You Only Look Once, the neural network algorithm	Marking of pests to predict the distribution location and occurrence time of pests and diseases	Pest identification rate of 90%	Chen et al. (2020a)
Artificial weeds	Embedded graphics processing unit (NVIDIA GTX 1070 Ti) smart sprayer	Mapped weeds, developed sensor fusion algorithms to remove noise and improve weed localization accuracy	71% overall accuracy rate	Partel et al. (2019)
Amaranthus weed	Graphics processing unit (NVIDIA Jetson TX2) smart sprayer		59% overall accuracy rate	
Salad	"Rover" sprayer car	Color detection and segmentation algorithms to find plants; high-pressure variable speed spraying of pesticides	55% reduction in pesticide spraying	Facchinetti et al. (2021)
Tomato	Intelligent and integrated pest and disease management (Intelligent I^2PDM) programs; convolutional neural networks	Cascade deep learning classification algorithm detects and identifies pests on sticky paper traps for image classification	Pesticide doses were reduced by about 16%	Rustia et al. (2022)
Oil palm (Elaeis guineensis Jacq) in Indonesia	Android fertilizer application	Stock and flow diagrams calculation solution development	Simulation of nutrient availability and loss during oil palm care or cultivation	Putra et al. (2020)
Cotton	Efficient water and fertilizer control system for cotton with wireless sensor network	Wireless sensor network data collection transmits data to the decision support system, considering soil conductivity and moisture content	10.89% reduction in fertilizer application (0.76 to 0.87 tons of chemical fertilizer)	Du et al. (2021)

Using algorithms, artificial intelligence accurately calculates and sprays chemicals on pests and fertilizer application points. Combining artificial intelligence with fertilizers and pesticides can increase their efficiency, thereby reducing the amount of fertilizers and chemicals used in agriculture. In addition, artificial intelligence is expected to reduce the environmental impact of agricultural chemicals and fertilizers management excellence model. These management methods are usually analyzed from a macro perspective. Integrating artificial intelligence into traditional industries facilitates a digital transformation that allows for micro-level monitoring of industrial processes. Artificial intelligence can optimize energy usage and reduce emissions by analyzing data and feedback mechanisms, leading to greater energy conservation and efficiency. This section will analyze the application of artificial intelligence in industrial processes.

Artificial intelligence optimizing industrial processes preconstruction

Artificial intelligence optimizes preindustrial process design by managing product design and industrial process layout. Neural networks are computational algorithms that simulate human brain analysis and processing of information through artificial intelligence. Artificial intelligence can use neural network learning to create process plans using geometric data, decision logic, and algorithms. It incorporates manufacturing process plans for new goods based on part forms, materials, and other factors. The system's primary input is a description of the geometry. Leo Kumar (2017) mentioned that designers could quickly get input from it, which closely coordinates with product modeling activities. Artificial intelligence can increase the space usage of the model by optimizing the model, thus saving more material-saving products, increasing industrial process efficiency, and reducing emissions from the point of view of the product's use of materials. Artificial intelligence optimizes industrial process layouts to save energy and reduce scrap rates. Manufacturing has seen success with machine learning, automation and robotics, machine vision, data mining, big data, and expert systems. Sarker (2022) stated that artificial intelligence technology could understand the operation of each process step to identify the problem, timely adjustment, and optimization. The same artificial intelligence can help planners determine the allocation of human resources earlier so that projects can proceed earlier.

In conclusion, artificial intelligence optimizes the upfront layout of industrial processes with a more rational product design and a more appropriate division of labor. Artificial intelligence saves energy by providing granular data to help people make more rational decisions in the early design stages.

Optimizing mid-stage industrial process construction with artificial intelligence

The most important aid of artificial intelligence in industrial processes is to monitor control and detect equipment losses in advance. Collecting data using hardware sensors to monitor industrial production processes is traditional. However, there are some challenges in the use of hardware sensors. For example, temperature, humidity in different working environments, cumbersome personalization requirements, slow measurement data transfer, and higher cost of hardware sensors all impact measurement results. Perera et al. (2023) applied traditionally. This issue has been resolved by applying straightforward fixes like removing data points with missing values or substituting them with the average values of the variables they influence. However, these technologies are not regarded as the ideal answer due to the possibility of affecting model performance. Xie et al. (2020) reported autoencoder is a deep neural network that can extract relevant information features and reconstruct data in several sets. Suppose the potential variable is a random variable, and its probabilistic variant is called a variational autoencoder by building a new soft sensor framework. Data loss due to sensor failure in industrial processes can also work well with neural network learning. The most recent artificial intelligence-based algorithms allow soft sensors to increase computational efficiency and forecast accuracy by resolving the drawbacks of conventional modeling methods compared to classical statistics and machine learning-based models. This model enables better monitoring and control of the process, lowering pollutants and material and energy waste. Perera et al. (2023) mentioned that industrial processes use soft sensors to monitor operations. However, they typically have the following four issues: missing data from tiny datasets, dimensionality reduction, process adaptation, and feature extraction from time and space. Specialists from various fields use artificial intelligence to solve the issues in Table 4.

Artificial intelligence also controls various catalysts in industrial processes and associated toxic gas emissions. Sun et al. (2019a) mentioned that refineries could continuously monitor and keep emissions under the required limits thanks to using soft sensors, which directly impact environmental sustainability. Fernandez de Canete et al. (2021) reported that soft sensors could be created for the pulp and paper sector to detect levels of bleached wastewater containing hazardous chemicals. The pulp and paper sector uses soft sensors to anticipate chemical oxygen demand for financial gain and material efficiency, enabling influential paper washing with fewer chemicals.

Artificial intelligence helps industrial processes perform complex operations. The assembly industry is the process by which mechanical parts or components are connected according to the technical requirements of the design, combining mechanical parts or components into machines. The assembly industry can effectively reduce some links in industrial processes and speed up the use of raw materials by using assembly-style preconditioners that can effectively reduce manual errors. Cohen et al. (2019) stated that precomponent production requires significant data analysis. In modeling, if component data problems produce

Table 4 Common sensor problems and their solutions This table details the most common issues with soft sensors and the corresponding solutions

Problem	Problem cause	Solution	References
Missing data from small datasets	Frequent hardware sensor failures	A sequence neural network model that can handle short data sets could be proposed. The model's encoder makes predictions and processes the variable's dynamics. In terms of prediction accuracy, this prediction method outperforms conventional artificial neural networks	Chou et al. (2020)
		Categorize lost data as lightweight, medium, or heavy and delete the corresponding levels. Use average interpolation to supplement the missing data and apply neural network learning	Xie et al. (2020)
Dimensionality reduction	Redundant variables that result from dimensionality reduction may unnecessarily increase the complexity of the soft sensor model. The performance of soft sensors may thus suffer as a result of this	Extract features from the previous layer and then build a model to restore data using this information, ensuring that information can be passed between different levels to better store data	Yuan et al. (2020)
		The model divides the data into subsets and then determines the subset's variables, maximizing the data set's responsiveness	Hikosaka et al. (2020)
Adapting to varying process conditions	The machine's performance changes due to process operating conditions, weather, or seasonal changes. The related performance of the machine changes and the relevant parameters are affected	Training adaptive soft sensors update historical data sets to predict data at an early stage of change after cumulative training	Sun et al. (2020)
		Use special metrics to work with data samples and select the most relevant data from the historical data set to model。	Zheng et al. (2021)
Extracting temporal and spatial features	Industrial processes have a strong temporal dependence. Traditional static models are unable to derive from process data relevant dynamic information	The network contains time and spatial attention modules that extract time and space features from the data. Then use the spacetime fusion module to merge the extracted features. The data obtained by this feature can fit highly with dynamic data	Wu et al. (2021)

The following table outlines soft sensor-related issues, their causes, and corresponding solutions. Developing neural network models increases the availability of complementary soft sensors. Through the development of empirical models, the team of experts expedites the processing of data collected by soft sensors. By reducing their conditions, artificial intelligence can also facilitate using soft sensors in various working environments waste, reducing the enterprise's productivity can also cause resource waste. Cioffi et al. (2020) mentioned that one is for intelligent manufacturing. This fully integrated collaborative production system reacts in real time to changing conditions in the factory, supply network, and customer needs. The other solution is lean manufacturing, which aims to reduce costs while maximizing efficiency. A transformational "cyber-physical production system" converts data from connected systems into predetermined and required operations for elastic performance. The use of digital twin technologies supports the product lifecycle. Both techniques may guarantee the preconditioners' precision, enhancing efficiency and lowering emissions.

To summarize, in the middle of an industrial process, artificial intelligence assists soft sensors in monitoring pipeline data. Although there are some problems with soft sensors, artificial intelligence minimizes the impact of problems in soft sensors by building models. More accurate data can help people control the use of chemicals and reduce emissions.

Artificial intelligence optimizes industry processes in the late stage

Artificial intelligence optimization for the later stages of industrial processes is mainly optimized for the process. After some time in industrial processes, managers use artificial intelligence to address inappropriate and inefficient resource allocation. Dwivedi et al. (2021) reported that artificial intelligence improves efficiency by combining management methods. For example, the combination of artificial intelligence and lean production, through which each production link calculates the efficiency of the link and then reduces the waste of related raw materials due to idle, can also help the management of the enterprise to optimize the production line. The primary use of artificial intelligence here is as a tool for data analysis and, thus, for interpreting or evaluating results to improve energy and resource management.

Flexible manufacturing on mature production lines can benefit from using artificial intelligence. Resilient manufacturing involves adapting to sudden changes in the production process to ensure continuous production activities. As needed, intelligent optimization and field conditions are utilized to modify the control system. Additionally, artificial intelligence can upload information from related devices to the cloud, allowing for remote manipulation of production processes even when relevant managers are not present onsite. This feature enhances the agility and resilience of the production process. Oruganti et al. (2023) mentioned that this model helps the assembly line in industrial processes cope with accidents while reducing pressure on managers.

In this section, artificial intelligence can optimize convection lines in mature industrial processes, reducing risks and scrap rates. It can also provide information support for industrial processes by uploading relevant pipeline information to mobile devices, enabling remote access to essential data.

In summary, artificial intelligence improves product design through data modeling and enhances the monitoring of industrial processes through soft sensors, thereby reducing scrap rates. Additionally, in mature industrial systems, artificial intelligence can optimize assembly lines, increase productivity by eliminating unnecessary processing steps, assist managers in flexible production, and reduce the burden on managers. Ultimately, artificial intelligence helps reduce the impact of labor on industrial processes and improves overall efficiency.

Artificial intelligence for natural resource management: reducing deforestation and emissions

In recent years, the difficulties and potentials regarding natural resource management (especially land, water, and forests) have been a hot topic of exploration worldwide. Humans are losing valuable ecosystem services and critical habitats that sustain biodiversity through the loss of forests, so artificial intelligence models are thought to reduce the risk of natural resource loss (Buchanan et al. 2008; Newman et al. 2014). In order to forecast incremental deforestation and deforestation rates in the Amazon rainforest, Dominguez et al. (2022) employed a dense neural network to model spatially static data and an extended short-term memory network to model temporal data on deforestation. The rate of future forest loss is estimated by comparing the prediction results and performing retraining to update the model with new data so that action can be taken in advance. The freely available dataset generated reasonable deforestation risk maps using all techniques in the Mexico and Madagascar study areas. Mayfield et al. (2017) had more consistent predictive performance through Gaussian processes. However, they could not use the model to predict the amount or total area of deforestation and risk factors and could only determine whether deforestation risk exists. In addition, the weightless neural network architecture created by the field-programmable gate array in conjunction with an unmanned aerial vehicle for deforestation monitoring and visual navigation assessment in green rural regions is shown to provide a greater level of processing of visuals (Torres et al. 2020). Tien Bui et al. (2017) modeled forest fires by particle swarm optimization neurofuzzy, which can determine the optimal values of parameters and reasonably predict the causes of forest fires generated in Vietnam, random forest, and support vector machine. Tien Bui et al. (2016) developed fire sensitivity maps effective for planning and management of forest fires.

In order to manage the environmental restoration of terrestrial ecosystems by creating a biological retreat configuration for the Changsha–Zhuzhou–Xiangtan urban area, Yin et al. (2021) suggested an artificial intelligence-assisted intelligent planning framework. Its identification of environmental components in existing biodefense zones supports the effectiveness of machine learning in green resource prediction, demonstrating that retreat configurations help better understand urban growth's impact on environmentally relevant processes. The basis for ecological berm vegetation screening and backpropagation is soil moisture susceptible to climatic change and vegetation growth conditions. Liu et al. (2022a) suggested a neural network regression model optimized by a genetic algorithm for roads in the Zhejiang province to modify the system's greater processing power and address the problems with local minima. Controlling or managing land pollution through prediction, clustering, data-centric analysis, and soil quality evaluation requires artificial intelligence and machine learning (Gautam et al. 2023).

Managing varied and complex urban water resources requires using current technological platforms owing to increased water demand brought on by climate change, urbanization, and population expansion (Mrówczyńska et al. 2019). A more simplified procedure to increase water efficiency is adaptive intelligent dynamic water resource planning, which uses a subset of artificial intelligence technology to maintain the water environment in metropolitan settings (Xiang et al. 2021). Liu et al. (2019) added dynamic inertia weights to the moth flame algorithm in the projection tracking water quality evaluation model with higher stability and reliability, improving the regional water environment evaluation accuracy. Afzaal et al. (2020) used recurrent neural networks and long- and short-term memory to solve the problem of dynamic inputs of climate change in Prince Edward Island, Canada. In order to complement crop water needs, accurate calculation of reference evapotranspiration may give helpful data for water management and sustainable agriculture. It can also provide immediate feedback on water deficiency in potatoes. Also, artificial neural networks can be used to predict and evaluate leachate infiltration from landfills into groundwater, Bagheri et al. (2017) analyzed the cost of leachate concentration at different depths by building a fuzzy logic model of leachate infiltration into groundwater in Kurdistan province for more accurate determination of molybdenum, sodium and chemical oxygen demand ($R^2 = 0.99998$).

The socioeconomic, environmental, and ecological activities that take place in urban areas, as well as the lives of the populations that inhabit them, are significantly influenced by urban land use planning. By using aerial imaging analysis to pinpoint physical surface materials or human land use, these investigations may be carried out at a considerable cost and time savings. Geospatial data and environmental information may be captured using remote sensing imaging technology for ground observation. Deep learning models can be used to categorize land cover or land use, and they can also be trained with high accuracy to classify different types of habitations (Alem and Kumar 2022). Using an intelligent planning support system based on a multiagent system and applying Bayesian learning methods in Zanjan, northwest Iran, it is possible to perform automated urban land use planning consultations (Ghavami et al. 2017). In addition, convolutional neural networks that can perform many image classification tasks have higher performance for land cover/land classification than support vector machines, random forests, and k-nearest neighbors (Carranza-García et al. 2019).

In summary, artificial intelligence plays a crucial role in natural resource management, as shown in Fig. 6. This includes forest resource management, ecosystem restoration, water resource management, and land use planning. Artificial intelligence facilitates the management of natural resource use, rationalizes the allocation of natural resources, and reduces unnecessary waste.

Using artificial intelligence in developing sustainable and resilient cities

As a refuge for modern people, cities inhabit over half of the world's population, providing convenience for human modernization while consuming a large amount of energy. Greenhouse gases emitted by cities account for three-quarters of the total emissions, making them the core strategy for mitigating global climate change. The impacts of climate change on towns and the relationship between it and sustainable urban development are complex (Mi et al. 2019). With the gradual severity of climate issues, cities face increasing uncertainties and unknown risks. In addition to the urgent need to solve issues like energy shortages, air pollution, and waste management, people are becoming increasingly interested in how "resilient" communities are at handling calamities (Zhu et al. 2019). Resilient cities are a new urban governance concept that has emerged after intelligent cities to improve the city's ability to withstand disasters and self-recover in emergencies. Zhu et al. (2020b) explored the connections and differences between smart and resilient cities.

Artificial intelligence can be applied to various aspects of waste management, such as waste-to-energy, waste sorting, waste generation models, plastic pyrolysis, logistics, disposal, and resource recovery. It can also help reduce illegal dumping and improve public health. By implementing artificial intelligence in waste logistics, transportation distance can be reduced by up to 36.8%, cost savings by up to 13.35%, and time savings by up to 28.22%. Artificial intelligence can

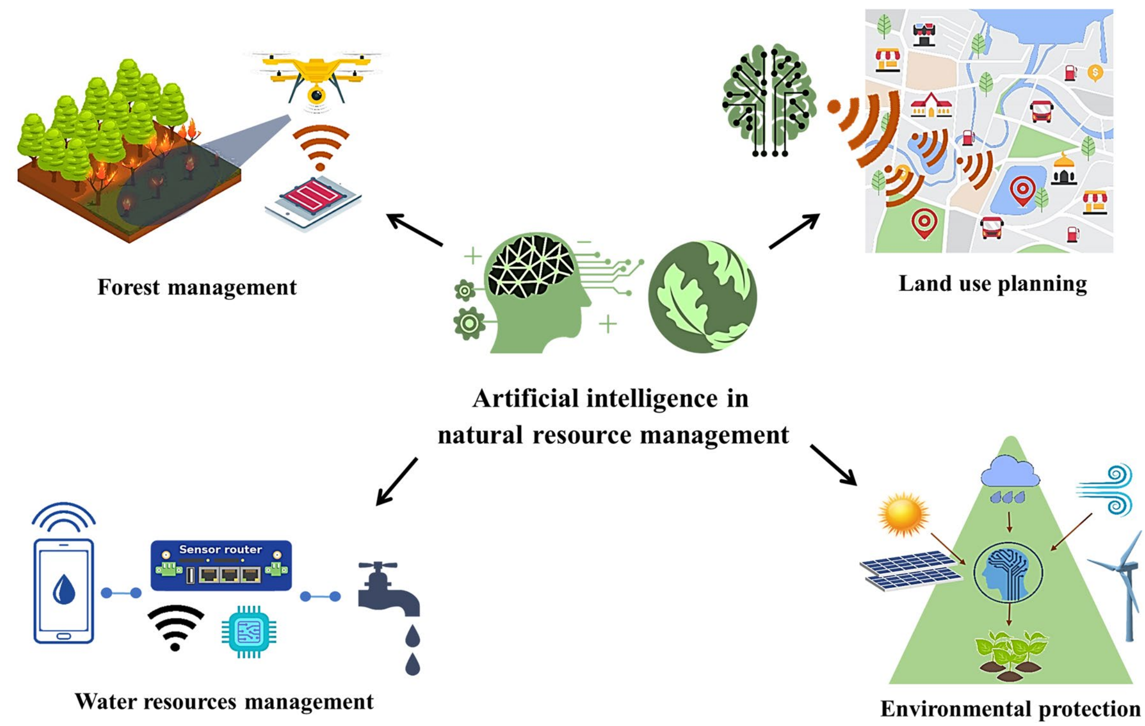

Fig. 6 Applications of artificial intelligence in natural resource management. Artificial intelligence can monitor forests, reduce deforestation, and assist decision-makers in issuing early fire warnings. Using artificial intelligence to manage intelligent ecosystem restoration and adapt to climate change can reduce ecosystem pollution and implement effective conservation measures. Artificial intelligence is necessary for the effective management of urban water resources. Remote sensing and geographic information systems technologies improve urban land use and planning

accurately identify and sort waste with 72.8–99.95% accuracy (Fang et al. 2023). Combining artificial intelligence with chemical analysis can improve waste pyrolysis, carbon emission estimation, and energy conversion. This technology can also increase efficiency and reduce costs in waste management systems for smart cities (Fang et al. 2023).

Since 1973 Holling introduced the concept of resilience into ecosystem research, and the connotation of resilience has greatly enriched and expanded. Rapidly developing cities are easily affected by natural disasters such as floods, earthquakes, and hurricanes. Besides, terrorist attacks and sudden viruses also cause cities to face massive crises. As urban vulnerability increases (Szewrański et al. 2018), Building resilient cities is receiving increasing academic attention. Artificial intelligence is not a panacea for addressing climate issues. However, as an efficient and reliable framework, it can help humans plan and establish sustainable livelihoods, enhancing the resilience of cities. Table 5 demonstrates the application of artificial intelligence in building sustainable and resilient cities.

The increase in climate uncertainty poses enormous challenges to urban water resource management. Artificial intelligence's rational planning and constraints on water resource applications make cities safer, more resilient, and more sustainable. By streamlining the information transformation process with artificial intelligence modeling, Xiang et al. (2021) presented an adaptive intelligent dynamic water resource planning to sustain metropolitan regions' water environment and increase water resource usage. Pluchinotta et al. (2021) used the system dynamics model to explore different sustainable urban water resources management policies in Ebbsfleet garden city. They created a novel technique that uses a coupled dynamic artificial neural network architecture, a Bayesian framework, and a genetic algorithm to predict irrigation water use over the short term with little information. Additionally, Maurya et al. (2020) proposed a framework based on the comprehensive management of urban water resources and stress state response for urban water resource planning and management.

By enhancing its whole ecological environment, a city can become more resilient. Artificial intelligence can be used to build a detailed, multidimensional, multiscale, and resilient city. Yin et al. (2021) created a novel technique that uses a coupled dynamic artificial neural network architecture, a Bayesian framework, and a genetic algorithm to predict irrigation water use over the short term with little information. The ecological sources are categorized, the environmental channel and strategy points are established,

Table 5 Utilization of artificial intelligence in resilient city buildings

Research contents	Particular year	Research area	Research method	References
Water resources management	2020	Melbourne, Australia	An example of a method that examines hybrid crow search techniques and artificial neural networks by combining a discrete wavelet transform with an adaptive neural fuzzy inference system	Zubaidi et al. (2020)
Water resources management	2021	Ebbsfleet, Britain	Explore sustainable solutions for urban water resource management through system dynamics models	Pluchinotta et al. (2021)
Water resources management	2018	Bembézar, Spain	Using the integration of a dynamic artificial neural network architecture, a Bayesian framework, and a genetic algorithm, the irrigation water demand with restricted data availability was examined	González Perea et al. (2019)
Urban heat island	2019	Ningbo, China	The impact of the urban morphology index on the land surface temperature at three observation scales is distinguished using ordinary least squares regression and random forest regression	Sun et al. (2019b)
Air quality	2021	Tehran, Iran	One can compare and forecast the daily concentration of nitrogen dioxide in the atmosphere using multiple linear regression and a multilayer perceptron neural network	Shams et al. (2021)
Disaster resilience	2018	Shenzhen, China	Support vector machines and the Delphi analytic hierarchy process assessed streets' physical and social resilience	Zhang et al. (2019b)
Urban heat island	2020	Hangzhou, China	To investigate the effect of urbanization and landscape design on habitat quality, a complete assessment framework of environmental services and trade-offs was built using ordinary least squares and a regionally weighted regression model	Zhu et al. (2020a)
Urban heat island	2021	Pearl river delta, China	Propose a Malmquist Luenberger model for measuring green total factor productivity based on relaxation measurement	Li and Chen (2021)
Air quality	2018	Taiwan, China	A shallow multioutput short- and long-term neural memory network model is proposed, which combines small batch gradient descent, dropout neurons, and L2 regularization to conduct regional multistep advance air quality prediction	Zhou et al. (2019)
Air quality	2018	Athens, Greece	Five air contaminants' results were compared using multiple linear regression, artificial neural networks, and a set of correlation, difference statistical measurements, and residual distribution	Alimissis et al. (2018)

Water resource management, urban ecological management, air quality testing, and disaster monitoring are crucial elements in constructing resilient cities. By employing big data and deep learning technologies, artificial intelligence can analyze and predict real-time data, optimizing urban operations and resource utilization and enhancing urban resilience

and planning is provided for urban growth and ecological restoration of the terrestrial ecosystem. To better understand how urbanization has impacted Beijing, Tianjin, and Hebei's urban ecosystem, Kang et al. (2018) created a framework combining ecosystem services and health. Using probabilistic risk assessment, Liu et al. (2023) estimated the likely risk of a flood occurring in urban areas and assessed the effect of future climate change on urban flood risk. To recognize the complexity of the urban ecosystem's health in the future, Yue et al. (2023) developed a hybrid technique. The urban ecosystem's condition was identified using an ecological model to thoroughly assess ecosystem health.

The internet of things is also essential in improving the efficiency of resilient urban transportation. Cities' many components are now connected thanks to the use of artificial intelligence in the internet of things, which has cultivated the city's capacity for adaptability and helped it grow into an organism of interconnected things. In order to properly manage resources and optimize energy consumption, artificial intelligence can process vast amounts of data provided by the internet of things. This can create an intelligent network that connects everything on the physical Earth (Ullah et al. 2020). Zhang et al. (2021) proposed a new method to assign each network layer reasoning calculation to the equipment of the multilayer internet of things system. Moreover, they designed a dynamic programming algorithm to balance the corresponding time of calculation and transmission cost minimization. Lv et al. (2021) develop a brand-new network information physics system, a machine learning-based assessment framework, and an online sorting algorithm to enable real-time online analysis and evaluation. In order to improve the network architecture of smart cities, blockchain and artificial intelligence are integrated into the internet of things network (Singh et al. 2020).

In addition to harming human health, air pollution impedes sustainable ecological growth. To build a resilient city, air quality must be tested and managed. Almalawi et al. (2022) used linear regression, support vector regression, and gradient enhancement decision trees to build a one-step model and analyze the air quality index using sensors. Furthermore, Catalano and Galatioto (2017) designed a new model. They compared it with a specific background statistical model, focusing on testing the air quality in Manchester and enhancing the prediction of traffic-related air pollution. Mihăiţă et al. (2019) utilized mobile and fixed air quality detection equipment, combined with machine learning methods, to gather data and model the information using decision trees and neural networks. Their findings suggest that noise and humidity are the primary factors influencing predictions of nitrogen dioxide concentration at mobile collection sites. To compare the results of air pollution in the five schools utilizing correlation, different statistical metrics, and residual distribution, Alimissis et al. (2018) used artificial neural networks and multiple linear regression. They found that artificial neural networks have computational advantages when the density of air quality networks is limited.

In summary, artificial intelligence technologies are crucial in promoting urban resilience and sustainable development. With big data and deep learning techniques, artificial intelligence can offer real-time data, analysis, and predictions, optimizing urban operations and resource management. This, in turn, enhances urban resilience to disasters and improves the overall happiness and quality of life for urban residents.

Perspective

Numerous industries are swiftly integrating disruptive technologies such as artificial intelligence (Shao et al. 2022). However, the exponential expansion of computational and energy demands associated with many modern machine learning technologies and systems can result in substantial carbon emissions (Hanifa et al. 2023). Machine learning models can establish different orders of magnitude and hierarchies among diverse models, facilitating a thorough and more accurate assessment of carbon dioxide quantification and the environmental efficiency of industrial activities. Developing and defining a clear, robust, and general method to calculate the energy consumption of artificial intelligence models can reduce the carbon footprint (Henderson et al. 2020). Cloud for data storage, hardware for computing, and hardware providers are essential for energy consumption evaluation of artificial intelligence algorithms, thus advancing the evaluation criteria, including precision, accuracy, or recall for the calculation of energy consumption of the project. Also, to automate system control and enhance the automation of grid intelligence, appropriate functioning of renewable energy-producing equipment is required (Ghadami et al. 2021; Zahraee et al. 2016). Promote new smart infrastructure that uses less energy and policies that support the sustainable advancement of artificial intelligence to lessen grid instability. Energy segmentation can assist artificial intelligence ecosystems or systems of systems by supporting organized data management, data mining capabilities, and machine learning techniques, permitting artificial intelligence-enabled smart grids (Ashfaq et al. 2022). Moreover, a sizable initial investment will be needed to restructure and modernize the electric system's data management systems, enabling the deployment of data-intensive solutions to address privacy and cyberattack issues. Utility companies will need time and money to develop the necessary degree of "data ready" to successfully implement artificial intelligence solutions. The data layer is the support layer for future investments.

Transportation infrastructure combined with the internet of things technology to collect and process real-time data in the field to effectively alleviate traffic congestion. Intelligent monitoring of urban surface and underground space anomalies based on digital twin for urban construction and operation management (Wu et al. 2022). A city information model creates a three-dimensional city space model, achieves all-encompassing three-dimensional visualization management of urban traffic planning, construction, and operation, supports urban traffic simulation, analysis, and verification, and achieves intelligent supervision of urban transportation. Using long-range, ZigBee, wireless fidelity, 5G, and emerging narrow-band internet of things communication technologies, ample opportunity exists to create cost-effective, autonomous, energy-efficient, and easy-to-use internet of things (IoT)-based agriculture solutions with robust architecture and low maintenance (Cicioğlu and Çalhan 2021). A potential strategy is to employ crop simulation models in conjunction with remote sensing for crop phenotype data, and using artificial intelligence models to integrate phenotypic and genotypic data at the plot level can further help address complex challenges in agriculture (Khaki and Wang 2019; Ma et al. 2018). Artificial intelligence can drive positive change in cities and societies and contribute to achieving multiple sustainable development goals (Vinuesa et al. 2020). However, it is also essential to advance the implementation of appropriate policies and regulations to reduce the damage caused by artificial intelligence to the most vulnerable urban and social groups and nature. In conclusion, the algorithmic computation of artificial intelligence improves efficiency gains for future practical applications and makes timely, rational, and optimized decisions. The adoption of the internet of things and telecommunication technologies facilitates the advancement of social transportation systems and agricultural systems, thus conforming to the process of sustainable urbanization.

Conclusion

As the global economy and population have expanded, energy demand has increased exponentially. Traditional patterns of energy production have proved to be detrimental to the environment, with excessive emissions of harmful gases causing global warming and extreme weather events such as tornadoes, hail, and thunderstorms causing severe damage to human habitats and posing a serious threat to human life and property. Artificial intelligence technology is emerging as a new tool in the energy sector, offering a promising direction for combating climate change to address these issues and mitigate their adverse environmental effects. Artificial intelligence contributes to climate change mitigation in the energy sector by predicting energy demand and enhancing energy efficiency to reduce environmental pollution. Numerous nations use artificial intelligence to improve energy efficiency and reduce energy waste.

In addition, artificial intelligence has improved weather prediction technology, enabling more accurate weather forecasting and modeling to better prepare for and respond to extreme weather events via early warning systems. Artificial intelligence enables a deeper comprehension of natural factors such as climate and geography, thereby facilitating the selection of optimal sites for renewable energy. It can predict renewable energy production, adjust grid output, and guarantee a continuous electricity supply. Moreover, artificial intelligence can optimize residential architecture by determining optimal house orientation and window placement, thereby reducing energy consumption and enhancing living conditions. Addressing traffic emissions is also essential, and artificial intelligence can enhance bus systems by utilizing large data samples to develop neural networks that optimize routes, vehicle rounds, and passenger traffic.

Artificial intelligence is essential to reduce the environmental impact of agrochemical use. Precision agriculture employs artificial intelligence to collect and analyze environmental data related to crop growth, enabling farmers to make informed decisions, reduce chemical use, and increase yield. In the industrial sector, traditional hardware sensors cannot provide relevant information to decision-makers. Artificial intelligence enables decision-makers to optimize industrial processes by analyzing data, developing models, and completing missing information from hardware sensors to conserve energy and reduce emissions. People's understanding of nature is enhanced by artificial intelligence, allowing for more accurate predictions of future deforestation and tree loss, which can assist governments in protecting the environment and promoting sustainable energy. By calculating relevant data to ensure residents' safety, artificial intelligence can also aid in developing sustainable and resilient cities by minimizing damage caused by extreme weather events. In addition, artificial intelligence significantly mitigates climate change by increasing energy efficiency and providing decision-makers with accurate data.

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Declarations

Conflict of interest The authors declare no conflict of interest.

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