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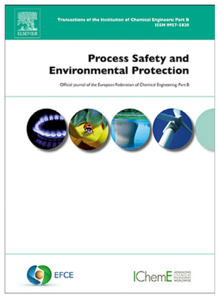

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Artificial Intelligence for Climate Change Mitigation and Adaptation: A Domain-Structured Review of Methods, Applications, and Research Gaps for Seven High-Impact Domains

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Abstract

Artificial intelligence (AI) offers transformative potential for climate change mitigation and adaptation, yet the rapid advancement of machine learning (ML) and deep learning (DL) methods has outpaced systematic efforts to organize and evaluate them. Following a rigorous multi-stage screening protocol, we developed a domain-driven taxonomy spanning seven sectors: energy and carbon management, buildings and cities, transportation, industry, agriculture, ecosystem conservation, and weather and disaster forecasting, synthesizing task typologies, representative algorithms, benchmark datasets, and case studies for each. Results show that DL dominates forecasting and monitoring applications, while hybrid and physics-informed approaches remain underutilized. Energy and emission-related mitigation studies are well represented, whereas hydrological systems, ecosystem resilience, and compound hazard prediction remain comparatively limited. Key challenges include data scarcity, uncertainty quantification, and limited transferability to diverse regions and climatic conditions. Unlike prior domain-specific surveys, this review unifies all seven sectors under one taxonomy while explicitly linking technical applications to socio-technical challenges including bias, interpretability, and AI's own carbon footprint, providing researchers and practitioners with an actionable framework for responsible climate AI.

Keywords: climate change, artificial intelligence, machine learning, deep learning, carbon footprint

1 Introduction

Climate change, which represents the most urgent global challenge of the 21st century, demands immediate and transformative action (Abdulameer, Al Maimuri, Nama, Rashid, & Al-Dujaili, 2025; Kaack et al., 2022). The Intergovernmental Panel on Climate Change (IPCC) warns that the window to limit global warming to 1.5 °C above pre-industrial levels, a threshold critical for avoiding irreversible ecological and societal harm, is rapidly closing, with only a narrow timeframe remaining to implement effective measures (Kikstra et al., 2022). Exceeding this threshold risks catastrophic, irreversible consequences, including intensifying extreme weather events, accelerated sea-level rise, and large-scale ecosystem collapse (Abbass et al., 2022). While existing literature proposes strategies to reduce climate change impacts, these approaches are increasingly undermined by the accelerating severity of climate disruptions. Therefore, there is an urgent need to develop proactive, adaptive frameworks capable of anticipating, analyzing, monitoring, and mitigating escalating climate risks. This includes advancing predictive modeling, integrating real-time data systems, and designing scalable solutions that address both immediate threats and long-term uncertainties.

Artificial intelligence (AI) has emerged as a powerful tool for accelerating climate change mitigation and adaptation, with machine learning (ML) and deep learning (DL) driving transformative advances in mitigation and adaptation (L. Chen, Chen, et al., 2023). By analyzing high-dimensional datasets from satellites, sensor networks, and climate models, AI systems enable scalable, real-time solutions, including extreme weather prediction, renewable energy grid optimization, and deforestation monitoring (de Souza et al., 2022; K. Guo et al., 2020; Saha et al., 2020). These capabilities significantly enhance climate modeling precision, pinpoint emission sources, and quantify localized risks (e.g., temperature escalation, sea-level rise, and ecosystem collapse), generating actionable insights for policymakers on cascading threats like intensified storms and biodiversity loss (Amiri, Heidari, & Navimipour, 2024; L. Chen, Chen, et al., 2023). However, current AI applications predominantly address short-term forecasting, leaving a critical gap in long-term strategic planning. To exploit AIs full potential for sustainable climate futures, the emerging field of climate informatics (Informatics, 2025) demands urgent investment in foundational research, particularly in integrating physical climate processes with DL architectures and developing robust uncertainty quantification (UQ) for long-term planning.

1.1 Prior surveys and gaps

Table 1 summarizes key existing surveys on AI applications for climate change, highlighting their principal contributions and describing how they cover complementary aspects of the landscape. Amiri et al. (2024) provide a systematic review of machine learning (ML) and deep learning (DL) applications for climate-change mitigation across six domains, including ecosystems, industry, buildings, transportation, agriculture, and hybrid systems, while introducing a taxonomy of DL methods evaluated on accuracy, scalability, and interpretability. Focusing on food security, (Karanth, Benefo, Patra, & Pradhan, 2023) concentrate on AI-driven prediction of climate-induced microbiological risks along the farm-to-fork chain. Moreover, they emphasize the integration of diverse data streams (satellite imagery, microbial assays, and supply-chain data) and discuss associated social, ethical, and legal constraints. In the area of governance and ethics, (Cowls, Tsamados, Taddeo, & Floridi, 2023) examine AI's potential to enhance understanding of climate phenomena and mitigation strategies, quantify the technology's carbon footprint, assess ethical risks, and propose thirteen policy recommendations focused on EU governance. Broadening the scope to infrastructure, (L. Chen, Chen, et al., 2023) survey AI-based solutions in energy, agriculture, and the built environment, emphasizing integration with IoT and big-data platforms while providing quantitative impact estimates. Finally, Kaack et al. (2022) provide a foundational framework that categorizes ML's impact on greenhouse gas (GHG) emissions, identifies research and data gaps, and proposes policy measures to drive emission reductions. Collectively, these works underscore the multifaceted nature of AI in climate change mitigation, ranging from technical taxonomies to ethical governance and sector-specific deployment.

This survey distinguishes itself from existing literature by addressing three critical gaps through the following extensions. First, it covers a comprehensive range of domains: energy, agriculture, industry, transportation, infrastructure, ecosystem conservation, and disaster forecasting. Crucially, weather/disaster forecasting and ecosystem conservation are not treated as additional sectors but as central pillars of climate resilience, as they directly govern exposure to extreme events and the stability of long-term ecosystem services (Eddamiri, Bassine, Hakam, Kambiet, & Chehbouni, 2025; Silvestro, Goria, Sterner, & Antonelli, 2022). By jointly examining monitoring, adaptation, and mitigation within each domain, this work clarifies how AI systems can support end-to-end climate responses rather than isolated technical tasks. Second, moving beyond standard accuracy metrics, we provide a comparative evaluation of ML and DL architectures across deployment-relevant dimensions, including latency, interpretability, ecosystem compatibility (e.g., integration with legacy software, hardware, and data pipelines), and trustworthiness. While often underreported in prior surveys, these factors are decisive for the reliable, large-scale implementation of AI in safety-critical, resource-constrained, and regulated climate applications. Finally, by

Table 1 Overview of related surveys in AI and climate applications with emphasis on each works focus and extensions provided by this survey. Note: Ref = Reference.

Ref	Contributions	How our survey differs
Amiri et al. (2024)	• Systematic review of ML and DL applications for climate change mitigation on six domains (ecosystems, industry, buildings, transportation, agriculture, hybrid). • Novel taxonomy of DL methods mapped to mitigation tasks. • Quantitative evaluation of methods on accuracy, scalability, interpretability.	• Extend beyond mitigation to also cover monitoring and adaptation tasks (e.g. disaster forecasting, urban resilience). • More granular taxonomy by sub-domains (e.g. carbon management, process optimization). • Comparative analysis across both ML and DL, with metrics beyond accuracy (latency, trustworthiness) and ecosystems.
Karanth et al. (2023)	• Analyze the applications of AI for predicting climate-induced microbiological food safety risks on the farm-to-fork chain. • Emphasis on integrating diverse data streams (satellite imagery, microbial assays, supply chain data). • Discussion of social, ethical, and legal limitations of AI in food safety contexts.	• Cover both ML and DL methods on more application domains (not just food safety). • Detailed taxonomy by domain (e.g. energy, agriculture, built environment), rather than a single sector. • Comparative analysis of algorithmic performance, datasets, and tools for each domain.
Cowls et al. (2023)	• Identification of two key opportunities of AI: improving understanding of climate phenomena and enabling more effective mitigation. • Analysis of AIs carbon footprint and ethicalsocial risks of compute-intensive models. • Thirteen policy recommendations for governance (with focus on EU leadership).	• Provide a systematic survey of methods (MLDL architectures and case studies). • Delve into open technical challenges and propose concrete future research directions. • Include a standalone section on AIs own environmental footprint with mitigation strategies.
L. Chen, Chen, et al. (2023)	• Review of AI-based solutions in energy, sequestration, weather, agriculture, and built environment. • Quantitative impact estimation. • Discussion of integration of AI with IoT and big-data platforms for sustainability.	• A deeper analysis of ML and DL architectures on various domains. • A search-strategy and taxonomy development methodology. • Case studies highlighting both successes and lessons learned.
Kaack et al. (2022)	• Systematic framework categorizing how ML impacts present and future greenhouse gas emission. • Assessment of research and data needs for measuring these impacts. • Identification of policy levers to utilize AI to minimize emissions.	• Incorporate Kaack et als footprint framework into a broader technical survey. • The Open Challenges section emphasizes technical (data, interpretability) and policy considerations. • Customize the framework with a comparative analysis of software ecosystems and benchmarks.

integrating the emissions framework proposed by (Kaack et al., 2022) into a broader technical survey, we explicitly link model- and system-level design choices, such as model size, training approaches, and data center characteristics, to their associated carbon footprints. This synthesis addresses a crucial yet underexplored dimension in the literature, ensuring that AI-for-climate solutions do not inadvertently undermine their intended mitigation benefits through excessive computational costs.

1.2 Objectives and contributions

Rapid advances in machine learning (ML) and deep learning (DL), together with growing urgency around climate change, have produced a rapidly expanding but fragmented body of work on AI for mitigation, adaptation, and impact assessment. Existing reviews typically focus on a subset of sectors, emphasize either high-level concepts or narrow technical topics, and rarely provide a systematic, cross-domain assessment of how ML and DL methods concretely support climate mitigation goals. This fragmentation makes it difficult for researchers, practitioners, and policymakers to obtain a coherent picture of how ML and DL are currently deployed for mitigation, what has been demonstrated in practice, and where the most promising gaps and challenges lie. In contrast, there is now a need for an integrated, up-to-date synthesis that (i) spans key mitigation-relevant sectors, (ii) maps AI techniques to specific tasks and data modalities, and (iii) critically evaluates persistent technical and socio-technical challenges.

To address this gap, this survey conducts a Systematic Literature Review (SLR) of peer-reviewed studies applying ML and DL to climate change mitigation, while also considering adaptation and impact assessment where they intersect with mitigation outcomes. The main objective is to systematically map and critically evaluate how AI is deployed for key climate-related domains, and to identify opportunities for more effective and responsible use of ML and DL in this context. Concretely, the review is guided by the following research questions (RQs):

1. Have existing review papers covered AI for climate mitigation at a comparable scope, and how does our work differ (sector coverage, taxonomy, time span, and depth of method analysis)?
2. How is AI, particularly ML and DL, applied to major climate mitigation domains, and what representative examples illustrate each category?
3. Which AI paradigms and techniques are used for which tasks and domains, and with what comparative performance?
4. What datasets, data modalities, and data sources are used to support AI-based mitigation applications?
5. What important open problems remain, and what promising research and deployment directions could advance responsible and effective use of AI for climate mitigation?

Building on these research questions, this survey advances the field in four concrete ways. First, it is the only review to span all seven major climate-relevant domains, including the two adaptation-oriented domains often absent from prior literature, under a single SLR-validated taxonomy. This unified framework enables cross-domain comparisons that were previously impossible. Second, by analyzing over 280 peer-reviewed studies and organizing them into structured tables detailing tasks, algorithms, datasets, and quantitative performance metrics across all seven domains, this survey provides actionable insights for algorithm and dataset selection in climate AI applications. Third, unlike previous surveys that treat AI's resource consumption as a minor concern, this review devotes a dedicated section to the carbon footprint, energy demands, and governance of AI infrastructure itself. Fourth, it rigorously evaluates model transferability and geographic generalization across diverse climatic contexts, addressing the critical challenge of deploying models trained in data-rich regions to data-scarce environments.

Following the introduction, the review is organized into five sections to serve both researchers and practitioners. Sections 2 and 3 introduce core climate and AI concepts, prior surveys, and our SLR methodology and taxonomy, providing background for readers from both communities. Section 4 is primarily oriented toward practitioners and applied researchers: it organizes existing work by domain, task type, and data modality, and highlights representative models, datasets, and case studies that can inform concrete deployments. Section 5 is primarily aimed at the research community, synthesizing cross-cutting technical and socio-technical challenges and outlining opportunities for advancing methods, benchmarks, and theory. Finally, Section 6 concludes with a summary highlighting the reviews strengths and limitations.

2 Background and Terminology

2.1 Climate change challenges

2.1.1 Greenhouse Gas (GHG) emissions

Human activities have driven atmospheric GHG concentrations to unprecedented levels. In 2023, global anthropogenic emissions reached 53.0 gigatons (Gt) of carbon dioxide (CO_2) equivalent (CO_2e). It marks a 1.9% increase from 2022 and extends an upward trajectory since 2000 (Commission, 2025). Fossil fuel combustion and industrial processes, which are responsible for approximately 75% of total emissions, primarily originate from energy production (e.g., coal-fired power plants), transportation (e.g., internal combustion engines), and industrial manufacturing (e.g., steel production). The remaining 25% comes from methane (CH_4) and nitrous oxide (N_2O) emissions associated with agriculture, waste management, and land use changes such as deforestation for agricultural expansion. In addition, major emitters, including China, the United States, and India, account for over half of global emissions and drive much of this growth.

Figure 1 provides a comprehensive overview of GHG emissions by sector and their corresponding mitigation potential according to the Climate change 2023 synthesis report by IPCC (Calvin et al., 2023). Subfigure 1(a) shows current emissions distribution, with the energy sector accounts for the largest share (37%), followed by Industry (26%), Agriculture, Forestry, and Other Land Uses (AFOLU) (18%), Transport (14%), and Buildings (5%). Subfigure 1(b) reveals critical disparities in both emission magnitude and reduction capacity by comparing each sector's current annual emissions (green bars) against achievable mitigation potential (blue bars) in Gt of CO_2e per year.

The sector-by-sector comparison highlights where targeted interventions would maximize decarbonization impact:

- Energy: As the largest emitter (20.0 Gt/year), it offers the highest absolute mitigation potential (12.6 Gt/year), achievable through rapid renewable deployment, grid modernization, and aggressive energy efficiency measures.

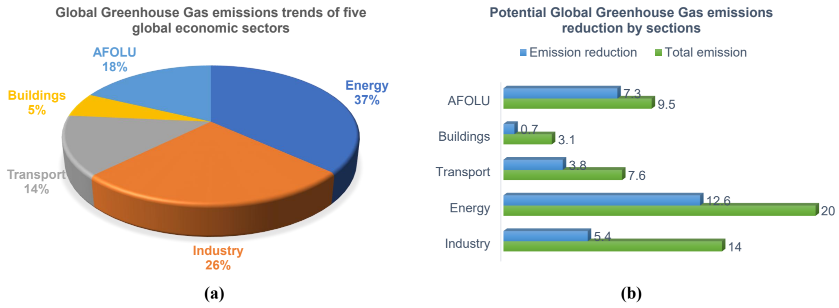


Fig. 1 Global GHG by sector and sector-specific mitigation potential.

- Industry: With 14.0 Gt/year of emissions, the sector could reduce about 5.4 Gt/year via process electrification, circular economy practices, and low-carbon material innovation (e.g., low-carbon steel and cement).
- AFOLU: Contributing 9.5 Gt/year, AFOLU presents the largest proportional mitigation opportunity, roughly 7.3 Gt/year (about 77%), through large-scale reforestation, sustainable land management, and emission-optimized agricultural practices.
- Transport: Emissions of 7.6 Gt/year could fall by about 3.8 Gt/year (about 50%) via rapid vehicle electrification, expanded public and active transport, and improvements in fuel efficiency and logistics.
- Buildings: At 3.1 Gt/year, the sector can reduce emissions by 0.7 Gt/year through deep retrofits, improved building envelopes, and widespread heat pump adoption.

Emerging technologies, especially AI, are enabling innovative, practical approaches to climate mitigation. In energy systems, AI-based smart grid control and demand forecasting models reduce dependence on fossil fuels, increase renewable integration, and improve grid efficiency. In industry, ML and DL methods cut energy waste and emissions by optimizing processes in real-time. AI combined with remote sensing (RS) and advanced analytics also provides precise GHG monitoring. For example, computer vision (CV) models can detect methane leaks in near real-time, and satellite-based ML systems track deforestation and land use change at scale.

2.1.2 Extreme weather events

Rising global temperatures have pushed the planet to a critical threshold, with 2024 marking the first year where the annual average temperature exceeded 1.5 °C above pre-industrial levels (WMO, 2025a). This warming intensifies extreme weather events, including heatwaves, storms, droughts, and floods, by amplifying atmospheric energy and moisture cycles (Howe, 2021). For example, 2024 saw unprecedented global heatwaves and record rainfall, while warmer air masses significantly increased atmospheric moisture, exacerbating flood severity (Q. Zhao, Gao, Meng, & Zhu, 2024). Driven by prolonged drought and heat, wildfire activity has surged catastrophically, as evidenced by Canadas 2023 fire season, which burned 18.4 million hectares, nearly seven times the historical average (2.5 million hectares) (Jain et al., 2024). These escalating extremes impose severe costs on various sectors. For example:

- Agriculture suffers crop failures from heat stress and flooding (Karanth et al., 2023).
- Infrastructure faces billion-dollar damage from storms and erosion (Shafiq et al., 2024; Y. Zhang et al., 2023).
- Energy systems experience disruptions due to drought-reduced hydropower and grid failures during heatwaves (Perera, Nik, Chen, Scartezzini, & Hong, 2020).
- Public health contends with rising heat-related mortality and climate-induced displacement (Tran et al., 2023).

AI offers transformative potential to improve resilience against these threats. ML and DL models now enhance the precision of sub-seasonal to seasonal forecasts, such as hurricane intensification trajectories (H. Su et al., 2020), heatwave onset prediction (P. Li, Yu, Huang, Wang, & Sharma, 2023), and real-time flood mapping (Panahi et al., 2021), enabling earlier, more targeted interventions. Beyond forecasting, AI-driven analytics convert multi-source climate, satellite, and Internet of Things (IoT) sensor data into actionable insights for dynamic risk assessment, optimized evacuation routing, and resilient infrastructure planning. These tools not only improve disaster response, but they also inform proactive adaptation strategies, such as climate proofing the supply chains, designing flood-adaptive urban infrastructure, and prioritizing resource allocation to vulnerable communities, ultimately reducing human and economic losses in an increasingly volatile climate.

2.1.3 Ecosystem degradation

Climate change is accelerating ecosystem collapse worldwide, driving biodiversity loss at a pace unprecedented in human history. Major drivers, such as deforestation, habitat fragmentation, pollution, and rising temperatures, are pushing ecosystems beyond critical thresholds of resilience. More than one million species are currently at risk of extinction (WMO, 2025b), and global wildlife populations have declined by an average of 73% since 1970 (WF, 2025). A striking illustration is the 2014–2017 global coral bleaching event, which affected over 80% of the worlds reefs (Eakin, Sweatman, & Brainard, 2019), threatening both marine biodiversity and coastal economies. These ecological disruptions affect multiple sectors: agriculture and fisheries depend on pollinators, fertile soils, and stable fish stocks, while tourism and coastal protection rely on healthy reefs and forests

ML and DL algorithms can analyze satellite and drone imagery to detect deforestation, illegal logging, and land-cover change in real-time (Chai & Li, 2023; S.-H. Lee et al., 2020). Moreover, AI-enabled bioacoustic sensors and camera trap systems enable continuous biodiversity monitoring by automatically identifying species vocalizations and behaviors (Müller et al., 2023). ML and DL further support conservation planning by mapping species distributions, forecasting climate-driven habitat shifts, and prioritizing high risk areas for intervention (Pichler & Hartig, 2023). AI models trained on large-scale environmental datasets, from soil moisture and RS indices to ocean temperature anomalies, support strategic actions such as designing protected areas and optimizing sustainable resource management practices. These technologies help bridge the gap between ecological research and actionable ecosystem protection.

2.2 AI foundations

Classical ML techniques, such as support vector machines (SVMs), random forests (RFs), and linear regression, have long been applied to climate science for tasks like weather classification and regression from historical records (Saha et al., 2020; Z. Tian, Li, Wang, & Wang, 2018). These models typically rely on hand-crafted features and perform well on low dimensional or highly structured problems, but they often struggle with the high-dimensional, nonlinear patterns found in raw climate data (e.g., global gridded fields or satellite imagery).

On the other hand, DL models learn hierarchical representations directly from raw inputs and can process large-scale spatial and temporal datasets to capture complex spatio-temporal dependencies. This capability makes DL particularly well suited to modern climate tasks, including high-resolution forecasting, anomaly detection, and multimodal data fusion, where large datasets and complex spatio-temporal structure are critical.

- Convolutional neural networks (CNNs): CNNs excel at spatial pattern recognition via learned convolutional filters, which is crucial for satellite image analysis tasks such as rainfall nowcasting and land cover mapping (Fayaz, Dang, & Moon, 2025; W. Zhang, Yu, Qi, Shu, & Wang, 2019).
- Recurrent architectures: Recurrent neural networks (RNNs) and long short-term memory networks (LSTMs) are specialized for sequential data and retain memory of prior inputs, making them suitable for modelling climate time series, such as temperature, precipitation, emissions (W. Kong et al., 2017; Mtibaa et al., 2020).
- Transformers: Self-attention mechanisms of transformers allow them to capture long-range and cross-regional dependencies. Transformers have achieved state-of-the-art results in vision and sequence tasks and are increasingly applied to medium-range weather prediction and large-scale climate pattern analysis (Jin et al., 2023; Mo et al., 2024; H. Wang, Li, Xue, Fan, & Liu, 2024).
- Graph neural networks (GNNs): Handle irregular, relational structures, such as atmospheric dynamics on spherical grids, river networks, or infrastructure interdependencies, by learning over nodes and edges (M. Ma et al., 2023; X. Wang et al., 2020).
- Hybrid architectures: Combine strengths of different models to better handle complex spatiotemporal tasks. For example, using CNNs to encode local spatial structure together with recurrent networks or Transformer layers to model temporal dynamics and long-range dependencies (Bashir, Wang, Tahir, & Zhang, 2025; R. Chen et al., 2019). The hybrid approaches improve accuracy and generalization by capturing fine-grained spatial features and temporal context.

Table 2 offers a side-by-side comparison of AI models, the data types and requirements they work best with. Traditional ML models (Ladi, Jabalameli, & Sharifi, 2022), such as SVM and RFs, excel at tabular data and short-sequence time series. However, they demand extensive feature engineering to process RS imagery and fail to capture graph structures or long-term dependencies. DL architectures (Alzubaidi et al., 2021), which specialize in high-dimensional and large-scale, unlock new capabilities. For example, CNNs have achieved state-of-the-art performance in numerous CV tasks by automatically learning localized, hierarchical spatial features directly from data. RNNs and their gated variants (LSTMs/GRU) exploit recurrent connections to model temporal dependencies of sequential and time-series data. More recently, Transformers (Nayak et al., 2024) have achieved state-of-the-art results by utilizing self-attention to capture long-range temporal dependencies in time-series, adopting patch-based attention for CV, and extending to graph data via structural (positional) encodings. GNNs (J. Zhou et al., 2020) model relational systems, such as power grids, ecological networks, and transportation infrastructure, by representing entities as nodes and interactions as edges.

Advanced approaches, such as ensemble methods (bagging and gradient boosting) deliver strong performance on tabular datasets and imbalanced datasets. However, they are not a natural fit for graph structure or long-range spatiotemporal dependencies, and typically require feature engineering to compete on raw RS imagery or long sequence modeling, so they are less suitable when end-to-end representation learning is needed. Hybrid frameworks (Meng, Griesemer, Cao, Seo, & Liu, 2025) embed domain knowledge by enforcing governing equations and constraints via hard/soft penalties or differentiable simulators. It allows physically consistent extrapolation beyond observed regimes while maintaining competitive accuracy for diverse data types. Model selection should prioritize data geometry (tabular, grid, graph, sequence) and temporal horizon requirements, with physics integration essential for safety-critical extrapolation in climate systems.

Table 2 Comparison of AI model families across data types (tabular, RS imagery, time series, graphs) and requirements (long-range temporal context, physics/constraints) for climate change mitigation. Note: ✓ = well-suited; ∼ = workable with care or common extensions; ✗ = not a natural fit.

Model	Tabular	RS imagery	Time series	Graph data	Long-range temporal	Physics/ constraints
SVMs	✓	∼	∼	✗	✗	∼
RFs	✓	∼	∼	✗	✗	∼
Ensembles models	✓	∼	∼	✗	✗	∼
CNNs	✗	✓	∼	✗	✗	∼
RNNs	∼	✗	✓	✗	∼	∼
Transformer	∼	✓	✓	∼	✓	∼
GNNs	∼	∼	∼	✓	∼	✓
Hybrid approaches	∼	∼	∼	∼	✓	✓

3 Survey Methodology

3.1 Search strategy and selection

We employed a rigorous, multi-stage screening process to identify relevant literature on AI for climate change. As illustrated in Figure 2, we initially retrieved 427 peer-reviewed articles published between 2015–2025 from major academic databases and publishers (ScienceDirect/Elsevier, IEEE Xplore, SpringerLink, ACM Digital Library, and Wiley Online Library) using Boolean searches (AND, OR) over keywords including:

- Core themes: AI, machine learning (ML), deep learning (DL), climate change, carbon reduction, environmental sustainability
- Extreme weather detection: extreme weather prediction, climate modeling, hurricane forecasting, heatwave detection, flood risk assessment, drought monitoring, wildfire prediction, storm tracking
- Ecosystem degradation and recovery: ecosystem restoration, biodiversity conservation, habitat recovery, deforestation monitoring, soil health analysis, species extinction prevention, land degradation assessment, ecological resilience

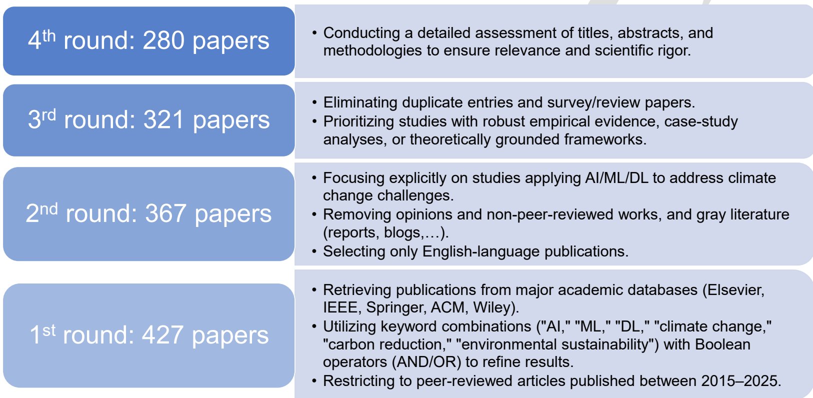


Fig. 2 SLR methodology illustrating the four-stage selection process and refinement criteria for the final paper list.

After that, the selection was narrowed to 367 by excluding gray literature (e.g., reports, blogs), non-English publications, and studies lacking explicit applications of AI/ML/DL to climate-related challenges. After removing duplicates and prior reviews, 321 studies remained that met initial relevance and methodological criteria (empirical evidence, case studies, or theoretically grounded frameworks). Finally, a detailed screening of titles, abstracts, and methods, focused on scientific validity and direct relevance, produced the 280 papers included in this systematic review.

The inclusion and exclusion criteria were each selected for specific methodological reasons. The 20152025 publication window reflects two simultaneous inflection points: the Paris Agreement establishing the 1.5 °C target and the mainstream adoption of DL, meaning pre-2015 studies rely on shallow ML methods and outdated policy frameworks that no longer represent the field's current state. Peer-reviewed articles only were retained to ensure a minimum standard of independent methodological scrutiny across the 427 retrieved items, with gray literature excluded due to the impracticality of systematic quality assessment at that scale. The explicit AI/ML/DL application to a climate outcome criterion maintained thematic coherence by excluding general-purpose AI benchmarks without climate context and pure climate science studies without AI methods. Opinion pieces, non-English publications, and prior review articles were excluded to prioritize primary empirical evidence, minimize language-assessment constraints, and avoid circular citation. Finally, studies retained in the corpus were required to present empirical evidence, case-study analysis, or a theoretically grounded framework, ensuring every included work makes a concrete, assessable contribution rather than merely describing potential applications.

3.2 Taxonomy development

This survey develops a domain-driven taxonomy based on a systematic analysis of over 280 peer-reviewed climate-related AI studies. We began with (Amiri et al., 2024)'s five main categories (ecosystems, industry, buildings/cities, transportation, agriculture), widely used in prior reviews (L. Chen, Chen, et al., 2023), but found important omissions after classifying papers by primary objective. Domains such as energy and carbon management and weather and disaster forecasting were not represented in the original schema. To ensure comprehensive coverage of the climate problem space, we therefore introduce two additional domains: Energy and Carbon Management and Weather and Disaster Forecasting.

We derived domain to method mappings through a three-phase analysis:

- Algorithm prevalence: Identify the dominant AI families used in each domain. For example, CNNs are prevalent for satellite-based deforestation monitoring in ecosystem conservation, while LSTMs and transformers are commonly applied to extreme weather prediction in the Weather and Disaster Forecasting domain.
- Data and task alignment: Associate input modalities (e.g., satellite imagery, time-series data, RS data) with domain-specific tasks and challenges to reveal which data sources drive particular algorithmic choices.
- Evaluation and operational relevance: Cross-reference techniquedomain pairs with performance and operational metrics (accuracy, scalability, latency, interpretability, and ecosystem compatibility) to validate practical applicability.

Figure 3 provides a comprehensive mapping of the AI/ML landscape within climate change mitigation, intersecting seven key domains with three core task families: prediction, classification, and optimization. The matrix reveals that prediction (forecasting, regression) is the most mature area of research across all sectors, predominantly using RNNs/LSTMs and Transformer architectures to handle time-series and sequential data. Classification (detection, mapping) is equally well-studied, particularly in fields like ecosystem reservation and agriculture where CNNs are used for spatial analysis, while optimization (control, scheduling) emerges as a critical but more specialized task, frequently employing RL and GNNs for infrastructure and grid management. Notably, the inclusion of Physics-Informed Neural Networks (PINNs)/Hybrid models in some sectors signals a shift toward physics-aware AI and hybrid approaches to enhance model performance, while the empty cells in weather forecasting highlight underexplored research frontiers where AI has yet to be fully integrated.

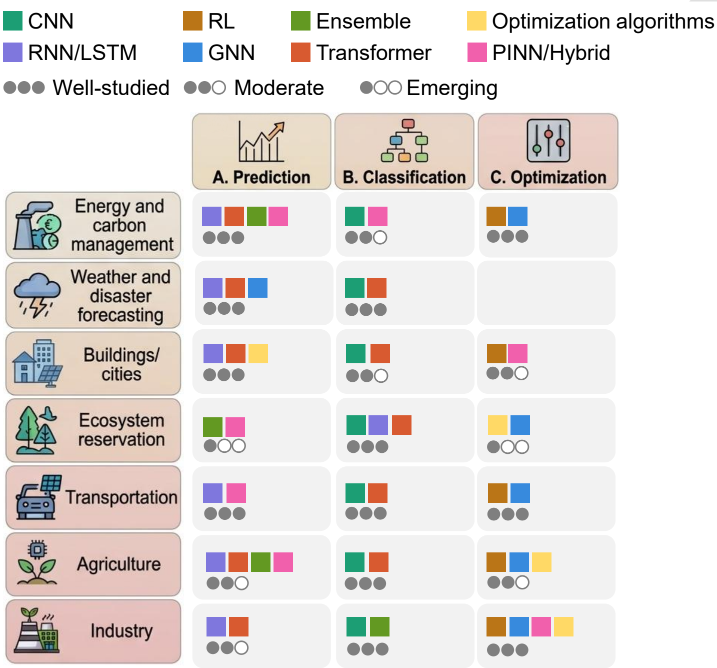


Fig. 3 A comprehensive matrix of domain and AI task-family taxonomy for climate change mitigation and adaptation for seven sectors. Rows represent the seven domains (Sections 4). Columns represent three AI main tasks: prediction (forecasting, regression), classification (detection, mapping), and optimization (control, scheduling). Note: Colored squares indicate dominate model families applied at each domain-task intersection.

3.3 Methodological quality of the reviewed literature

A recurring limitation across the 280 reviewed studies is insufficient methodological rigor in reporting, evaluation design, and reproducibility. The most common issue is train-test data leakage in spatiotemporal climate datasets, where observations from geographically adjacent locations or temporally overlapping periods are naively split across training and test sets. For instance, flood susceptibility and land-use change models (Sections 4.6 and 4.7) frequently employ random pixel-level splits (Panahi et al., 2021; J. Wang, Hadjikakou, Hewitt, & Bryan, 2022) rather than spatial or temporal holdout strategies. Consequently, models implicitly learn from the spatial autocorrelation of nearby test samples.

A related concern is overfitting to narrow validation contexts. Industrial fault detection studies are often evaluated exclusively on the Tennessee Eastman process simulation (Arunthavanathan, Khan, Ahmed, & Imtiaz, 2021; Cheng, Zhu, Wu, & Shao, 2018), while agricultural studies, such as those by (Chandel et al., 2025; Sami et al., 2022), report results derived from single fields or single growing seasons. Such limited validation offers insufficient guidance for practitioners considering multi-site deployment. Class imbalance represents a third under-addressed challenge. Although extreme weather events, equipment faults, and deforestation incidents are rare, many reviewed classification models report overall accuracy without disaggregating performance on the minority class (Bui et al., 2020; Panahi et al., 2021). This practice obscures whether the model can reliably detect these critical rare events.

Furthermore, UQ remains largely absent or weakly implemented. In contrast to the few studies that explicitly quantify and communicate uncertainty (Choubin, Jaafari, Henareh, Karimi, & Hosseini, 2025; Dikshit & Pradhan, 2021), the majority of regression and forecasting models report only point-estimate metrics (e.g., RMSE or MAE) without confidence intervals or probabilistic calibration scores. This omission causes risk-informed deployment decisions difficult to justify. Finally, significant reproducibility gaps, including absent code repositories, unspecified hyperparameter settings, and reliance on proprietary or undisclosed datasets, affect a substantial share of the literature. This is particularly evident in the industrial and transportation domains, where our manual screening during the SLR revealed that most studies lack sufficient implementation detail for independent replication.

3.4 Bibliometric and statistical analysis

Figure 4 presents a bibliometric analysis of the reviewed literature. As shown in Figure 4(a), annual publication volume grew substantially over the review period, closely following the broader adoption curve of DL within the research community. The inflection point around 2019–2020 was driven by the widespread availability of pre-trained transformer models, large-scale climate datasets (e.g., ERA5 and GPM), and open-source frameworks that significantly lowered the barrier to applying DL in climate research.

Figure 4(b) illustrates the distribution of reviewed studies across the seven domains under consideration. Energy and carbon management constitutes the largest share (21%), reflecting the sector's dual role as the largest source of GHG emissions and the domain with the longest history of computational modeling. Transportation (15%) and agriculture (14%) follow, driven by strong industry interest in autonomous systems and precision farming, respectively. Ecosystem conservation and weather and disaster forecasting each represent approximately 12–13% of the corpus, while buildings and cities and industry account for roughly 14% and 12%, respectively.

Figure 4(c) reveals a pressing geographic imbalance in the literature. Asia accounts for approximately 35% of all studies (led by China, Japan, South Korea, India, and Vietnam), followed by North America (26%, predominantly the United States) and Europe (22%, led by Germany, the UK, the Netherlands, and France). Global or multi-region studies comprise roughly 11% of the corpus. Most strikingly, Africa (1%), South America (2%), and Oceania (3%) together account for fewer than 20 of the 280 reviewed studies, despite these regions collectively containing a disproportionate share of the world's climate-vulnerable populations and critical ecosystems. Sub-Saharan Africa, home to over 1.4 billion people who depend heavily on rain-fed agriculture and face escalating drought, flood, and food security risks, is represented by only a handful of studies, nearly all of which focus on remote sensing-based land cover classification rather than operationally deployable AI mitigation tools (Eddamiri et al., 2025). This geographic skew reflects a structural gap that limits the generalizability of current models and undermines the equity of AI-driven climate solutions.

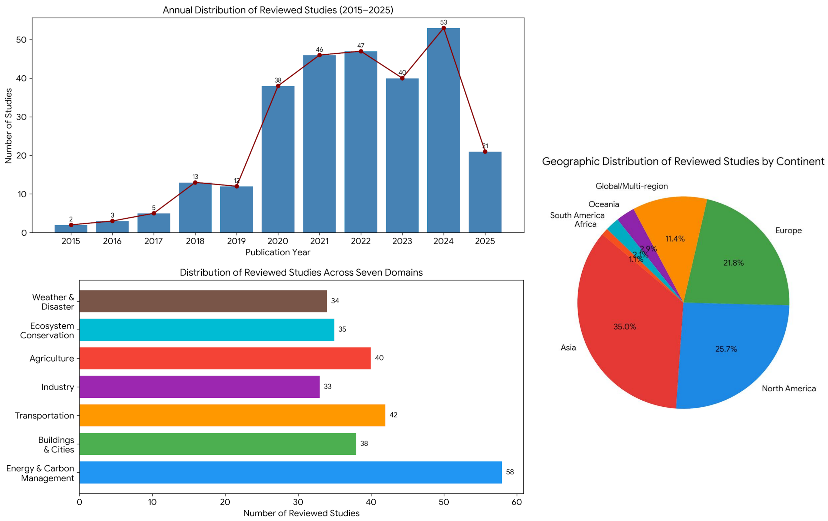


Fig. 4 Bibliometric analysis of the 280 reviewed studies: (a) Annual publication trend from 2015 to 2025; (b) distribution for seven domains; (c) Geographic distribution by continent. Note: Percentages in (b) are rounded.

4 AI Applications for Climate Change Mitigation

This section systematically examines AI solutions for seven high-impact domains, organized according to their primary climate function. Domains 4.1–4.5 (energy and carbon management, buildings and cities, transportation, industry, and agriculture) are categorized as mitigation-focused, emphasizing emissions reduction, resource optimization, and decarbonization pathways. Domains 4.6 (ecosystem conservation) and 4.7 (weather and disaster forecasting) are classified as adaptation-focused, prioritizing climate resilience, hazard preparedness, and ecosystem stability. These adaptation-oriented domains are included because they directly enable and reinforce mitigation outcomes, and because the IPCC AR6 framework explicitly recognizes them as complementary to emissions reduction strategies (Calvin et al., 2023). Within each domain, individual tasks are explicitly labeled as mitigation, adaptation, or hybrid to ensure terminological consistency throughout the review.

4.1 Energy and carbon management

As the global economy expands and the population rises, energy demand surges, driving an increase in heat-trapping GHG emissions. Many of these emissions result from burning fossil fuels for power generation, industrial processes, and transportation (Amiri et al., 2024). To meet growing energy needs while achieving net-zero targets, coordinated supply- and demand-side measures are required. On the supply side, renewable energy sources, such as solar, wind, and hydro, have grown at roughly 14% per year since 2010 (T.I.E. Agency, 2025), but still account for only about 13% of total global energy consumption. Although the International Energy Agency (IEA) projects that renewables could reach roughly 20% of total energy by 2030 (T.I.E. Agency, 2025), this projection potential will depend on solutions that manage grid instability from intermittent generation and improve resource allocation, storage, and system flexibility.

Simultaneously, effective carbon management practices, including carbon sequestration and GHG monitoring, play a vital role in reducing GHG emissions. Carbon sequestration captures CO_2 from industrial processes and power generation and stores it securely, preventing its release to the atmosphere. The IEA reports there are roughly 45 commercial capture facilities operating worldwide, with a combined capture capacity of more than 50 million tons of CO_2 per year (Parisi et al., 2024). In addition, nature-based carbon solutions, such as forests, soils, and managed agricultural systems, naturally absorb CO_2 and are essential for climate mitigation. Protecting and restoring these natural systems is therefore crucial to comprehensive carbon management and to achieving a sustainable transition to low-carbon economies. Overall, technological and nature-based approaches are complementary and necessary for deep decarbonization.

AI is essential for energy management by turning large, noisy data streams into real-time decisions that boost efficiency and enable decarbonization at scale. ML models improve demand and renewable generation forecasts, allowing operators to schedule resources and storage more accurately. Reinforcement learning (RL) and optimization algorithms allocate distributed energy resources, battery dispatch, and demand-response actions to minimize costs and emissions. AI enables predictive maintenance for power plants and grid assets, reducing outages and extending equipment life, and digital twins/simulation tools let planners test scenarios for high renewables futures. When deployed carefully with good data governance, attention to model interpretability, and human oversight, AI can increase renewable integration, lower system costs, and speed the transition to a low-carbon energy system.

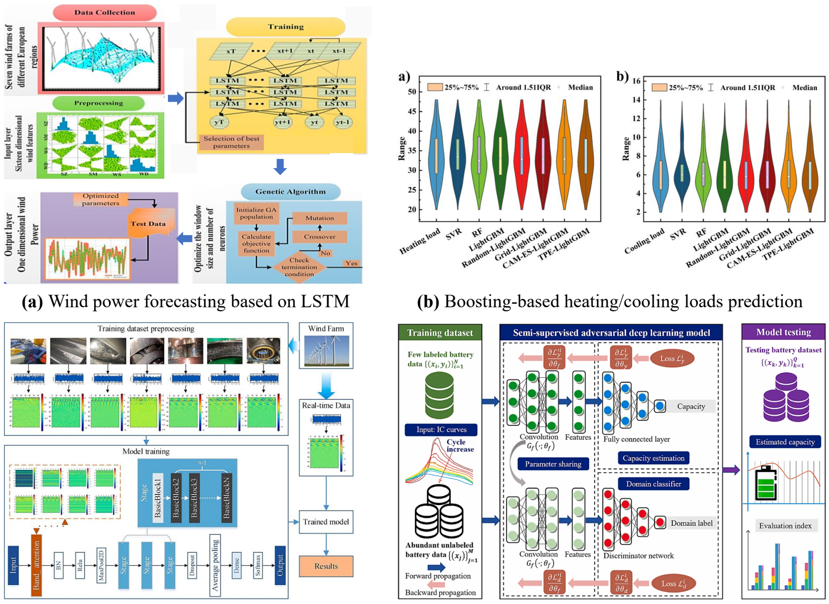
4.1.1 Energy management

Energy management targets the largest source of global GHG emissions: how we produce, distribute, and consume energy. Effective energy management reduces demand through efficiency measures, shifts consumption toward low-carbon electricity, and increases system flexibility by integrating renewables, storage, and demand-response programs. By lowering overall energy use, smoothing peaks, and enabling higher shares of variable renewable generation, strong energy management both cuts emissions and reduces costs and resilience risks for communities and utilities.

AI has become an essential component of modern energy systems, enhancing efficiency, reliability, and the integration of renewable resources. Its main applications are renewable energy forecasting, grid and load management, fault detection and predictive maintenance, and energy storage optimization. By leveraging advanced ML and DL techniques, AI improves both the accuracy and effectiveness of these tasks and supports the transition toward a more sustainable and resilient energy infrastructure.

Figure 5 illustrates the four representative AI-based approaches for core energy management tasks. Figure 5(a) describes a hybrid LSTM and Genetic Algorithm (GA) framework proposed by (Shahid, Zameer, & Muneeb, 2021) for wind power forecasting. Raw turbine measurements are preprocessed and fed into a multi-step LSTM network, while a GA tunes hyperparameters to minimize prediction error. Figure 5(b) depicts a residential load forecasting pipeline in which building parameters and occupancy patterns are used to construct a synthetic dataset (J. Guo et al., 2023). After that, various boosting algorithms are applied to predict heating and cooling demands. Figure 5(c) shows a real-time wind turbine fault detection system based on a deep CNN ensemble that analyzes multi-scale vibration and timefrequency image data to detect gearbox anomalies (K. Zhang, Tang, Deng, & Liu, 2021). Finally, Figure 5(d) summarizes a semi-supervised adversarial model for battery state-of-health estimation proposed by (Yao, Chang, Han, & Tian, 2024). These workflows demonstrate how task-specific data preprocessing, model innovation, and optimization strategies enable robust AI solutions for grid stability, demand and response efficiency, predictive maintenance, and storage longevity.

- Renewable energy forecasting, particularly for wind and solar, plays a pivotal role in enhancing grid stability and seamless integration of clean energy sources. For example, the intermittent nature of renewable energy poses significant challenges for grid operators, who must balance supply and demand in real-time. Therefore, accurate predictions of solar and wind power generation reduce the risk of blackouts, minimize energy waste, and lower operational costs by aligning supply with demand. AI techniques, such as ML and DL models, have contributed significantly to improving the accuracy of these forecasts. ML models, such as SVMs and Regression, and DL models, such as RNN/LSTM and Transformers, have been used to predict energy output with higher accuracy than traditional methods (Aslam, Aung,



(a) Wind power forecasting based on LSTM **(b)** Boosting-based heating/cooling loads prediction

(c) DL Wind turbines gearbox fault diagnosis **(d)** Capacity estimation of battery energy storage systems

Fig. 5 Representative AI approaches for each key task of energy management. (a) Renewable energy forecasting (Shahid et al., 2021); (b) Grid/load management (J. Guo et al., 2023); (c) Fault detection and maintenance (K. Zhang et al., 2021); and (d) Energy storage (Yao et al., 2024).

Rafsanjani, & Majeed, 2025). Recent advances include (X. Li et al., 2022) probabilistic solar irradiance model, which used eXtreme Gradient Boosting (XGBoost) for point prediction and kernel density estimation to generate forecasts with confidence intervals. Similarly, Bashir et al. (2025) proposed hybrid CNN-ABiLSTM and CNN-Transformer-Multilayer Perceptron (MLP) frameworks that combined short-term pattern recognition with long-term sequence modeling for solar/wind forecasting. These studies highlight the crucial role of renewable forecasting in stabilizing grids and accelerating decarbonization.

- Grid/load management is essential for ensuring supply and demand alignment to prevent overloads and blackouts. For example, grid load forecasting allows operators to strategically optimize the grid load during peak demand, minimizing reliance on carbon-intensive backup power. Z. Deng et al. (2019) introduced TCMS-CNN, a DL model that enhanced multi-step short-term electric load forecasting by combining multi-scale CNNs with a time perception strategy. In addition, deep RL optimized dynamic load balancing and renewable integration through smart charging systems, minimizing transmission losses. (Rocchetta, Bellani, Compare, Zio, & Patelli, 2019) validated this with a non-tabular RL framework using Artificial Neural Network

(ANN) ensembles for grid maintenance scheduling. The framework improved grid resilience and reduced emissions. These approaches stabilize grids and accelerate the transition to low-carbon energy systems.

- Fault detection and maintenance, such as anomaly detection in wind turbines/solar panels and grid condition monitoring, are vital for optimizing system reliability and resource utilization. AI technologies like vibration analysis and anomaly detection enable early defect detection in critical components (e.g., gearboxes), preventing energy losses and unplanned downtime (Tautz-Weinert & Watson, 2017). (Le et al., 2021) achieved 94% anomaly detection accuracy and 86% fault classification (12 types) using infrared imaging and ensemble residual DNNs on 20,000 real-world solar photovoltaic (PV) images. Similarly, Xiang, Yang, Hu, Su, and Wang (2022) advanced wind turbine monitoring via a Supervisory Control and Data Acquisition (SCADA) data pipeline: quartile-based cleaning, Pearson correlation feature selection, and spatio-temporal feature extraction using CNN-attention-BiGRU networks for precise anomaly localization. The experimental results showed that this approach effectively detects early operational anomalies and pinpoints failed components. These methods extend asset lifespans, boost decarbonization, and fortify grid resilience.
- Energy storage plays a critical role in integrating renewable energy sources into the grid by addressing their inherent intermittency and variability (Dang, Nguyen, et al., 2024). Storage systems enable dynamic balancing of supply and demand by storing excess energy during periods of high renewable output. K. Zhou, Zhou, and Yang (2022) integrated modified DL predictors (for photovoltaic (PV)/load) with RL agents to optimize storage scheduling under uncertainty. The proposed system reduced solution time by 61.17% compared to mixed-integer linear programming for real-time microgrid applications. Yao et al. (2024) addressed battery capacity estimation via semi-supervised adversarial DL. The model transformed unlabeled voltage and current data into incremental capacity-based features to minimize labeled-data dependency. The model outperformed existing methods and offers a scalable solution for industrial battery energy storage systems (BESS) capacity estimation. These AI-based approaches enhance grid flexibility, maximize renewable utilization, and accelerate the transition to low-carbon energy systems.

4.1.2 Carbon management

This review adopts a consistent four-level terminology hierarchy for carbon and GHG-related AI tasks, following the analytical distinctions recommended in the literature: (1) GHG monitoring refers to sensor- or satellite-based direct measurement of greenhouse gas concentrations or fluxes; (2) emission estimation refers to statistical or ML-based inference of emission quantities from indirect indicators; (3) emission forecasting refers to time-series or DL prediction of future emission levels; and (4) carbon accounting refers to the annualized compilation of emission inventories across sectors or entities. These terms carry distinct analytical meanings and are used accordingly throughout this survey.

Carbon management is fundamental to achieving net-zero emissions by combining emissions reduction, removal, and long-term storage to limit atmospheric concentrations of CO_2 and other GHG. It relies on engineered approaches, such as active GHG monitoring and carbon capture and storage (CCS), and nature-based solutions, such as afforestation, soil carbon sequestration, wetland restoration, to actively remove carbon from the atmosphere. AI is transforming carbon management by enhancing the precision, scalability, and cost efficiency of CCS processes. GHG monitoring through AI models enables precision detection of inefficiencies and leakage in real-time. Moreover, data-driven sequestration strategies optimize geological storage integrity through real-time reservoir characterization and injection control. AI-based geospatial analytics and digital twins support site selection and risk assessment for storage and nature-based projects. Crucially, deploying AI for carbon management must include UQ, transparency, and human oversight to ensure reliable, verifiable, and ethical outcomes.

GHG monitoring is the systematic measurement, analysis, and reporting of GHG emissions. It combines in-situ sensors, flux towers, atmospheric sampling, RS from satellites and aircraft, emissions inventories, and model-based methods (e.g., atmospheric inversion and data fusion) to produce consistent, spatially and temporally resolved estimates of CO_2, methane, and other gases. Reliable monitoring enables governments, companies, and land managers to track progress against net-zero pledges, target high impact mitigation actions, verify outcomes for carbon markets, and detect leaks or hotspots that require rapid response. AI offers powerful tools to enhance GHG monitoring by improving the accuracy, scale, and timeliness of GHG measurement and reporting. ML and DL models can process vast streams of data from satellites, drones, ground-based sensors, and atmospheric models to detect emissions patterns, quantify carbon fluxes, and identify anomalies such as methane leaks or illegal deforestation. Frameworks like CarbonTracker (Anthony, Kanding, & Selvan, 2020) allows experts to monitor real-time energy use and emissions. Given that household emissions constitute significantly to global carbon footprints, (An et al., 2024)s explainable XGBoost-Tree-structured Parzen Estimator (TPE) emission estimation model estimates provincial/city footprints across China (20062021) with 87.4% accuracy using only five features. While advances in sensors and AI are rapidly improving resolution and timeliness, challenges remain in attribution, harmonizing methodologies, and ensuring fair access to monitoring capabilities across regions.

Carbon sequestration securely capturing and storing atmospheric carbon through advanced techniques such as storage estimation, CO_2 sequestration simulation, and optimization. It involves both natural processes and engineered solutions. Natural carbon sequestration occurs through ecosystems such as forests, wetlands, grasslands, and soils, which absorb and store CO_2. Engineered approaches, including CCS and direct air capture, involve capturing CO_2 from industrial emissions or directly from the atmosphere and securely storing it in geological formations or using it in long-lasting products. ML and DL models are increasingly being applied to enhance carbon sequestration strategies by improving efficiency, monitoring, and scalability. For example, (L. Xi, Shu, Sun, Huang, & Song, 2023) proposed a two-stage RS framework to optimize sequestration infrastructure deployment, which improved forest carbon sink quantification by 18.3% compared to conventional methods. Simulation tools, like nonlinear autoregressive RNN model (Punnam, Dutta, Krishnamurthy, & Surasani, 2023), enabled engineers to forecast post-injection CO_2 trapping dynamics in heterogeneous reservoirs. The tool accelerated geological storage analysis by 40% while maintaining integrity. Recently, Hernandez-Mejia, Imhof, and Pyrcz (2024) developed a hybrid anomaly detection system for geological carbon sequestration that identified subsurface leakage, fracture, or fault risks in CO_2 storage. These innovations not only reduce atmospheric CO_2 concentrations but also align with global net-zero targets.

4.1.3 Discussion

Table 3 summarizes typical energy management tasks, along with representative applications, methods, and datasets. Across reviewed energy and carbon management studies, transformer-based and hybrid LSTM-optimization models consistently outperform conventional baselines in renewable forecasting (Aslam et al., 2025; Bashir et al., 2025; Shahid et al., 2021), although performance sensitivity to data resolution and geographic context remains significant. CNNs and sequence models are preferred for spatiotemporal satellite data, achieving 94% anomaly detection accuracy in solar PV fault monitoring (Le et al., 2021). In real-time dispatch and storage scheduling, RL demonstrates superior efficiency, achieving up to a 61.17% reduction in computation time compared to Mixed-Integer Linear Programming (MILP) (K. Zhou et al., 2022). However, RL deployment in regulated grid environments remains constrained by stringent interpretability requirements.

Table 4 summarizes AI applications for two critical CCS tasks: GHG monitoring and carbon sequestration. Ensemble tree methods (e.g., XGBoost) offer an optimal accuracyinterpretability trade-off for tabular inventory data, reporting 87.4% accuracy with only five input features (An et al., 2024).

Despite these advances, persistent challenges remain in deploying AI for energy and carbon management. High-performing DL models often require substantial computational infrastructure that many grid operators in developing economies struggle to sustain reliably (Zheng, Wu, Li, & Song, 2025). In addition, UQ in storage scheduling and CCS simulation models is inconsistent, with overconfident predictions posing financial and safety risks. Future research should prioritize physics-informed hybrid architectures embedding power flow equations and thermodynamic constraints, which reduce reliance on large-scale annotated datasets while ensuring physical plausibility across diverse grid configurations.

4.2 Buildings/cities

Buildings/Cities consume the majority of energy and materials across their lifecycle through operational energy for heating, cooling, lighting and through embodied carbon in construction. According to Intergovernmental Panel on Climate Change (IPCC) Sixth Assessment Report, buildings alone consume roughly 31% of global energy and contribute over 21% of GHG emissions (Kikstra et al., 2022). Efficient and resilient urban and building infrastructure is fundamental to emission reduction, as it directly shapes the energy intensity of daily life and the emissions embedded in construction and operation.

Table 3 Summary of four task areas for AI in energy management, including (1) *renewable energy forecasting*; (2) *grid/load management*; (3) *fault detection & maintenance*; and (4) *energy storage*. Column 2 reports the best quantitative metric drawn from reviewed studies and a cross-study comparison of model families. Abbreviations: SVM = support vector machine; RNN = recurrent neural network; LSTM = long short-term memory; DNN = deep neural network; RL = reinforcement learning; SCADA = supervisory control and data acquisition; BESS = battery energy storage system; RMSE = root mean square error.

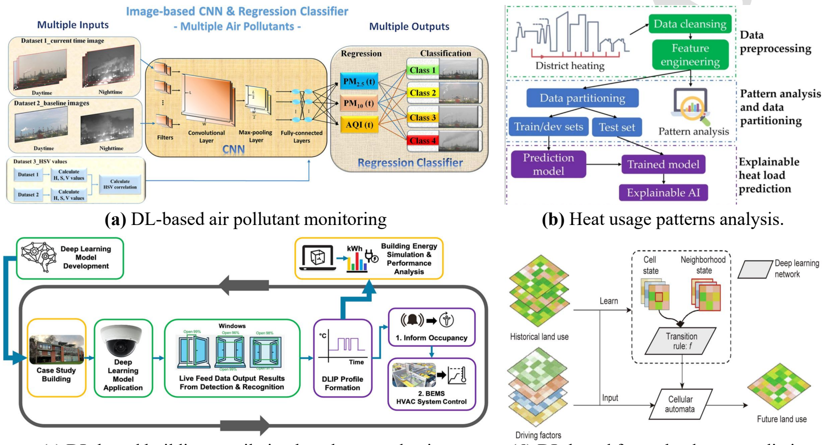
Tasks	Key metric & cross-study finding	Representative methods	Representative data
Renewable energy forecasting (wind, solar)	RMSE reduced by 30.21 %; std. dev. 50.36 % vs. ensemble mean (J. Zhao, Guo, Guo, Lin, & Zhu, 2021); wind value +20 % (Deepmind, 2025a). *Similarity:* Hybrid LSTM-GA and CNN-Transformer consistently outperform SVM and single-architecture DL. *Difference:* Gains vary substantially with data resolution and geographic context; transfer across climatic regions remains unvalidated.	SVM (Jang, Bae, Park, & Sung, 2016; Z. Tian et al., 2018); Ensemble (X. Li et al., 2022; Torres-Barrán, Alonso, & Dorronsoro, 2019); RNN/LSTM (Harrou, Kadri, & Sun, 2020; Shahid et al., 2021); Transformers (Mo et al., 2024; H. Wang, Li, et al., 2024); Hybrid (Bashir et al., 2025; Ren, Yu, Gao, Yu, & Yu, 2022)	Wind farm SCADA (Maldonado-Correa, Martín-Martínez, Artigao, & Gómez-Lázaro, 2020); SDWPF (J. Zhou et al., 2024); Fingrid PV; Kaggle (Afroz, 2025; Modi, 2025)
Grid/load management	Scheduling time reduced by 61.17 % vs. MILP (K. Zhou et al., 2022). *Similarity:* RL outperforms rule-based controllers; DNN-based load forecasting outperforms Autoregressive integrated moving average (ARIMA) across datasets. *Difference:* RL requires simulation environments; DNN performance affected by sparse or low-frequency smart meter data.	RL (Y. Liu, Lu, Yu, Chen, & Yang, 2024; Rocchetta et al., 2019); RNN/LSTM (W. Kong et al., 2017; Muzaffar & Afshari, 2019); DNNs (Z. Deng et al., 2019; Lara-Benítez, Carranza-García, Luna-Romera, & Riquelme, 2020; Tarmanini, Sarma, Gezegin, & Ozgonenel, 2023; Tightiz, Dang, & Yoo, 2023); Boosting (J. Chen, Zhang, & Nanehkaran, 2021; Dang, Shin, et al., 2023; J. Guo et al., 2023)	Smart meter (Alemazkoor, Tootkaboni, Nateghi, & Louhghalam, 2022; Pereira, Costa, & Ribeiro, 2022); Building loads (Emami, Sahu, & Graf, 2023)
Fault detection & maintenance	94 % anomaly detection; 86 % fault classification (12 types) (Le et al., 2021). *Similarity:* CNN-ensemble and hybrid models outperform single-architecture DNNs across PV and wind benchmarks. *Difference:* Results concentrated on solar PV imagery; generalization to wind turbine SCADA requires domain-specific retraining.	DNNs (J. Chen, Li, Chen, Wang, & Jiang, 2020; Le et al., 2021; B. Su, Chen, & Zhou, 2021; H. Zhao, Liu, Hu, & Yan, 2018); Dimensionality reduction (Y. Wang, Ma, & Qian, 2018); Hybrid (Xiang et al., 2022; K. Zhang et al., 2021)	Turbine/PV SCADA (Tautz-Weinert & Watson, 2017); Sensor streams (vibration, temp.) (Mendeley, 2025)
Energy storage	Solution time 61.17 % vs. MILP (K. Zhou et al., 2022); semi-supervised DL outperforms supervised baselines for capacity estimation (Yao et al., 2024). *Similarity:* RL agents outperform rule-based storage controllers. *Difference:* Semi-supervised approaches reduce labeled-data dependency; statistical models remain competitive on small datasets.	RL (Cordeiro-Costas, Villanueva, Eguía-Oller, & Granada-Álvarez, 2023; Duan et al., 2019; K. Zhou et al., 2022); Statistical (Hafiz, Awal, de Queiroz, & Husain, 2020; Ordoñez, Barco-Jiménez, Pantoja, Revelo-Fuelagán, & Candelo-Becerra, 2024); DNNs (J. Wang, Yin, Liu, & Cai, 2023; Yao et al., 2024)	Simulated or real BESS market data; Historical price/time series

Table 4 Summary of two task areas for AI in carbon management, including (1) *GHG monitoring and emission estimation*; and (2) *carbon sequestration*. Column 2 reports the best quantitative metric and cross-study comparison. Abbreviations: CNN = convolutional neural network; RNN = recurrent neural network; LSTM = long short-term memory; DNN = deep neural network; XCO_2 = column-averaged dry-air mole fraction of CO_2.

Tasks	Key metric & cross-study finding	Representative methods	Representative data
GHG monitoring & emission estimation	87.4 % accuracy with five features (An et al., 2024); forest carbon sink quantification +18.3 % (L. Xi et al., 2023). *Similarity:* Ensemble methods (XGBoost) and CNNs consistently outperform purely statistical approaches. *Difference:* Ensemble methods preferred for tabular inventory data; CNNs preferred for spatiotemporal satellite inputs (OCO-2, Sentinel-5P).	CNNs (Anthony et al., 2020); Ensemble (An et al., 2024; W. Liu et al., 2024); RNN/LSTM (Verma, Ranga, & Vishwakarma, 2023); Hybrid (L. Xi et al., 2023)	OCO-2/3 XCO_2 (Nasa, 2025); Sentinel-5P (Copernicus, 2025b); simulated dioxid plume (Esa, 2025); GHGSat (Ghgsat, 2025)
Carbon sequestration	Geological storage analysis 40 % faster than conventional tools (Punnam et al., 2023); anomaly detection for subsurface leakage (Hernandez-Mejia et al., 2024). *Similarity:* DNN/RNN hybrids outperform classical reservoir simulators in simulation speed. *Difference:* PINNs more reliable when tested under new environments; purely data-driven models require large labeled datasets that are often unavailable for novel geological sites.	DNNs (Hernandez-Mejia et al., 2024; Punnam et al., 2023; You et al., 2020); RNN/LSTM (Chao, Maimai, Hanzhang, Zhibo, & Xiaohui, 2023; Jia et al., 2024; Z. Zhong, Sun, Yang, & Ouyang, 2019); Hybrid (L. Xi et al., 2023)	Well logs; seismic surveys; porosity/permeability maps

AI offers powerful tools to create efficient and resilient cities/buildings by enabling long-term climate resilience and sustainable growth. Ding, Ke, Levine, and Zhou (2024) projected that AI applications could reduce building energy consumption and associated emissions by 8–19% by 2050 beyond conventional approaches. In practice, AI utilize sensor networks and historical data to improve design, operation and planning, recommend high-impact retrofit packages, and optimize Heating, Ventilation, and Air Conditioning (HVAC) and lighting operations.

Figure 6 illustrates how ML and DL models address four representative tasks in buildings/cities for climate change mitigation. In Figure 6(a), CNNs process multi-source satellite and ground imagery to support near-real-time pollution monitoring (Kow, Hsia, Chang, & Chang, 2022). Figure 6(b) presents an explainable AI (XAI) pipeline by (Dang, Shin, et al., 2023) that produces transparent, interpretable heat demand forecasts for district heating systems. In Figure 6(c), Tien (Tien et al., 2021) feeds live CCTV streams into a vision-based DL model to detect window-opening events in real-time. This reduces winter heating losses by eliminating unnecessary ventilation while maintaining indoor air quality. Finally, Figure 6(d) shows a hybrid DLcellular automaton approach from (Hao, Wang, & Chen, 2024) that learns land use transition rules from historical maps and driving factors to project future urban scenarios for low-carbon planning. These examples demonstrate how AI can accelerate that decarbonization by targeted preprocessing, interpretable modeling, occupant-level sensing, and data-driven scenario projection.



(a) DL-based air pollutant monitoring **(b)** Heat usage patterns analysis.

(c) DL-based building ventilation heat losses reduction **(d)** DL-based future land uses prediction

Fig. 6 Representative AI approaches for each key task in buildings/cities. (a) Environmental monitoring and emission reduction (Kow et al., 2022); (b) Energy efficiency and management (Dang, Shin, et al., 2023); (c) Human-centric and behavioral recognition (Tien et al., 2021); and (d) Urban planning and infrastructure optimization (Hao et al., 2024).

4.2.1 Energy efficiency and management

According to United Nations Environment Programme (UNEP) (UNEP, 2025), buildings account for approximately 40% of global energy use and one-third of GHG emissions, predominantly from heating, cooling, and electricity demands. In buildings and cities, AI enables real-time energy monitoring, predictive maintenance, and adaptive control of heating, cooling, and lighting systems, which dramatically cut energy waste. For instance, Olu-Ajayi, Alaka, Sulaimon, Sunmola, and Ajayi (2022) validate various DL models and identify deep neural networks (DNNs) as the most effective predictive model for estimating annual building energy consumption during the early design phase. Building retrofitting, which involves upgrading existing structures with energy efficient technologies and systems, such as improved insulation, HVAC, windows, or lighting, also has huge potential to reduce energy consumption and improve performance. Retrofitting existing buildings with smart technologies, such as EV integration, solar panels, and digital twin simulations, is increasingly utilized to reduce emissions. For example, D. Ma, Li, Lin, Zhu, and Yue (2023) validated this approach by using static and dynamic building features to train models that improve the efficiency and accuracy of retrofit strategies under changing climate conditions.

4.2.2 Urban planning and infrastructure optimization

Urban planning and infrastructure optimization in the buildings sector play a critical role in mitigating climate change. Building standards can be optimized to employ smart sensors and renewable energy sources to ensure that urban services run more efficiently and with lower carbon footprints. Modern cities generate massive data streams from traffic sensors, cell phones, utility meters, and satellite imagery, which AI analyzes to optimize urban environments. For example, optimizing urban geometry, such as building orientation, density, and green spaces, can lower carbon emissions by over 50% in new constructions compared to conventional designs (Al-Waked, Nasif, Groenhout, & Partridge, 2017). Y. Zhang et al. (2023) extend this to infrastructure management, where multi-objective optimization algorithms were implemented to help infrastructure managers strategically plan maintenance and replacement interventions for long-term resilience and resource efficiency planning. (Hao et al., 2024) integrated AI into scenario planning to enhance cities ability to anticipate and respond to uncertain futures. Green infrastructure integration, including green roofs, passive solar design, and flood resistant infrastructure, not only cuts emission and minimizes urban heat islands but also reduces long-term energy consumption. AI can be used to optimize green space distribution and building materials. For example, digital twin technology can be employed to forecast how new buildings, or green spaces affect city-wide energy demand or flood risk (Schrotter & Hürzeler, 2020).

4.2.3 Environmental monitoring and emission reduction

AI plays a crucial role in environmental monitoring by enabling the real-time collection, integration, and interpretation of vast, various data streams from networks of IoT sensors that continuously collect data on air quality, temperature, humidity, and noise. The collected data is fed into predictive ML and DL models to detect anomalies and emerging trends in real-time. For example, (L. Zhu, Husny, Samsudin, Xu, & Han, 2023) used a ConvLSTM model to capture spatio-temporal pollution dynamics in pollution data. The model significantly improved water and air quality assessments in rapidly urbanizing areas. For air pollution, AI models are used to forecast pollutant concentrations and evaluate emission sources (Wu et al., 2023). (J. Liu, Zhou, Yang, & Wu, 2022) integrated peer-to-peer energy trading and green vehicle storage into an uncertainty-aware energy planning framework for net-zero energy communities. This approach offers actionable insights for achieving carbon neutrality in the building sector by addressing uncertainties in weather parameters.

4.2.4 Human-centric and behavioral recognition

This approach utilizes AI to monitor and influence human behavior in buildings and cities to enhance sustainability. Networks of IoT devices and wearables feed real-time data to AI models that detect occupant activities and adjust systems like heating or lighting to save energy. For example, (Tien et al., 2021) introduced a vision-based DL framework that detects and recognizes manual window operations in real-time to reduce unnecessary heat loss. Beyond energy, this approach enhances human well-being, productivity, and energy efficiency. (Bardoutsos et al., 2020) integrated IoT, DL, and citizen engagement to monitor air pollution and noise at high spatial resolution in urban environments. (M. Deng, Wang, Li, & Menassa, 2022) used a novel Digital ID concept to predict and track individual occupants real-time indoor comfort states. On a larger scale, AI can promote sustainable behaviors in entire communities or cities by analyzing patterns and providing personalized recommendations for reducing energy consumption or waste.

4.2.5 Discussion

Table 5 illustrates concrete applications of AI on four critical domains: energy efficiency and management, urban planning and infrastructure optimization, environmental monitoring and emission reduction, and occupancy behavior recognition. Across the reviewed studies on buildings and cities, DNNs and boosting algorithms demonstrate the strongest performance for building energy consumption forecasting. Notably, DNNs show advantages in early-design-phase predictions where physical sensor data is unavailable (Olu-Ajayi et al., 2022). RL-based HVAC control systems consistently outperform rule-based controllers, reporting energy reductions of 9–13% in large buildings and campuses (Luo et al., 2022; Nweye et al., 2025). However, these systems often rely on simulation environments that fail to capture the full variability of real-world occupant behavior. Although XAI methods, such as SHapley Additive exPlanations (SHAP), are increasingly integrated into building energy tools to enhance practitioner trust (Dang, Shin, et al., 2023), a systematic quantification of their computational cost remains absent from the literature.

A key methodological concern is that many reviewed studies are validated on single buildings or controlled environments, with very few reporting cross-building or multi-year generalization performance (Shen et al., 2026). This suggests that benchmark results in this domain may be systematically optimistic. Additionally, the literature is dominated by single-asset optimization, with scarce attention paid to how building-level AI decisions aggregate into grid-level flexibility or neighborhood-scale emission reductions (Hintz, Gross, Creutzig, & Kaack, 2026).

4.3 Transportation

Transportation is the largest source of global GHG emissions driven mainly by road vehicles and freight. Globally, the transportation sector contributes approximately 23% of energy-related CO_2 emissions, with road vehicles, including cars and trucks, accounting for about 70% of direct transport emissions (U.S.E.P. Agency, 2025). In the United States, transportation accounts for 29% of total emissions in 2022

Table 5 Summary of four task areas for AI in buildings and cities, including (1) *energy efficiency and management*; (2) *urban planning and infrastructure optimization*; (3) *environmental monitoring and emission reduction*; and (4) *human-centric and behavior recognition*. Column 2 reports the best quantitative metric and cross-study comparison. Abbreviations: ASHRAE = American Society of Heating, Refrigerating and Air-Conditioning Engineers; CNN = convolutional neural network; RL = reinforcement learning; RNN = recurrent neural network; LSTM = long short-term memory.

Tasks	Key metric & cross-study finding	Representative methods	Representative data
Energy efficiency & management	Energy use reduced by 9–13 % in large buildings (Nweye et al., 2025); emissions reduced by 8–19 % by 2050 (Ding et al., 2024); DNNs best for early-design-phase prediction (Olu-Ajayi et al., 2022). *Similarity:* RL and DNNs consistently outperform rule-based controllers and statistical baselines. *Difference:* RL validated almost entirely in simulation; DNN performs poorly when physical sensor data is unavailable.	CNNs (Dang, Shin, et al., 2023; Y. Gao, Ruan, Fang, & Yin, 2020; Olu-Ajayi et al., 2022); RL (T. Liu, Tan, Xu, Chen, & Li, 2020); RNN/LSTM (Mtibaa et al., 2020; J.Q. Wang, Du, & Wang, 2020); Boosting (Ali et al., 2024; D. Ma et al., 2023); Hybrid (Elsisi, Tran, Mahmoud, Lehtonen, & Darwish, 2021; Z. Li, Ma, Tan, Guo, & Li, 2023)	Energy usage logs; ASHRAE energy; Pecan Street; Building sensor data
Urban planning & infrastructure	Carbon emissions reduced by 50 % with optimized urban geometry (Al-Waked et al., 2017). *Similarity:* Multi-objective optimization outperforms single-objective baselines for long-horizon planning. *Difference:* Digital twin approaches show advantage for scenario projection; CNN-based methods preferred for remote sensing inputs.	Optimization (Y. Zhang et al., 2023; Y. Zhong & Li, 2024); CNNs (S. Gao & Wang, 2023; Shehadeh, Alshboul, & Tamimi, 2024; Zou, Lou, Xia, Lun, & Yin, 2021); RL (Hao et al., 2024); Digital twins (Petri, Rezgui, Ghoroghi, & Alzahrani, 2023)	Satellite imagery (Sentinel-5P); Government monitoring networks
Environmental monitoring & emission reduction	Spatiotemporal pollution assessment improved vs. static CNN models (L. Zhu et al., 2023). *Similarity:* ConvLSTM outperforms CNN-only for spatiotemporal dynamics. *Difference:* Performance gap between controlled-environment and real-world deployment consistently observed; hybrid models improve robustness.	CNNs (Kow et al., 2022; L. Zhu et al., 2023); Regression (J. Liu et al., 2022); Hybrid (Shafiq et al., 2024; Wu et al., 2023)	CCTV; Sentinel-5P; EPA AQS
Human-centric & behavior recognition	Vision-based window detection reduces heating losses (Tien et al., 2021). *Similarity:* IoT-integrated DL models outperform threshold-based rule systems. *Difference:* Vision-based models require CCTV infrastructure unavailable in many buildings; IoT-integrated approaches generalize better for various building types.	CNNs (Tien et al., 2021); Regression (Bardoutsos et al., 2020); RL (Gupta, Badr, Negahban, & Qiu, 2021); Hybrid (M. Deng et al., 2022; Konstantakopoulos et al., 2019; Mathew, Kurian, & Augustine, 2023)	UCI occupancy dataset; Smart meter readings

(U.S.E.P. Agency, 2025). In the European Union (EU), road transport alone generates 73.2% of the region's transport GHG emissions (E.E. Agency, 2025). As urbanization accelerates and global mobility demands rise, transportation-related emission reduction becomes a critical priority for mitigating climate change. The sector's emissions are influenced by factors such as economic growth, urban expansion, and technological advancements. For example, while total U.S. domestic emissions declined by approximately 50% from 1990 to 2020, transportation emissions only decreased by 23% over the same period (EPA, 2025). Addressing this challenge requires effective mitigation strategies including electrifying passenger cars and buses, switching freight to rail and low-emission trucks, expanding and improving public transit, shifting freight logistics and modal choices, adopting low-carbon fuels, and promoting behavioral shifts toward sustainable transport options.

AI can accelerate and scale those transportation solutions by extracting insights from huge, heterogeneous data streams and turning them into actionable control, planning, and policy tools. AI's ability to process vast amounts of data, predict patterns, and optimize systems in real-time, contributing to significant emission reductions for these tasks. Examples include real-time traffic prediction and adaptive signal control that lower congestion and fuel burn; route planning and freight assignment algorithms that minimize kilometers and empty runs; demand forecasting and dynamic transit scheduling that boost public transport efficiency and ridership; smart charging and battery management algorithms that optimize EV load to match renewable generation and enable vehicle-to-grid services; predictive maintenance for fleets that keeps vehicles operating efficiently.

Figure 7 depicts four main tasks where AI can decarbonize and optimize transportation networks. In figure 7(a), G. Zhang, Chang, Jin, Yang, and Huang (2024) implement Deep RL for adaptive traffic signal control to eliminate reliance on extensive historical data. In figure 7(b), R. Wang et al. (2024) show an accurate, data-driven probabilistic energy model for vehicle routing problem formulated as second-order cone programming. Figure 7(c) illustrates a RL-based bus timetable optimization from (Ai, Zuo, Chen, & Wu, 2022), where passenger loads, traffic conditions, and vehicle status are input to the model so departure times can be adjusted dynamically to reduce idle time. Finally, Figure 7(d) highlights modern EV infrastructure, such as AI-based smart charging-station by (Hemavathi & Shinisha, 2022) and autonomous driving frameworks such as Nvidia DRIVE (Nvidia, 2025), which together support greener, more resilient mobility.

4.3.1 Traffic optimization

Congested roadways cause vehicles to spend more time idling or accelerating and decelerating frequently, which leads to higher fuel consumption and pollutant output per mile travelled. By smoothing traffic flow through measures like adaptive signal control and dynamic lane assignments, vehicles can minimize stop-and-go conditions, shorten trip durations, and encourage shifts to more efficient modes. AI can be applied to various tasks of traffic optimization, such as managing flow, predicting congestion, and adjusting signals using real-time CCTV feeds. For instance, Google's Project Green Light initiative uses AI and Google Maps driving trends to model

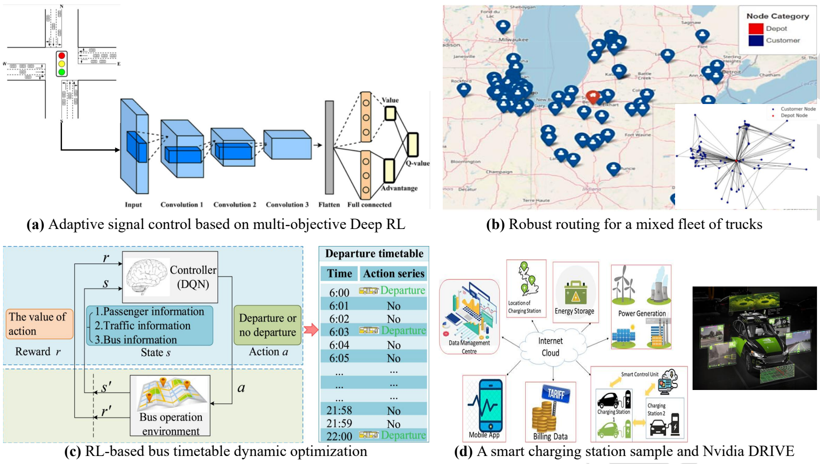


Fig. 7 Representative AI approaches for each key task in transportation transformation. (a) Traffic optimization (G. Zhang et al., 2024); (b) Fleet management (R. Wang et al., 2024); (c) Public transit (Ai et al., 2022); and (d) Electric vehicles (Hemavathi & Shinisha, 2022).

traffic patterns and optimize existing traffic light plans at over 70 intersections globally. The project demonstrates that AI can decrease vehicle stops by up to 30% and GHG by 10% (Matias, 2025). In another significant advancement, Shang et al. (2025) developed a deep RL-based traffic signal control method integrated with Cooperative Vehicle-Infrastructure Systems and a Day-to-Day Dynamic Traffic Assignment model to dynamically optimize signal timings and traveler behavior using real-time traffic data and road network simulations. Their Sioux Falls network case study demonstrated a 21-27% reduction in CO_2 emissions across various scenarios, with a remarkable 54.9% reduction on high traffic Link 28. Similarly, Bogaerts, Masegosa, Angarita-Zapata, Onieva, and Hellinckx (2020) introduced a DNNs combining graph convolutional layers for spatial traffic patterns and LSTM units for temporal dynamics. Applied to DiDi's GPS data in Xi'an and Chengdu, their model achieved high accuracy in multi-step traffic predictions (5 minutes to 4 hours), which supported traffic management that reduces stop-and-go emissions at urban intersections. These AI-based approaches collectively demonstrate how intelligent traffic management can substantially contribute to urban sustainability goals by optimizing vehicle flow and reducing transportation-related emissions.

4.3.2 Fleet management

Fleet management is crucial in reducing transportation's carbon footprint by ensuring that commercial and public vehicle fleets operate as efficiently as possible. AI can be applied to various tasks of fleet utilization, such as optimizing vehicle routing, minimizing empty or underloaded trips, monitoring driver behavior, and predicting maintenance needs, to significantly enhance operational efficiency while reducing carbon emissions. For example, optimizing hard acceleration and braking can improve fuel efficiency by 33%, while proactive maintenance can boost it by 4% (Raziel, 2025). Manchella, Haliem, Aggarwal, and Bhargava (2021). developed a dynamic framework integrating multi-hop goods transfer, negotiation-based pricing, and RL for real-time dispatch optimization. Their simulations demonstrated a 15% increase in fleet utilization and 20% higher operational profits compared to conventional methods, with success in combined passenger and freight transport scenarios where adaptive routing reduced empty vehicle miles. AI is also driving a major shift in logistics automation. For instance, China is rapidly scaling up its deployment of driverless lorries for the Beijing-Tianjin route (BBC, 2025). These systems operate at Level 4 autonomy, which enables drivers to disengage from active driving during highway segments while maintaining oversight. Together, these AI-based fleet management studies enable fleets to operate leaner, greener, and more cost-effectively.

4.3.3 Public transit

Public transit is a key factor of climate change mitigation because it shifts travel demand away from high-emission private vehicles toward more efficient, shared modes. Well-designed transit networks reduce per-passenger energy use by operating larger vehicles at higher average load factors. A report by (Ben Welle & Albuquerque, 2025) demonstrates that public transport reduces GHG emissions by up to two-thirds per passenger-kilometer compared to private vehicles. AI dramatically boosts these environmental advantages by optimizing routes, schedules, and operations to enhance reliability and efficiency. RL algorithms continuously adjust route alignments and headways in response to service disruptions, traffic conditions, or special events. For example, Ai et al. (2022) introduced a bus timetable optimization method that uses a Deep Q-Network to dynamically adjust departure intervals based on real-time passenger demand. By analyzing real-time passenger demand from smart card and sensor data, their method reduced operational costs through optimized vehicle deployment while cutting average wait times during peak fluctuations with lower fuel consumption per passenger compared to fixed scheduling. Similarly, Schmaranzer, Braune, and Doerner (2021) engineered a two-phase optimization framework combining evolutionary algorithms with multi-directional search to process real-world demand data from mobile networks and infrared counters. Their method achieved superior Pareto front accuracy and spread in balancing cost and service-level objectives.

4.3.4 Electric vehicles (EVs)

EVs are the most useful by-product of renewable technologies in transportation domain due to eco-friendly and user-friendly nature. When charged from renewable energy sources, EVs achieve significantly lower lifecycle GHG footprints than their gasoline or diesel counterparts (Hemavathi & Shinisha, 2022). Widespread EV adoption also drives economies of scale in battery manufacturing by encouraging innovation in energy storage that benefits the wider renewable sector, such as grid-scale batteries for wind and solar integration. Z. Zhong, Hu, and Zhao (2024) demonstrated that aligning EV charging with renewable energy supply and low-demand periods reduced EV-related GHG emissions by 2738% compared to uncontrolled charging. AI is reshaping the EV ecosystem at every level, from design and production to operation and infrastructure management. Advanced driver-assistance systems (ADAS) and autonomous driving algorithms improve energy efficiency through smoother acceleration, optimized routing, and cooperative platooning. For example, Teslas Autopilot (Tesla, 2025) and NVIDIAs DRIVE platform (Nvidia, 2025) employ advanced deep learning algorithms to improve navigation and collision avoidance by processing real-time sensor data. Smart charging platforms utilize AI to forecast grid load, renewable generation, and electricity prices. For example, Roberge, Brooks, and Tarbouchi (2024) showed that a particle swarm optimization (PSO)-based recharge scheduling system managed hundreds of EVs in a parking lot in real-time.

4.3.5 Discussion

Across the reviewed transportation studies summarized in Table 6, deep RL consistently delivers superior performance for adaptive traffic signal control and EV charging optimization. Documented GHG reductions range from 10% at the intersection level (Matias, 2025) to 21–27% at the network scale (Shang et al., 2025). However, most RL deployments are validated primarily in simulation environments using benchmark networks such as Sioux Falls (Shang et al., 2025) or real-world GPS traces from DiDi in Xi'an and Chengdu (Bogaerts et al., 2020), leaving the gap between simulated and real-world performance poorly characterized. GNN-based traffic forecasting models outperform LSTM baselines in capturing spatial dependencies across road networks. However, they rely on high-quality graph topology data that is often unavailable or outdated in many cities outside North America, Europe, and East Asia. In fleet management, optimizing driving behaviors (e.g., mitigating hard acceleration and braking) has been shown to improve fuel efficiency by up to 33% (Raziel, 2025), while RL-based dispatch optimization achieves 15% higher fleet utilization and 20% higher operational profits compared to conventional methods (Manchella et al., 2021). Notably, these promising results stem largely from simulations or GPS-derived datasets rather than live operational deployments.

A critical unresolved issue exists between individual vehicle optimization and system-level emission outcomes. Studies that optimize routing, charging, or signal timing for individual assets in isolation may yield poor or even counterproductive results at the network level (Mazzarino, Macii, Bottaccioli, & Patti, 2023). This is particularly evident when EV charging peaks coincide with periods of grid stress. Future research should shift from single-intersection or single-fleet evaluations toward city-scale multi-agent frameworks that explicitly model the complex interactions between traffic flow, energy grids, and transit systems.

4.4 Industry

Industry is a major climate challenge, responsible for roughly 26% of global CO_2 emissions and more than 37% of the worlds energy use (T.I.E. Agency, 2025). Its energy-intensive activities such as mining, manufacturing, construction, and waste management, still rely heavily on fossil fuels. This sector contributes significantly

Table 6 Summary of four task areas for AI in transportation, including (1) *traffic optimization*; (2) *electric vehicles (EVs)*; (3) *fleet management*; and (4) *public-transit optimization*. Column 2 reports the best quantitative metric and cross-study comparison. Abbreviations: GNN = graph neural network; RL = reinforcement learning; CNN = convolutional neural network; EV = electric vehicle; GTFS = General Transit Feed Specification; PeMS = Performance Measurement System.

Tasks	Key metric & cross-study finding	Representative methods	Representative data
Traffic optimization	GHG reduced by 10 % at intersections (Matias, 2025); CO_2 reduced by 21–27 % at network scale (Shang et al., 2025). *Similarity:* Deep RL and GNN-LSTM hybrids consistently outperform fixed-cycle and rule-based signal control. *Difference:* GNNs outperform LSTMs for spatial dependencies; most RL deployments validated in simulation only.	GNNs (K. Guo et al., 2020; X. Wang et al., 2020); RL (Shang et al., 2025; P. Sun, Hu, Lan, Tian, & Chen, 2019); Hybrid (Bogaerts et al., 2020; W. Zhang et al., 2019)	Traffic4cast (Neun et al., 2023); PeMS (PeMS, 2025)
Electric vehicles (EVs)	EV GHG reduced by 27–38 % with renewable-aligned charging (Z. Zhong et al., 2024). *Similarity:* Renewable-aligned scheduling substantially outperforms uncontrolled charging across all reviewed studies. *Difference:* PSO and RL-based schedulers perform comparably with different data requirements; RL requires grid topology data.	CNNs (C. Chen, Wang, et al., 2023; Y. Sun, Li, Xu, & Shi, 2022; Yi, Liu, Wei, Chen, & Dai, 2022); RL (Liang, Wang, Yang, & Xing, 2018; Z. Zhu & Zhao, 2021); Hybrid (Codevilla, Müller, López, Koltun, & Dosovitskiy, 2018; J. Tian, Xiong, Shen, & Lu, 2021)	Waymo Open Dataset (P. Sun et al., 2020); BDD100k (F. Yu et al., 2020); Cityscapes (Cordts et al., 2016)
Fleet management	Fuel efficiency +33 % from driving optimization (Raziel, 2025); fleet utilization +15 %, profits +20 % (Manchella et al., 2021). *Similarity:* RL dispatch outperforms heuristic routing. *Difference:* RL gains degrade significantly under supply disruption scenarios not represented in training data.	RL (K. Lin, Zhao, Xu, & Zhou, 2018; Manchella et al., 2021); Evolutionary (Ke, Siłka, Wieczorek, Bai, & Woźniak, 2022; R. Wang et al., 2024; Y. Wang, Limmer, Olhofer, Emmerich, & Bäck, 2021); Hybrid (J. Zhang, Chen, Cui, Guo, & Zhu, 2020)	Airborne/satellite thermal imagery; Uber Movement (Kaggle, 2025)
Public transit optimization	Average wait time reduced; operational cost optimized (Ai et al., 2022). *Similarity:* Deep Q-Network outperforms fixed-schedule and evolutionary baselines for dynamic timetable adjustment. *Difference:* Benefits concentrated in high-density urban corridors; generalization to rural or low-frequency networks unvalidated.	RL (Ai et al., 2022; Yan, Cui, Chen, & Ma, 2022); Evolutionary (H. Lin & Tang, 2021; Schmaranzer et al., 2021); Hybrid (J. Zhang et al., 2020)	GTFS feeds (gtfs, 2025); Simulated data

through energy-intensive processes like steel and cement production, chemical manufacturing, and textiles, often relying on fossil fuels that drive emissions. Mitigation efforts within the industry focus on transitioning to low-carbon technologies, improving energy efficiency, adopting circular economy practices to reduce waste, and integrating renewable energy sources to curb emissions from electricity and heat production, which are major contributors.

AI can significantly enhance mitigation efforts by leveraging data analytics, predictive modeling, and optimization to reduce emissions across various sectors. It is being integrated into various parts of the industrial sector, such as supply chain and logistics optimization, emissions monitoring and management, process control and parameter optimization, and predictive maintenance, to reduce environmental impact.

4.4.1 Supply chain and logistics optimization

According to European Commission (Comission, 2025), logistics activities, such as transportation of goods, warehousing operations, and delivery, account for approximately 2.9% of global CO_2 emissions. Inefficient routing, imbalanced load factors, and underutilized assets increase unnecessary energy use, while excess inventory block storage and handling. AI is revolutionizing the supply chain optimization by bringing real-time data analytics, ML DL, and advanced automation into every part of the sector. For instance, Kalusivalingam, Sharma, Patel, and Singh (2022) developed a novel supply chain optimization framework that integrates deep RL and predictive analytics. This approach improved supply chain efficiency by enhancing real-time decision making and forecasting potential disruptions. Similarly, Issaoui, Khiat, Bahnasse, and Ouajji (2021) proposed an innovative framework based on LSTM model to optimize resource allocation and task scheduling in dynamic logistics environments. The simulation results demonstrated a high accuracy of over 92% for logistics optimization. These AI applications provide a proof of concept for reducing emissions-intensive practices.

4.4.2 Process control and parameter optimization

This is a fundamental component of industrial efficiency, which directly influences energy consumption, raw material use, and emission output. In energy-intensive sectors such as cement, steel, and petrochemicals, process inefficiencies can lead to significant energy waste and excess greenhouse GHG emissions. On the other hand, small deviations in parameters, such as temperature, pressure, flow rates, or mixing ratios, can lead to disproportionately large increases in fuel use, unburned feedstock, or defective products. AI-based process control systems utilize real-time data from sensors and historical records to dynamically optimize operational parameters. For example, Zimmerling, Poppe, Stein, and Kärger (2022) developed an RL framework that trains an NN to eliminate surrogate model reconstruction for new component geometries. This model provided a lean and adaptive solution for rapid part and process development by showing that the network generalized to unseen geometries and reused existing data instead of requiring new samples. Similarly, K. Huang, Wei, Li, Yang, and Gui (2022) established theoretical stability for an LSTM-based model predictive control (MPC) system in industrial processes by unifying multi-mode system prediction without explicit mode switching strategies. Supported by theoretical analyses of stability and feasibility, their approach achieved a 10% reduction in overshoot and improved control accuracy compared to existing learning-based methods. With a different approach, X. Kong and Ge (2021) presented a novel industrial process monitoring framework that integrated hierarchical latent feature extraction with Bayesian inference and a weighting strategy to combine diverse monitoring statistics. By converting layer-based features into posterior probabilities and merging them into unified probabilistic statistics, this method offered a more comprehensive and accurate monitoring index, validated on the Tennessee Eastman process. These studies demonstrate significant potential of AI for improving industrial efficiency and sustainability.

4.4.3 Predictive maintenance

Predictive maintenance ensuring that industrial assets, from motors and pumps to turbines and boilers, operate at peak efficiency and do not consume excess energy due to wear or impending failures. Unplanned downtime often forces facilities to run backup equipment, scrap partially processed materials, or perform emergency fixes that generate waste and excess emissions. By anticipating failures before they occur, AI-based predictive maintenance minimizes unplanned stops, prevents the energy spikes associated with restarting heavy machinery, and reduces reactive maintenance costs by up to 25% (Molęda, Małysiak-Mrozek, Ding, Sunderam, & Mrozek, 2023). DNNs and ensemble models can identify non-linear patterns in high-frequency vibration, temperature, pressure, or acoustic signals that traditional threshold-based systems would miss. For example, Cheng et al. (2018) proposed a novel machine health monitoring framework that processed data across time, frequency, and time-frequency domains. Their method used a Euclidean distance-based algorithm to pinpoint key degradation indicators and applied adaptive kernel spectral clustering to spot anomalies. The authors further enhanced this with an LSTM-RNN model, which delivered precise failure time predictions and performed well on test-to-failure datasets. In a separate study, Arunthavanathan et al. (2021) deployed a hybrid CNN-LSTM model to detect emerging process fault symptoms within predicted data windows. This technique proves highly effective for timely fault detection in complex systems, as validated on the Tennessee Eastman process. Digital twins have also been used to simulate fault progression under varying load and environmental conditions (C. Chen, Fu, Zheng, Tao, & Liu, 2023). Therefore, maintenance teams can optimize service intervals and parts replacement schedules in time.

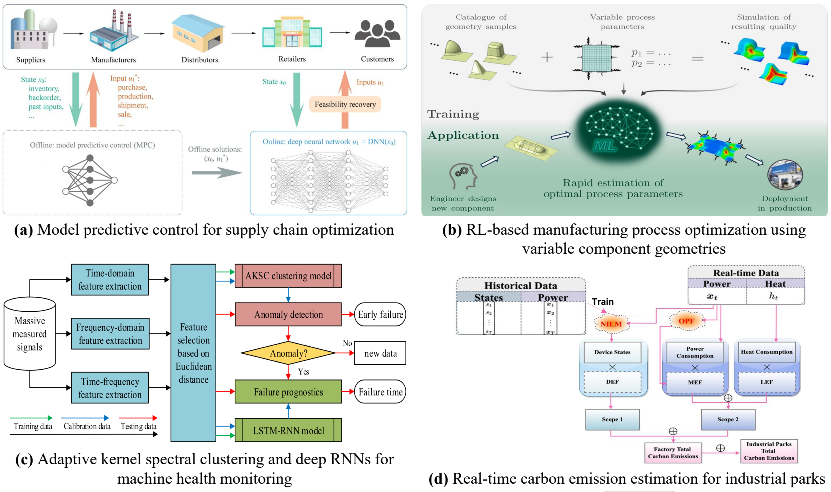
4.4.4 Emissions monitoring and management

Emissions monitoring and management is crucial for industries to track, report, and reduce industrial GHG outputs effectively. Frameworks like the UN's Global Climate Change Statistics and Indicators provide 44 metrics to evaluate emission drivers, impacts, and mitigation efforts (Nations, 2025a). Traditional monitoring systems, such as stack-mounted continuous emissions monitors (CEMs), periodic manual sampling, and mass balance calculations, offer snapshots of CO_2, nitrogen oxides (NOX), sulfur oxides (SOX), and volatile organic compound (VOC) emissions but often lack the real-time responsiveness to catch fugitive leaks. Robust management frameworks then translate this data into compliance reporting, emissions trading and offset strategies, and targeted mitigation projects. AI is transforming the field by enhancing both detection and decision-making capabilities on various scales. For example, J. Liu et al. (2023) developed a real-time, data-driven framework for industrial park carbon emission estimation. The framework utilized a DL-based non-intrusive load monitoring algorithm for Scope 1 emissions with locational marginal factors for Scope 2 emissions (J. Liu et al., 2023). The 93.4% device identification accuracy and a 0.44% annual estimation error of the framework demonstrated AI potential to revolutionize emissions management. On the other hand, Khayyam et al. (2021) developed an innovative waste heat recovery system for carbon fiber stabilization, which integrated ANNs and nonlinear regression to predict energy use (Khayyam et al., 2021). The system boosted energy efficiency by 86% and cut the carbon footprint by 28.5 tons annually under real manufacturing settings.

Figure 8 display representative AI techniques for four keys industrial decarbonization tasks. Figure 8(a) shows a DL-based MPC scheme for real-time, responsive supply chain management proposed by (J. Wang, Swartz, & Huang, 2023). A DNN is trained offline using optimal state-input pairs obtained from solving the MPC problem for various scenarios. Once deployed online, the DNN provides near-instant control decisions and dramatically reduces the real-time computational burden of solving MPC. In figure 8(b), Zimmerling et al. (2022) use RL to train a NN that maps variable component geometries directly to optimal process parameters. The framework generalizes to previously unseen geometries without per-case retraining. Figure 8(c) presents the predictive maintenance workflow from (Cheng et al., 2018), which extracts time- and frequency-domain features using Euclidean-distance filtering, applies adaptive clustering, and employs LSTM-based RNNs to detect anomalies early and forecast remaining useful life. Finally, Figure 8(d) depicts a hybrid DL architecture by (J. Liu et al., 2023) that fuses historical and live meter data from an industrial park to produce continuous emission estimations at the unit-process level.

4.4.5 Discussion

Table 7 describes in detail how AI is being applied into every part of smart industrial transformation by aligning the mentioned four main tasks with their real-world applications, algorithmic approaches, and data sources. Hybrid CNN-LSTM and ensemble residual DNN architectures achieve the highest performance for fault detection. For instance, solar PV monitoring systems utilizing these approaches have reported 94% anomaly detection accuracy and 86% fault classification for 12 distinct fault types (Le et al., 2021). However, industrial process fault detection is frequently validated exclusively on the TEP simulation (Arunthavanathan et al., 2021; Cheng et al., 2018). This reliance on a single benchmark raises significant reproducibility concerns for cross-facility deployment, as very few studies validate models on multi-plant or multi-year operational data. In supply chain and logistics optimization, Deep RL and LSTM-based demand forecasting deliver consistent gains. Logistics optimization accuracy exceeds 92% (Issaoui et al., 2021), while RL-based real-time decision-making enhances supply chain disruption response (Kalusivalingam et al., 2022). However, model performance often degrades under supply disruption scenarios absent from training data. On



(a) Model predictive control for supply chain optimization

(b) RL-based manufacturing process optimization using variable component geometries

(c) Adaptive kernel spectral clustering and deep RNNs for machine health monitoring

(d) Real-time carbon emission estimation for industrial parks

Fig. 8 Representative AI approaches for each key task in industry transformation. (a) Supply chain and logistics optimization (J. Wang, Swartz, & Huang, 2023); (b) Process control and parameter optimization (Zimmerling et al., 2022); (c) Predictive maintenance (Cheng et al., 2018); and (d) Emissions monitoring and management (J. Liu et al., 2023).

the other hand, process control models embedded with physics-based constraints, such as LSTM-MPC systems that achieve a 10% reduction in overshoot compared to purely data-driven controllers (K. Huang et al., 2022), demonstrate superior generalization across operating regimes.

Recently, an emerging trend toward lifecycle emissions accounting in AI model evaluations has gained attention. However, Scope 3 emissions accounting remains significantly more challenging and less comprehensive than Scope 1 (direct) and Scope 2 (indirect energy) assessments, which primarily cover operational compute (Kim, Yoo, & Chung, 2025; J. Liu et al., 2023). This methodological limitation renders sector-wide mitigation estimation difficult and necessitates greater attention from the research community to develop robust frameworks for tracking value-chain impacts.

4.5 Agriculture

Agriculture, including associated land use, is a significant contributor to climate change and highly vulnerable to its impacts. Food and Agriculture Organization of the United Nations (FAO) data (FAO, 2025a) reveal that agrifood systems, including pre- and post-production activities, emitted about 16.2GtCO_2-eq, roughly 30% of total human emissions. Roughly half of those emissions come from on-farm crops and livestock processes (7.8Gt), with land use change (deforestation, biomass burning, peat degradation) contributing about 3.1Gt. Moreover, efforts to boost productivity, such as excessive pesticide use and monoculture farming, worsen environmental degradation.

Table 7 Summary of four task areas for AI in smart industrial transformation, including (1) *supply-chain and logistics optimization*; (2) *process control and parameter optimization*; (3) *predictive maintenance*; and (4) *GHG monitoring and management*. Column 2 reports the best quantitative metric and cross-study comparison. Abbreviations: RL = reinforcement learning; DNN = deep neural network; LSTM = long short-term memory; CNN = convolutional neural network; AE = autoencoder.

Tasks	Key metric & cross-study finding	Representative methods	Representative data
Supply chain & logistics optimization	Logistics optimization accuracy >92 % (Issaoui et al., 2021). *Similarity:* Deep RL and LSTM-based forecasting outperform heuristic schedulers. *Difference:* Performance degrades significantly under supply disruption scenarios absent from training data, which is the conditions most relevant to climate-resilient operations.	RL (Kalusivalingam et al., 2022; Oroojlooyjadid, Nazari, Snyder, & Takáč, 2022); DNNs (Bassiouni, Chakrabortty, Sallam, & Hussain, 2024; Han & Zhang, 2021; J. Wang, Swartz, & Huang, 2023); RNN/LSTM (Chandriah & Naraganahalli, 2021; Issaoui et al., 2021; H.D. Nguyen, Tran, Thomassey, & Hamad, 2021);	Transportation logs; GPS trajectories; Historical sales and shipment records
Process control & parameter optimization	Overshoot reduced by 10 % vs. existing learning-based MPC (K. Huang et al., 2022); RL generalizes to unseen geometries (Zimmerling et al., 2022). *Similarity:* LSTM-MPC with physics constraints outperforms purely data-driven controllers for various operating conditions. *Difference:* RL-based approaches generalize better to novel geometries; physics-constrained models show stronger out-of-distribution robustness.	AE (Ou et al., 2022) RL (Yoo, Kim, Kim, & Lee, 2021; Zimmerling et al., 2022); RNN/LSTM (K. Huang et al., 2022); Hybrid (X. Kong & Ge, 2021; Sing, Kuo, Shih, Ho, & Chua, 2021)	Process simulation data; Time-series process variables
Predictive maintenance	94 % anomaly detection; 86 % fault classification (12 types) (Le et al., 2021); validated on Tennessee Eastman (Arunthavanathan et al., 2021; Cheng et al., 2018). *Similarity:* CNN-LSTM hybrids outperform CNN-only and LSTM-only. *Difference:* Results concentrated on two benchmarks (solar PV, Tennessee Eastman), limiting cross-facility generalizability; real-world multi-plant validation almost entirely absent.	CNNs (Abdelaty, Doriguzzi-Corin, & Siracusa, 2021; Defard, Setkov, Loesch, & Audigier, 2021; W. Wang et al., 2021); RNN/LSTM (Cheng et al., 2018; F. Kong, Li, Jiang, Wang, & Song, 2021); Hybrid (Arunthavanathan et al., 2021; Mohammadi, Mahmoud, & Elbestawi, 2021; J. Yu et al., 2021);	Vibration and acoustic data; Maintenance logs and failure records
GHG monitoring & management	93.4 % device identification; annual estimation error 0.44 % (J. Liu et al., 2023); energy efficiency +86 %, carbon footprint reduced by 28.5 t/year (Khayyam et al., 2021). *Similarity:* DL-based monitoring outperforms manual CEMs for real-time detection. *Difference:* No reviewed study considers process-level gains through to Scope 3 supply chain emission reductions.	Boosting (Rubio-Loyola & Paul-Fils, 2022); DNNs (S. Chen et al., 2023; Khayyam et al., 2021); Hybrid (J. Liu et al., 2023)	Industrial sensor logs; Meteorological data; OCO-2/3 (Nasa, 2025)

At the same time, climate change is also harming global agriculture. For example, climate change is projected to cause a 65% decline in global bee populations by 2070, which are vital to 75% of global food crops (Rahimi & Jung, 2024). This unsustainable cycle of intensive agriculture undermines both ecological stability and long-term food production. Studies estimate that each 1 °C of warming reduces average staple crop yields by about 4.4% (Hultgren et al., 2025). Empirical data confirm that recent droughts and soil degradation could reduce maize yields by 11.4% in the top five maize-producing countries (including the U.S., China, Brazil, Argentina, and Mexico) under a 2 °C warming scenario (K. Li, Pan, Xiong, Xie, & Ali, 2022). At the same time, extreme weather events linked to climate change, such as record heat, droughts, floods, and cyclones, are causing acute losses. For example, FAO (2024) reported that Hurricane Helene led to flooding and rainfall, the most seen since Katrina in 2005, causing more than 200 deaths and tens of billions of dollars in economic losses.

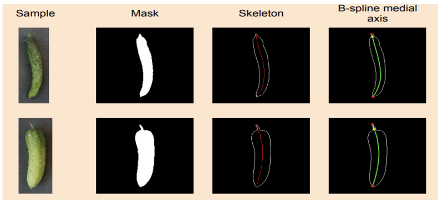
FAO (Wisser et al., 2023) identifies four key pathways for significantly reducing the GHG emissions while maintaining productivity: improved animal health and breeding, optimized manure management, precision nutrient application, and reduction of food loss/waste. In addition, precise agriculture practices, including precision fertilization, cover cropping, and agroforestry, can sequester carbon and cut per unit emissions. AI and data analytics are accelerating the transition to smart agriculture through precision resource optimization and early warning systems. Modern AI platforms that utilize advanced technologies such as satellite imagery, IoT sensors, drones, and data analytics to observe, measure, and respond to variability in crops within fields. This approach enables farmers to optimize field-level management regarding crop farming by applying inputs like water, fertilizers, and pesticides at variable rates based on real-time data, thus enhancing productivity, sustainability, and profitability while minimizing environmental impact.

Figure 9 illustrates representative AI approaches for three main agricultural tasks that contribute to climate change mitigation. In figure 9(a), Z. Zhang, Kayacan, Thompson, and Chowdhary (2020) present an autonomous corn stand counting robot that uses onboard RGB imaging and a mobile platform to automate stand counts and scouting, thus reducing field visits and the associated emissions. Figure 9(b), L.Q. Nguyen et al. (2023) shows high throughput phenotyping workflow, in which segmented fruit/plant masks are converted into skeletons and basic spline medial axes to extract precise shape and trait measurements that accelerate crop breeding pipelines. In figure 9(c), Kashyap, Kumar, Jaiswal, Prasad, and Gandomi (2021) demonstrate an IoTLSTM irrigation system that fuses distributed soil moisture, temperature/humidity and remote data through a gateway to a cloud-based LSTM model, enabling optimal irrigation scheduling and planning. Overall, these technologies improve resource efficiency, shorten breeding cycles, and lower GHG footprints through targeted interventions, leading to a more sustainable agricultural productivity.

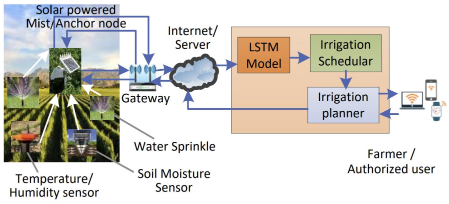
4.5.1 Crop breeding

Crop breeding is the scientific process of genetically improving plants to develop new varieties with desirable traits, such as enhanced yield, disease resistance, nutritional

(a) Illustrations of the corn stand counting robot



(b) Visualization of the phenotyping process that takes in an input mask



(c) IoT-LSTM network-based irrigation system

Fig. 9 Representative AI approaches for each key task in agriculture. (a) Emission reduction (Z. Zhang et al., 2020); (b) Crop breeding (L.Q. Nguyen et al., 2023); and (c) Precision farming (Kashyap et al., 2021).

quality, and adaptability to environmental conditions. By developing crop varieties resilient to both abiotic stresses (e.g., drought, heat, salinity, and flooding) and biotic stresses, this approach sustains productivity under adverse conditions, reduces pressure to expand agricultural land, and enhances ecosystem services such as soil health and biodiversity (Marsh, Hu, Gill, Batley, & Edwards, 2021). AI accelerates crop breeding by integrating big data analytics, ML and DL to handle vast datasets from genomics, phenomics, and enviromics. Key applications include: (1) predictive breeding via genomic selection, where ML models accelerate the identification of superior genotypes; (2) high throughput phenotyping using vision-based imaging and sensors to non-invasively quantify plant traits; and (3) genotype to phenotype modeling that deciphers complex trait interactions for accurate prediction. Beyond breeding, AI further enables gene functional analysis to optimize genotype-by-environment interactions, and climate-resilient pipeline design. For example, L.Q. Nguyen et al. (2023) highlighted how AI analyzes genomic, environmental, and phenotypic data to optimize breeding, shorten timelines, and prioritize high-yield varieties under stress. Rai (2022) showed that the integration of speed breeding with AI tools like genomic selection and high throughput phenotyping accelerated the development of climate-resilient varieties, achieving 95100% germination in rice and 8 generations/year in wheat/barley. Additional evidence demonstrates how AI can be used to accelerate genomic prediction is Avalo's genome analysis (TechCrunch, 2025). Their approach emphasizes existing traits by simulating the genomes interaction in context to speed up and reduce the cost of breeding climate-resilient crops.

4.5.2 Emission reduction

Emission reduction in agriculture is a key strategy for climate change mitigation. It focuses on lowering GHG emissions from sources such as machinery fuel consumption, fertilizer application, livestock enteric fermentation and manure management, and soil disturbance. AI plays a pivotal role in emission reduction by optimizing machinery schedules and integrating robotics. For machinery schedules, AI models minimize fuel consumption and idle times by analyzing data on soil conditions, weather, and crop status. For example, a multi-objective GA by (Y. Guo, Zhang, Chang, Li, & Li, 2024) outperformed other methods by reducing machinery transfer distances by 17.18% and non-operational waiting time by 19.36% through time window prioritization and tabu search strategies. Moreover, robotics have been increasingly integrated into agriculture for labor-intensive tasks, such as fruit counting (Z. Zhang et al., 2020), harvesting (Miao et al., 2023; Zahedi, Shafei, & Shamsi, 2023), and quality inspection (Camci, Kripalani, Ma, Kayacan, & Khanesar, 2018), to optimize operations to cut fossil fuel use and GHG emissions.

4.5.3 Precision farming

In the context of climate change mitigation, precision farming reduces GHG emissions through efficient resource use, decreasing fertilizer runoff to prevent soil degradation and water pollution, conserving water to combat drought, and promoting carbon sequestration via improved soil health practices. For instance, the World Economic Forum (NUTRITION, 2018) estimates that, if 15-25% of farms adopted precision agriculture, global yield could be increased by 10-15% by 2030, while GHG emissions and water use could be reduced by 10% and 20%, respectively. AI allows farmers to make informed decisions about planting, managing, and harvesting, including localized fertilization and irrigation through real-time data analysis from satellites, drones, and environmental sensors. For example, Sami et al. (2022) showed that DL-based automated irrigation potentially cut water use by up to 43%. Chandel et al. (2025) proposed a high precision DL-based Variable Rate Application for real-time nitrogen stress detection in wheat and demonstrated that fertilizer use was reduced by 37.53% compared to traditional methods, with no significant yield loss. Modern DL frameworks, such as CNNs and transformers, have achieved state-of-the-art performance in predictive analytics tasks, including pest detection (Dang, Danish, et al., 2024; Y. Li, Wang, Dang, Sadeghi-Niaraki, & Moon, 2020; H. Wang, Li, Dang, & Moon, 2022) and disease detection (H. Wang, Nguyen, Nguyen, & Dang, 2024), by effectively processing high-resolution imagery along with historical and real-time sensor data. For example, the PD-TR transformer model (H. Wang, Nguyen, et al., 2024) achieved an mAP of 56.3 on a large-scale plant disease dataset with 12 classes, enhanced by BatchFormerV2 and CIoU loss for better feature learning. These predictions shift farmers from reactive to proactive measures. Moreover, the integration of DL with environmental variables has shown significant promise in constraining uncertainty in crop yield projections under climate change. For instance, L. Li et al. (2023) proved that CNNs can achieve high accuracy in these predictions, with an MAP of 98.6% for crop yield projections.

4.5.4 Discussion

Across the reviewed agricultural studies in Table 8, CNNs and transformer-based models dominate precision farming classification tasks. Notably, the PD-TR transformer achieves a mean Average Precision (mAP) of 56.3 for multi-class plant disease detection across 12 classes under natural field conditions (H. Wang, Nguyen, et al., 2024), while CNN-based crop yield projection models report accuracies reaching 98.6% (L. Li et al., 2023). For irrigation scheduling, LSTM and hybrid IoT-LSTM systems demonstrate superior performance, with reported water use reductions of up to 43% (Sami et al., 2022) and fertilizer use reductions of 37.53% without significant yield loss (Chandel et al., 2025). However, these results are highly site-specific and rarely validated beyond single growing seasons or specific crop types. In the area of crop breeding acceleration, AI tools integrating genomic selection and high-throughput phenotyping have consistently shortened development timelines (Rai, 2022).

However, deployment remains limited to well-funded research institutions with access to advanced genomic sequencing infrastructure. This creates a significant equity gap that risks restricting benefits to smallholder farmers in climate-vulnerable regions (Tzachor, Devare, King, Avin, & Ó hÉigeartaigh, 2022). Moreover, the integration of local and indigenous agricultural knowledge into AI systems remains an open research challenge. Standard supervised ML pipelines cannot capture place-specific understandings of soil-crop-climate interactions, pest cycles, and varietal adaptation unless such knowledge is digitized and labeled (Ahire, Hanchate, & Varadarajan, 2024). This process is not only technically demanding but also raises unresolved questions regarding data ownership and community consent, which are largely absent from the reviewed literature. Future agricultural AI research must treat community-based adaptation as a fundamental design constraint, prioritizing interpretable models whose reasoning can be interrogated and validated by farmers without data science expertise over opaque black-box systems.

4.6 Ecosystem conservation

Ecosystem conservation is primarily an adaptation-oriented and resilience-supporting domain, which focuses on utilizing nature-based solutions to protect, sustainably manage, and restore ecosystems. While ecosystem conservation directly sequesters carbon, it also contributes to mitigation, and these dual-function applications are explicitly identified in this section.

Activities such as forest conservation and reforestation, wetland restoration, and ocean protection, where healthy ecosystems like forests absorb billions of metric tons of CO_2 annually, acting as vital carbon sinks. According to the United Nations (Nations, 2025b), forests cover about 31% of the world's land surface, but deforestation has reduced this by 100 million hectares since 2000, primarily due to agricultural expansion, with rates slowing from 12 million hectares per year (20102015) to 10 million (20152020). Similarly, land degradation has risen to 15.5% globally, affecting 3.2 billion people, while biodiversity loss threatens around 1 million species, including 38% of assessed tree species. Positive developments include the Kunming-Montreal Global

Table 8 Summary of three task areas for AI in agriculture, including (i) *emission reduction*; (ii) *crop breeding*; and (iii) *precision farming*. Column 2 reports the best quantitative metric and cross-study comparison. Abbreviations: CNN = convolutional neural network; RNN = recurrent neural network; LSTM = long short-term memory; RL = reinforcement learning; IoT = Internet of Things; NDVI = normalized difference vegetation index.

Tasks	Key metric & cross-study finding	Representative methods	Representative data
Emission reduction	Machinery transfer distances reduced by 17.18 %; non-operational waiting time reduced by 19.36 % (Y. Guo et al., 2024). *Similarity:* Multi-objective GA outperforms single-objective scheduling across reviewed machinery optimization studies. *Difference:* Robotic harvesting reduces fuel use but hardware cost limits deployment in low-income contexts; results from single-region field trials.	CNNs (Miao et al., 2023; Z. Zhang et al., 2020); Hybrid (Camci et al., 2018; Zahedi et al., 2023); Evolutionary (Y. Guo et al., 2024)	IoT sensor data; Operational data; Vision sensors
Crop breeding	95–100 % germination in rice; 8 generations/year in wheat/barley (Rai, 2022). *Similarity:* AI-accelerated speed breeding consistently shortens development timelines compared to conventional phenotyping. *Difference:* Deployment limited to institutions with genomic sequencing infrastructure; no reviewed study addresses transfer of genomic models across crop species.	CNNs (Marshall et al., 2022; Nevavuori, Narra, & Lipping, 2019; L.Q. Nguyen et al., 2023); RNN/LSTM (Paudel et al., 2023; Shook et al., 2021); Hybrid (Gavahi, Abbaszadeh, & Moradkhani, 2021; Khaki, Wang, & Archontoulis, 2020)	Well logs; Seismic surveys; Porosity/permeability distribution maps
Precision farming	Fertilizer use reduced by 37.53 % (no yield loss) (Chandel et al., 2025); water use reduced by 43 % (Sami et al., 2022); crop yield mAP 98.6 % (L. Li et al., 2023); disease detection mAP 56.3 (H. Wang, Nguyen, et al., 2024). *Similarity:* CNN/Transformer outperforms SVM and RF for imagery; LSTM outperforms statistical baselines for irrigation. *Difference:* Site-specific results rarely validated on different growing seasons or crop types; smartphone-based tools (Nuru) enable deployment without cloud connectivity (Mrisho et al., 2020).	RNN/LSTM (Kashyap et al., 2021; Sami et al., 2022); RL (Alibabaei, Gaspar, Assunção, Alirezazadeh, & Lima, 2022); CNNs (Chandel et al., 2025; Y. Li et al., 2020; H. Liu et al., 2023; D. Su, Kong, Qiao, & Sukkarieh, 2021; H. Wang et al., 2022); Transformers (Dang, Danish, et al., 2024; H. Wang, Nguyen, et al., 2024); Hybrid (Akilan & Baalamurugan, 2024)	IoT sensor data; MODIS/Sentinel NDVI; PlantVillage, PlantDoc (Singh et al., 2020)

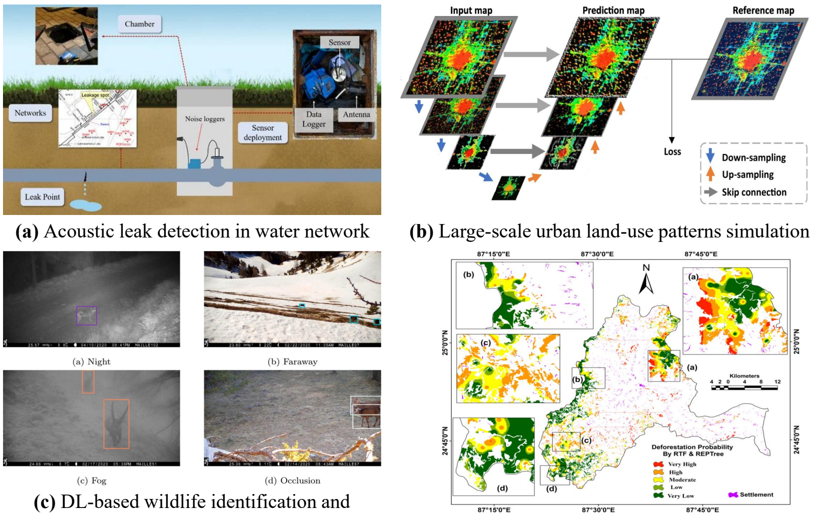
Biodiversity Framework (GBF, 2022), which sets 23 targets for 2030 to restore ecosystems and halt biodiversity decline, with increasing proportions of forests in protected areas and under long-term management plans. By prioritizing ecosystem health, this sector not only mitigates emissions but also builds resilience against climate impacts.

AI is transforming ecosystem conservation by providing tools to monitor, analyze, and manage natural systems with unprecedented efficiency. AI-based technologies like satellite imagery analysis allow real-time tracking of deforestation, species distribution shifts, and habitat degradation. For example, AI is applied in predictive modeling for conservation by forecasting species habitat ranges and climate-driven shifts, optimize the placement of new protected areas, and even detect illegal logging or poaching from satellite or sensor data.

Figure 10 illustrates four representative AI approaches aligned with the key applications in ecosystem conservation. In figure 10(a), R. Liu, Zayed, Xiao, and Hu (2025) target the largely unexplored use of sequential time-series models for acoustic leak detection in water distribution networks. The authors introduce a Time-Transformer that utilizes self-attention to capture those dependencies, tunes the model through parametric experiments, and demonstrates superior leak detection performance in Hong Kong field trials compared with 1D-CNN and CNNLSTM baselines. Figure 10(b) presents a large-scale urban land use simulation using a UNet architecture (J. Wang et al., 2022), which was trained on historical development for the North China Plain, validated against a 2018 reference map, and applied to forecast 2030 expansion. Visual inspection shows the model automatically learned neighborhood effects, gravity from large cities, and linear growth tendencies. In Figure 10(c), Simões, Bouveyron, and Precioso (2023) describe a practical three-step DL pipeline for turning camera trap videos into images, automatically annotating them with MegaDetector, extending MegaDetector via a Faster R-CNN (Inception-ResNet-v2) to detect and classify 13 classes of wildlife species. Evaluation on a French national park test set shows strong detection performance (mAP 96.88% at IoU=0.5 and 89.24% at IoU=0.75) but weaker classification (mAP 73.92%), with common classes like humans and rare classes like dogs. Finally, Figure 10(d) summarizes (Saha et al., 2020)s approach that couples Landsat-derived forest canopy density (FCD) maps, computed from indices like Advanced vegetation index (AVI), bare soil index (BSI), shadow index (SI), and scaled vegetation density (VD) with twelve socio-environmental drivers to model deforestation probability using binary logistic regression, RF and an ensemble of rotational forest and reduced error pruning trees approach.

4.6.1 Land use planning

Land use planning is the systematic process of allocating, regulating, and managing land resources to achieve sustainable social, economic, and environmental objectives. For example, L. Zhu, Song, Sun, Li, and Hu (2022) documented a cumulative loss of 0.39 petagrams of ecosystem carbon storage in Chinas coastal zones attributable to suboptimal land use policies. Effective planning reduces land competition, supports biodiversity, and aligns with global goals like net-zero emissions by 2050, where sustainable land use is essential to curb agricultural expansion and forest loss in the



(a) Acoustic leak detection in water network

(b) Large-scale urban land-use patterns simulation

(c) DL-based wildlife identification and estimation on camera trap CCTVs

(d) Deforestation probability map prediction

Fig. 10 Representative AI approaches for each key task in ecosystem conservation. (a) Water resource management (R. Liu et al., 2025); (b) Land use planning (J. Wang et al., 2022); (c) Environmental protection and wildlife conservation (Simões et al., 2023); and (d) Forest management (Saha et al., 2020).

tropics. AI enhances land use planning by processing vast datasets for predictive modeling, optimization, and monitoring, enabling more precise mitigation strategies. DL models have been used to classify land cover from satellite imagery (Fayaz, Dang, & Moon, 2024; Fayaz et al., 2025; Wambugu et al., 2021), while more advanced frameworks can predict non-linear land use change trajectories that exceed the capabilities of simple linear models (J. Wang et al., 2022). Urban growth and land change modeling further support climate mitigation by forecasting expansion patterns and identifying development scenarios that minimize ecological disruption. For example, (Masoumi, Coello Coello, & Mansourian, 2020) combined multi-objective optimization and clustering analysis to resolve competing criteria in urban land use decisions. These approaches enable policymakers to prioritize areas at high risk of deforestation or wetland loss during planning. In practice this means integrating spatial analysis, governance instruments and cross sector coordination to steer development away from high-carbon ecosystems while optimizing land for low-emission uses such as agroforestry or renewable energy installations.

4.6.2 Forest management

In the context of climate resilience, forest management focuses on enhancing forests as carbon sinks by increasing carbon sequestration in biomass, soils, and products, reducing emissions from degradation, and building resilience to climate impacts like wildfires, pests, and droughts. Recent advances in AI are transforming these practices by enabling data-driven decision making, real-time monitoring, and predictive analytics that optimize mitigation strategies. By integrating satellite imagery, UAV and ground sensor networks, and process models, AI improves carbon accounting, anticipatory risk management, and the design of smart forestry interventions (Shivaprakash et al., 2022). For example, Saha et al. (2020) used Landsat-derived vegetation and soil indices to map deforestation risk in India and reported that roughly 30% of the studied forest area had high or very high deforestation probability. Similarly, Marques, Carreira, Miragaia, Ramos, and Pereira (2024) developed an end-to-end system that combines UAV data capture with web-based visualization to enable autonomous, continuous forest monitoring.

4.6.3 Water resource management (WRM)

WRM contributes to ecosystem conservation by protecting and restoring freshwater habitats that are vital for climate mitigation and adaptation (Abdulameer et al., 2025). Healthy rivers, wetlands, and aquifers sequester carbon, regulate regional water cycles, buffer against extreme weather, and sustain biodiversity and food production. Under accelerating climate change, these systems face compounding pressures: altered precipitation regimes are intensifying flood peaks and prolonging droughts simultaneously, accelerating sediment redistribution, depleting groundwater reserves, and pushing river hydraulics into regimes that fall outside the historical envelopes on which conventional water management models were calibrated. Efficient WRM (Manzocco et al., 2015) therefore requires AI tools that can operate reliably under non-stationary conditions and across the full cascade from rainfall to runoff to groundwater to distribution (Abdulameer et al., 2025, n.d.). The reviewed literature is organized here into four application tracks that together span this cascade: urban water infrastructure, river hydraulics and flood-drought forecasting, groundwater and water quality, and integrated basin-scale management.

WRM research is strategically divided into two distinct tracks to reflect their fundamentally different operational scales: (1) Urban water infrastructure, focusing on demand forecasting (Salloom, Kaynak, & He, 2021), leak detection (R. Liu et al., 2025), and sewer inspection; and (2) Basin-scale hydrological modeling, addressing flood-drought forecasting (Frame et al., 2022), groundwater dynamics, and climate-driven flow regime shifts. These domains require distinct model architectures, validation protocols, and stakeholder interfaces.

- Urban water infrastructure represents the most mature application track. For example, Salloom et al. (2021) combined Gated Recurrent Unit (GRU) networks with K-means clustering to predict short-term water demand with improved supply control accuracy, while R. Liu et al. (2025) used self-attention mechanisms to analyze acoustic signals for precise leak detection in distribution networks. By integrating predictive analytics, sensor-driven monitoring and automated control, these innovations help address climate-exacerbated water sources scarcity and increase the resilience of coupled socio-ecological systems. Sewer inspection has been addressed through transformer-based defect detection frameworks achieving high detection accuracy on benchmark dataset (Dang, Wang, et al., 2023). These urban infrastructure tools address immediate operational losses, with optimized distribution practices yielding potential water savings of up to 30% (Manzocco et al., 2015), and are increasingly deployable in real-time through IoT sensor integration.

- Basin-scale hydrology management requires AI tools capable of simultaneously optimizing multiple objectives across spatially distributed and temporally coupled components. The CAMELS-DK dataset (J. Liu et al., 2024) exemplifies the large-sample, multi-catchment infrastructure necessary to train and validate such basin-scale models. RL is particularly well-suited for multi-objective reservoir operation under uncertainty, because unlike static operating rules calibrated to historical hydrology, RL can learn adaptive release policies that respond dynamically to real-time inflow forecasts and downstream demand signals. However, RL-based reservoir control remains largely at the proof-of-concept stage in the reviewed literature, with no studies reporting operational deployment under real-world climate uncertainty conditions. Foundational context for this emerging frontier is provided by recent global syntheses on climate change impacts on river hydraulics (Abdulameer et al., 2025) and comprehensive reviews of AI applications for dams and water resources (Abdulameer et al., n.d.).

River hydraulics and compound flood-drought forecasting represent the most rapidly expanding frontiers, driven by the recognition that single-hazard models are insufficient for the compound extremes generated by climate change. For instance, the Extreme Flood Forecasting system (Nearing et al., 2024), which applies LSTM networks to global streamflow data trained on CAMELS time series, provides 5-day forecasts with reliability comparable to 0-day GloFAS nowcasts. Similarly, Frame et al. (2022) demonstrated that DL rainfall-runoff models outperform calibrated process-based models during extreme flood events. Furthermore, hydroclimatic transformer architectures, such as the DCNN-Transformer network proposed by (Yang, Zhang, Liu, & Jing, 2023) at the Shanjiaodi station, successfully capture long-range teleconnections between large-scale climate drivers and basin-scale discharge relationships that traditional LSTM models often fail to represent. Despite these advances, significant gaps remain. While AI is increasingly applied to drought analysis, the compound co-occurrence of floods and droughts within the same basin across consecutive seasons remains almost entirely unaddressed. Similarly, river hydraulics modeling, including channel morphology changes, sediment transport, and bank erosion under altered flow regimes, has received limited AI attention despite its critical relevance to infrastructure safety, aquatic habitat preservation, and the Reservoir sedimentation that determine the long-term viability of hydropower and water storage capacity (Ho & Goethals, 2022).

Groundwater supplies approximately 50% of global drinking water and 40% of irrigation needs (Siebert et al., 2010). Recent studies, such as (Banerjee, Ganguly, & Kushwaha, 2024), have trained and compared various AI models, from simple Linear Regression to advanced DL architectures, for forecasting groundwater recharge. Their experiments identified XGBoost as the most effective predictor, with precipitation as the dominant driver followed by the aridity index, while soil type and slope exhibited the strongest inverse correlations. AI has also been increasingly applied to water quality monitoring. ConvLSTM models have been utilized to analyze spatiotemporal pollution dynamics in rapidly urbanizing areas (L. Zhu et al., 2023), and AI-based frameworks have enhanced the real-time detection of contamination events in distribution networks. However, coupling climate-driven changes in temperature and precipitation to downstream water quality outcomes remains a largely open research problem in the current AI literature.

A major research direction in WRM is the integration of AI with real-time sensor networks to enable adaptive water operations under climate uncertainty, with a particular focus on dam and reservoir management. Dams represent critical, increasingly stressed nodes in both water supply and flood control systems. Under climate change, the statistical assumptions embedded in their original design, such as historical inflow distributions, flood frequency curves, and seasonal storage cycles, are being systematically violated (Abdulameer et al., 2025). AI-driven adaptive control systems, which combine probabilistic inflow forecasting from upstream IoT sensor networks with RL-based release optimization, could empower reservoir operators to navigate flood protection, hydropower generation, ecological minimum flows, and downstream water supply in real time.

4.6.4 Environmental protection and wildlife conservation

Environmental protection and wildlife conservation are central to ecosystem conservation because they preserve and restore habitats, such as forests, wetlands, and coastal zones, that concentrate biodiversity and provide critical ecosystem services. Intact habitats increase ecosystem resilience, act as long-term carbon sinks, and support climate adaptation by buffering extreme events and stabilizing local climates. For example, Schmitz et al. (2023) estimate that wildlife-focused conservation could enable sequestration of 6.41 billion tons of CO_2 annually, which is about 95% of the Paris Agreements 1.5 °C target. AI is rapidly transforming conservation practice by providing scalable, data-driven tools for monitoring, threat detection, and management. Examples include IoT sensors and ML models that detect human intrusion via changes in sentinel herbivore behavior (de Knegt, Eikelboom, van Langevelde, Spruyt, & Prins, 2021); automated species identification systems such as TRex (Walter & Couzin, 2021), BirdNET (Kahl, Wood, Eibl, & Klinck, 2021), and DeepWILD (Simões et al., 2023) that permit continuous biodiversity monitoring; and Transformer-based drone frameworks for detecting marine debris in real-time, which achieved 81.5% mAP performance for multiple debris classes in complex coastal environments (Dang, Sagar, Bui, Nguyen, & Nguyen, 2025). These AI approaches reduce monitoring costs, enable faster responses to threats, and help protect the functional integrity of ecosystems under climate stress.

4.6.5 Discussion

Table 9 outlines four key AI applications in conservation: land use planning, forest management, water resource management (urban water systems and basin-scale hydrological modeling), and environmental protection and wildlife conservation. CNNs and Transformer-based architectures demonstrate strong detection performance. For instance, the DeepWILD pipeline achieves a mAP of 96.88% at an Intersection over Union (IoU) threshold of 0.5 for wildlife detection (Simões et al., 2023), while a transformer-based drone framework attains 81.5% mAP for marine debris classification in complex coastal environments (Dang et al., 2025). However, classification accuracy degrades substantially for rare classes. For example, wildlife classification mAP drops to 73.92% for rare species (Simões et al., 2023). For deforestation risk prediction utilizing structured socio-environmental covariates, ensemble tree approaches that combine binary logistic regression, RF, and Rotational Forest methods exhibit robust performance (Saha et al., 2020). This suggests that model selection in this domain should be driven by data modality rather than architectural novelty. In contrast, water resource management remains the least developed sub-domain in terms of AI sophistication. Previous studies focus mainly on urban leak detection and short-term demand forecasting, leaving basin-scale hydrological modeling, groundwater recharge prediction, and climate-driven flow regime shifts largely unaddressed.

A critical challenge across all ecosystem tasks is scale mismatch. Satellite and UAV models often operate at spatial resolutions and temporal frequencies that are misaligned with the ecological processes they aim to monitor (Feng, Wen, Li, Wu, & Yan, 2025). In addition, few studies explicitly validate whether detected changes in land cover or species distribution translate into measurable outcomes such as carbon sequestration or biodiversity recovery. Beyond prediction accuracy, the next generation of climate AI must evaluate success through meaningful ecological indicators (Islam, 2025), such as carbon sequestration rates and habitat restoration, to ensure that algorithmic performance translates into measurable conservation impact.

In data-scarce regions, where sensor networks, labeled datasets, and computational infrastructure are limited, lightweight approaches like transfer learning, few-shot learning, and physics-informed models show strong promise for reducing dependence on large historical training datasets (H.-M. Wang, Peng, & He, 2024). However, their operational deployment at scale in climate AI remains underutilized, warranting greater priority in future research. Moreover, as climate change simultaneously increases agricultural irrigation demand and reduces dry-season river flows, there is an urgent need for multi-objective optimization frameworks. Such frameworks could integrate hydrological, agronomic, legal, and community-preference data to help water managers navigate trade-offs between agricultural productivity, ecological minimum flow requirements, and downstream community needs more equitably (L. Deng, Guo, Yin, Zeng, & Chen, 2022; Nile, Al-Saadi, Abdulameer, Al Maimuri, & Al-Dujaili, 2025).

4.7 Weather and disaster forecasting

Weather and disaster forecasting is classified in this review as a resilience-supporting and adaptation-oriented domain. Its primary contribution is reducing the human and economic costs of climate-driven hazards through improved prediction and early warning, rather than directly reducing emissions. Its inclusion in this survey reflects the

Table 9 Summary of five task areas for AI in ecosystem conservation, including (1) *land-use planning*; (2) *forest management*; (3) *urban water systems*; (4) *basin-scale hydrological modeling*; and (5) *environmental protection and wildlife conservation*. Column 2 reports the best quantitative metric and cross-study comparison. Abbreviations: CNN = convolutional neural network; RNN = recurrent neural network; LSTM = long short-term memory; SVM = support vector machine; CAMELS = Catchment Attributes and MEteorology for Large-sample Studies.

Tasks	Key metric & cross-study finding	Representative methods	Representative data
Land-use planning	>70 % agreement with expert labels (Dynamic World) (Brown et al., 2022). *Similarity:* U-Net and CNN-based models outperform traditional land-use change models for large-scale spatial prediction. *Difference:* Ensemble methods competitive where structured socio-environmental covariates dominate; DL preferred for satellite imagery inputs.	Evolutionary (Inceyol & Cay, 2022; Masoumi et al., 2020); Ensemble (Chai & Li, 2023; Fayaz et al., 2024); CNNs (Fayaz et al., 2025; J. Wang et al., 2022); Hybrid (Geng, Shen, Cheng, & Dai, 2022; Wambugu et al., 2021)	Sentinel-2 (Copernicus, 2025a); Landsat (USGS, 2025); FAO land use data (FAO, 2025b)
Forest management	Forest carbon sink +18.3 % (L. Xi et al., 2023); ∼30 % of studied forest area at high deforestation risk (Saha et al., 2020). *Similarity:* CNNs and ensemble models outperform classical vegetation indices for burn area and deforestation detection. *Difference:* Ensemble tree methods outperform DL where structured socio-environmental covariates dominate (Saha et al., 2020); CNNs preferred for satellite imagery tasks.	CNNs (Marques et al., 2024; Seydi, Saeidi, Kalantar, Ueda, & Halin, 2022; Z. Xi, Hopkinson, Rood, & Peddle, 2020); Ensemble (Dogan et al., 2022; Forzieri, Dakos, McDowell, Ramdane, & Cescatti, 2022; Saha et al., 2020); SVMs (Bar, Parida, & Pandey, 2020)	Deforestation data (Landsat/-PlanetScope); UCI Forest Fires (UCI, 2025)
Urban water systems	Leak detection outperforms 1D-CNN and CNN-LSTM baselines (R. Liu et al., 2025); demand prediction outperforms statistical baselines (Salloom et al., 2021). *Similarity:* Transformer and GRU-based models consistently outperform statistical baselines for demand and leak detection. *Difference:* Transformer-based acoustic models outperform CNN baselines; sewer inspection accuracy depends heavily on dataset quality (Dang, Wang, Li, Nguyen, & Moon, 2022).	CNNs (J. Chen, Tang, Rakstad, Patrick, & Zhou, 2020; Fan, Zhang, & Yu, 2021; Y. Li, Wang, Dang, Song, & Moon, 2023); RNN/LSTM (Kavya, Mathew, Shekar, et al., 2023; Salloom et al., 2021); Transformers (Dang et al., 2022; R. Liu et al., 2025)	Sewer-ML (Haurum & Moeslund, 2021); Smart meter demand logs; IoT distribution sensor networks
Basin-scale hydrological modeling	5-day forecasts comparable to 0-day GloFAS nowcasts (Nearing et al., 2024); DL outperforms calibrated process models on extreme events (Frame et al., 2022); hydroclimatic forecasting +31 % vs. CNN (Yang et al., 2023). *Similarity:* LSTM and Transformer hybrids consistently outperform statistical and physics-based baselines for ungauged basin prediction. *Difference:* Global models generalize better than regional; PINN approaches show stronger physical plausibility in data-scarce areas.	RNN/LSTM (Frame et al., 2022; Nearing et al., 2024); Hybrid DCNN-Transformer (Yang et al., 2023)	CAMELS hydrological timeseries (J. Liu et al., 2024); ERA5 reanalysis (Hersbach et al., 2020); GloFAS streamflow records
Environmental protection & wildlife conservation	Detection mAP 96.88 % (IoU = 0.5); classification mAP 73.92 % (Simões et al., 2023); marine debris 81.5 % mAP (Dang et al., 2025). *Similarity:* Detection accuracy consistently higher than classification for collected wildlife monitoring studies. *Difference:* Performance degrades substantially for rare/endangered species with limited training samples the ecologically most critical classes; offline tools (MegaDetector) enable deployment without cloud connectivity (Beery, 2023).	CNNs (Kahl et al., 2021; Simões et al., 2023; Walter & Couzin, 2021); Transformers (Dang et al., 2025; C. Li, Chen, & Ye, 2024); SVMs (de Knegt et al., 2021)	Sentinel-2 (Copernicus, 2025a); Stationary sensor networks (camera/sound)

IPCC AR6 finding that adaptation capacity, particularly anticipatory risk management, is inseparable from effective mitigation strategy at the systems level (Calvin et al., 2023).

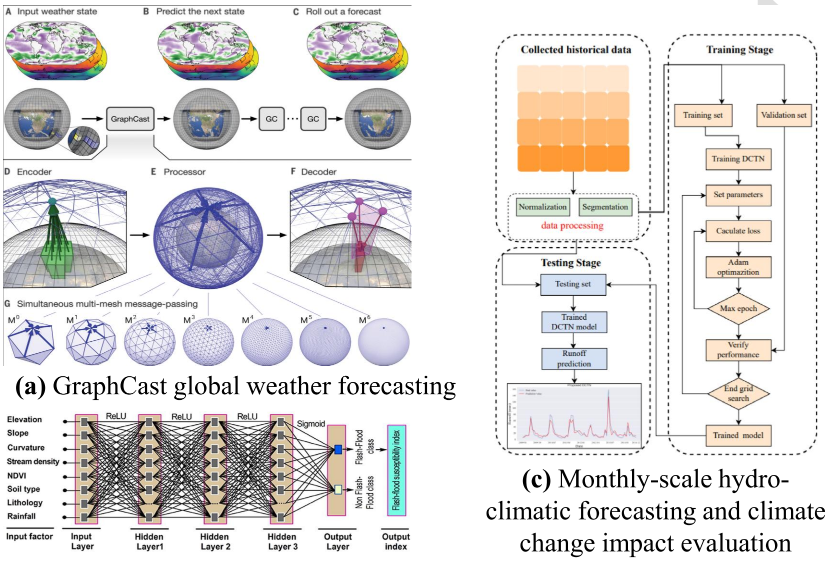
Global predictions from the World Meteorological Organization (WMO) (Organization, 2025) indicate that the period 2025–2029 will likely remain at or near record-high temperatures, with an 86% probability of at least one year exceeding 1.5 °C above pre-industrial levels and a 70% probability that the five-year average will surpass this threshold. The Germanwatch Climate Risk Index (CRI) 2025 (Adil, Eckstein, Künzel, & Schäfer, 2025) reinforces these trends, reporting more than 9,400 extreme weather events between 1993 and 2022 that caused over 765,000 deaths and USD 4.2 trillion in losses, and heatwaves in 2022 alone accounted for the majority of fatalities.

High quality weather forecasts and early warning systems play a critical role in climate change adaptation and resilience by supplying the risk-informed data decision makers need to act preemptively (L. Chen, Han, et al., 2023). Timely, accurate forecasts enable authorities to evacuate vulnerable populations, adjust reservoir releases, and prioritize resource allocation. These timely actions significantly reduce human and economic losses and can also lower emissions associate with disaster response and recovery. In recent years, meteorological forecasting has advanced dramatically thanks to high performance computing, dense satellite and RS networks, and novel data stream.

AI is transforming weather and disaster forecasting by dramatically improving the speed, accuracy, and granularity of predictions. AI models, particularly DL models trained on decades of historical observations, satellite data, and model output, can accelerate aspects of forecasting workflows, enabling more rapid generation of forecasts and faster dissemination of warnings. For example, WMO supported systems (WMO, 2025c) and national forecasting agencies (T. Nguyen, Brandstetter, Kapoor, Gupta, & Grover, 2023) increasingly integrate AI to improve lead times and reduce false alarms, which strengthens community resilience and enabling more effective disaster mitigation.

Figure 11 display representative AI approaches for key tasks in weather and disaster forecasting. In Figure 11(a), Lam et al. (2023) introduce GraphCast, an ML weather model trained directly on global reanalysis that predicts hundreds of atmospheric variables at 0.25ř resolution out to 10 days and can produce a global forecast in under one minute. During evaluations, it significantly outperformed the most accurate operational deterministic systems on 90% of 1,380 verification targets and improved forecasts of severe events such as tropical cyclones, atmospheric rivers, and extreme temperature episodes. Figure 11(b) presents a DL-based flash flood susceptibility mapping workflow by (Bui et al., 2020) for a high frequency tropical storm region of northwest Vietnam. The pipeline achieved high accuracy of 92.05% on a Geographic Information System (GIS)-derived dataset (elevation, slope, curvature, aspect, stream density, NDVI, soil type, lithology, and rainfall) with feature selection via information gain ratio. Finally, in Figure 11(c), Yang et al. (2023) combine deep convolutional modules for local feature extraction with a Transformer to capture long-range hydro-climatic dependencies. The model obtained a substantial improvement of roughly

31% over conventional approaches when applied to historical forecasting at the Shanjiaodi hydrology station (Dagu River Basin). These representative examples show how diverse AI architectures, graph models, CNNs, and Transformer hybrids, are accelerating both the speed and accuracy of forecasts for weather and extreme weather events.



(a) GraphCast global weather forecasting

(b) Flash-flood susceptibility prediction

(c) Monthly-scale hydro-climatic forecasting and climate change impact evaluation

Fig. 11 Representative AI approaches for each key task in weather and disaster forecasting. (a) Nowcasting (Lam et al., 2023); (b) Extreme weather prediction (Bui et al., 2020); and (c) Long-term climate modelling (Yang et al., 2023).

4.7.1 Nowcasting

Nowcasting is a specialized subset of weather forecasting that focuses on very short-term predictions, typically ranging from the present moment up to six hours ahead. It emphasizes a detailed description of the current atmospheric conditions and uses extrapolation techniques to forecast immediate changes (Shi et al., 2017). Unlike medium-range or long-range forecasting, nowcasting operates on an intermediate level, relying heavily on real-time observational data such as radar imagery, satellite observations, surface weather stations, and lightning detection systems to predict phenomena like precipitation, thunderstorms, fog, or wind shifts. For example, Hewage, Trovati, Pereira, and Behera (2021) introduced a lightweight, data-driven short-term forecasting architecture that combined Long Short-Term Memory (LSTM) networks with temporal CNNs. They benchmarked this DL approach against classical ML methods, conventional statistical techniques, a dynamic ensemble method, and the commonly used physical Weather Research and Forecasting (WRF) model. Their experiments, which covered both multi-input multi-output and multi-input single-output regression setups, showed that the proposed DL model outperformed the more complex WRF system for forecasts up to 12 hours ahead. Ponnoprat (2021) addressed nonlinear and seasonal patterns in daily precipitation by designing a seasonally integrated autoencoder that stacked two LSTM autoencoders: one to capture short-term dynamics and another to extract seasonal structure. Their results indicated the autoencoder-based model outperformed several baseline time-series and DL models with a substantial improved in forecastobservation correlation from about a 4% increase at a one-day horizon to roughly 37% at a three-day horizon. Nowcasting also directly supports renewable energy integration by providing high resolution, short-term forecasts of solar irradiance and wind. For instance, J. Zhao et al. (2021) developed a data-driven short-term wind speed system using ensemble weather research and forecasting (WRF) outputs, Gaussian-mixture clustering, and a multi objective evolutionary algorithm to optimize model structure and member weighting for each distinct pattern. According to their evaluation, this approach reduced average RMSE by about 30.21% and cut the RMSE standard deviation by about 50.36% relative to a simple ensemble mean, demonstrating clear gains in both accuracy and reliability for operational short-term wind forecasting.

4.7.2 Long-term climate modelling

Long-term climate modelling extends beyond short-term predictions (hours to days) by focusing on averaged patterns and trends, such as temperature shifts, precipitation changes, and sea-level rise, rather than specific daily events (Alizadeh, 2022). Long-term climate modelling is indispensable for climate resilience, as it provides probabilistic projections of future scenarios under different emission pathways. AI and ML are transforming long-term climate modelling by accelerating simulations, improving accuracy, and handling vast datasets, addressing traditional models' computational intensity and resolution limitations. For example, Pan et al. (2022) introduced Conditional Generative Forecasting, a probabilistic DL framework that utilized large ensembles of climate simulations to learn differences between general circulation model (GCM) formulations and to represent internal climate variability for dynamical seasonal forecasting. The experimental results showed that the model generated conditional ensembles of seasonal outcomes that matched the performance of traditional dynamical forecasts for global precipitation and 2 m air temperature predictions. Statistical downscaling techniques, such as bias correction and quantile perturbation, remain essential for translating coarse GCM outputs into actionable regional information. These methods improve the accuracy of local projections and therefore are critical for vulnerability assessments and the design of adaptation and resilience measures. Building on this idea, F. Wang and Tian (2022) evaluated a Super Resolution Deep Residual Network for multivariate bias correction and spatial downscaling of Climate Model Intercomparison Project 6 (CMIP6) daily temperature fields. Their approach sequentially stacked 20 GCMs to learn relative biases with respect to observations while explicitly preserving spatial structure and inter-variable dependencies. The experimental results showed the univariate configuration substantially reduced mean temperature bias relative to quantile delta mapping, and the multivariate model outperformed a dynamic Optimal Transport Correction by better correcting Tmax/Tmin biases and avoiding unrealistic spatial artifacts.

4.7.3 Extreme weather prediction

Extreme weather prediction involves forecasting rare, high impact atmospheric events that deviate significantly from typical conditions at a specific location and time, often characterized by unusual magnitude, duration, or extent. These events include heatwaves, cold snaps, heavy precipitation leading to floods, severe thunderstorms, hurricanes, tornadoes, droughts, blizzards, and ice storms, which can cause substantial damage to life, property, and ecosystems. Prediction relies on advanced observational data from radars, satellites, and ground stations, combined with numerical models that simulate atmospheric dynamics, thermodynamics, and probabilistic scenarios to anticipate event onset, intensity, and evolution. However, accurately predicting extreme weather remains difficult because extreme events are both rare and highly nonlinear, and their dynamics can change under a warming climate. Because of these challenges, recent research emphasizes hybrid approaches that combine AI with high resolution dynamical models and large ensembles to better capture both small-scale processes and model uncertainty. For example, Gan, Fu, Zhao, Chan, and He (2024) compared four mainstream DL approaches for short-term tropical cyclone track and intensity forecasting and examined how performance depends on input sequence length, sampling interval and lead time. The experimental results indicated that Temporal Convolutional Networks (TCNs) offered the best mix of accuracy, computational efficiency, and stability when using short input windows. For flood risk mapping, hybrid geospatial approaches are already operationally useful. Panahi et al. (2021) trained a hybrid CNNRNN system using a geospatial database of historical flash floods and stepwise weight assessment ratio analysis feature weights. The generated map identified roughly 40% of the area as highly susceptible to flash floods, which could be used as a reference to guide land use planning, mitigation strategies, and the deployment of early warning systems. Work at the interface of visualization and forecasting also helps experts extract signals from complex ensemble outputs. X-Weather (de Souza et al., 2022) is an interactive visual analytics system that provides statistics- and probability-based visualizations for rapid inspection and comparison of ensemble simulations. In two case studies of the devastating mountain region storms that struck Rio de Janeiro (2011 and 2020), X-Weather reduced the manual, error-prone effort normally required to interpret large physical ensembles and helped users identify extreme scenarios more efficiently.

4.7.4 Discussion

Table 10 summarizes representative weather and disaster forecasting applications where AI has been increasingly applied. GNN-based models, such as GraphCast, represent the current state of the art for medium-range global forecasting. These models outperform operational deterministic systems on 90% of 1,380 verification targets while generating 10-day forecasts in under 60 seconds (Lam, 2023). For extreme weather prediction, hybrid CNN-RNN architectures demonstrate robust local performance, with flash flood susceptibility mapping achieving 92.05% accuracy (Bui et al., 2020). Meanwhile, TCNs offer the optimal balance of accuracy, computational efficiency, and stability for short-input-window tropical cyclone forecasting (Gan et al., 2024).

A notable performance divergence exists between global-scale models trained on ERA5 reanalysis, which generalize well but often underresolve local topographic effects, and regional models that achieve higher local accuracy but lack transferability across geographic contexts without complete retraining. Similarly, long-term climate downscaling models show meaningful bias reduction compared to conventional quantile delta mapping (QDM) (F. Wang & Tian, 2022). However, their evaluation remains almost exclusively retrospective, leaving their calibration under novel future climate states unvalidated. The most critical unaddressed gap is compound hazard forecasting (Dulin et al., 2025). The reviewed literature predominantly treats floods, heatwaves, droughts, and cyclones as independent prediction targets. However, the most damaging real-world events increasingly involve the simultaneous or sequential co-occurrence of multiple hazards, whose joint dynamics cannot be captured by single-hazard models.

4.8 Algorithm selection framework for climate AI applications

Table 11 reports the comparative performance, UQ capabilities, and computational demands of the major AI model families reviewed across the seven domains. Classical ML models, such as RFs and SVMs, remain the standard for low-cost, tabular tasks like carbon footprint estimation. However, they lack the temporal memory required for complex climate sequences, a gap effectively addressed by LSTMs and Transformers. Notably, Transformer-based architectures like GraphCast have achieved a 90% skill score in extreme weather forecasting. DL variants, including CNNs and GNNs, dominate spatial tasks ranging from deforestation mapping to global weather projection, though they often demand significant computational resources and face challenges regarding spatial autocorrelation and distribution shifts.

Table 10 Summary of three task areas for AI in weather and disaster forecasting, including (i) *extreme-weather prediction*; (ii) *nowcasting and short-range prediction*; and (iii) *long-term climate modeling*. Column 2 reports the best quantitative metric and cross-study comparison. Abbreviations: DNN = deep neural network; ERA5 = ECMWF Reanalysis v5; CMIP6 = Coupled Model Intercomparison Project Phase 6; NWP = numerical weather prediction.

Tasks	Key metric & cross-study finding	Representative methods	Representative data
Extreme weather prediction	Flash flood susceptibility 92.05 % accuracy (Bui et al., 2020); TCN best efficiency for cyclone forecasting (Gan et al., 2024). *Similarity:* Hybrid CNN-RNN consistently outperforms single-architecture baselines for local hazard mapping. *Difference:* TCNs outperform LSTM on short-window cyclone forecasting; global models underresolve local topographic effects; compound multi-hazard forecasting almost entirely unaddressed.	Ensemble (de Souza et al., 2022; L. Huang et al., 2021); Transformers (W. Huang et al., 2024; Jin et al., 2023; Küçük, Giannakos, Schneider, & Jann, 2024; Marusov et al., 2024; T. Nguyen et al., 2023); DNNs (Anbarasan et al., 2020; Bui et al., 2020; Chattopadhyay, Nabizadeh, & Hassanzadeh, 2020; Frame et al., 2022; Gan et al., 2024; Grönquist et al., 2021; Hess & Boers, 2022; Jacques-Dumas, Ragone, Borgnat, Abry, & Bouchet, 2022); RL (Fan, Zhang, Wang, & Yu, 2023; X. Li et al., 2023); Hybrid (R. Chen et al., 2019; Panahi et al., 2021)	Radar and satellite composites (N.N.S.S. Laboratory, 2025); Global climate observations (EMDAT, 2025); High-resolution forecasts/permeability maps (Noaa, 2025)
Nowcasting	RMSE reduced by −30.21 % compared to ensemble approaches (J. Zhao et al., 2021); DL outperforms WRF up to 12 h lead time (Hewage et al., 2021). *Similarity:* DL nowcasting consistently outperforms physics-based WRF at short lead times (≤12 h) for all reviewed studies. *Difference:* Skill degrades at over 12 hour ranges where physics models become competitive; autoencoder-based approaches outperform standard DL for seasonal structure capture (Ponnoprat, 2021).	DNNs (Aderyani, Mousavi, & Jafari, 2022; Lam, 2023; M. Ma et al., 2023; Ponnoprat, 2021; Suleman & Shridevi, 2022); Transformers (Ji, He, Lei, Wang, & Tang, 2024; T. Nguyen et al., 2024); Ensemble (Weyn, Durran, Caruana, & Cresswell-Clay, 2021; J. Zhao et al., 2021); Hybrid (Adewoyin, Dueben, Watson, He, & Dutta, 2021; Q. Guo, He, & Wang, 2024; Hewage et al., 2021)	Weather radar/satellite (NEXRAD, GOES-16) (noaa, 2025); NWP data (HRRR, HREF) (NOAA, 2025)
Long-term climate modelling	Outperforms HRES on 90 % of 1,380 targets; 10-day forecast in <60 s (Lam, 2023); hydroclimatic forecasting +31 % vs. CNN (Yang et al., 2023); downscaling DL outperforms quantile delta mapping (F. Wang & Tian, 2022). *Similarity:* GNN-based models (GraphCast) represent the current state of the art; DCNN-Transformer outperforms LSTM for long-range hydroclimatic dependencies. *Difference:* Global foundation models generalize well but underresolve regional extremes; downscaling DL outperforms statistical methods for bias correction but lacks validation under non-stationary future climate states.	Hybrid (Adewoyin et al., 2021; Q. Guo et al., 2024; Hewage et al., 2021); Transformer (Yang et al., 2023); DNNs (Pan et al., 2022; Scher, 2018; F. Wang & Tian, 2022)	Global reanalyses (ERA5, MERRA-2) (ECMWF, 2025); CMIP6 simulations (of Melbourne, 2025); Gridded observational products

In addition, the table highlights specialized approaches such as Deep RL for real-time HVAC and traffic optimization, which has demonstrated the potential to reduce GHG emissions at intersections by up to 10%. However, most of these approaches are validated primarily in simulation environments, and their deployment in live climate systems remains limited. Hybrid architectures and PINNs offer superior generalization under data-scarce and non-stationary climate conditions. For instance, PINNs accelerate geological storage analysis by 40% while embedding physical constraints that prevent implausible extrapolations, and CNN-LSTM hybrids achieve 86% fault classification accuracy with moderate compute requirements, though both require substantial domain expertise for configuration. Foundation models, such as ClimaX, represent a frontier capability, matching Numerical Weather Prediction (NWP) approach at a fraction of the inference time. However, their prohibitive training costs, substantial carbon footprints, and the scarcity of fine-tuning data in the Global South constrain their responsible deployment in the very regions where climate AI is most urgently needed.

In summary, Table 11 reveals a persistent tension between performance and deployability, where the highest-performing model families (Transformers, GNNs, Deep RL, and foundation models) require the highest computational costs, exhibit weaker UQ, and suffer from the largest sim-to-real gaps. On the other hand, the most interpretable and deployable families (ensemble methods, XGBoost, and PINNs) remain underutilized in the reviewed literature relative to their demonstrated suitability for data-scarce and physically constrained climate applications. In addition, Table 11 also organizes decision dimensions into four questions a practitioner should answer before selecting a model: (1) What is the primary task type? (2) How important is interpretability or physical consistency? (3) What are the computing and deployment constraints? (4) Does the model need to generalize across geographies or climate regions? The interaction of these four factors produces distinct deployment profiles, each associated with a best-fit architecture and cautionary notes.

Table 12 highlights the transformative impact of AI for seven key sectors from 2017 to 2024, emphasizing measurable efficiency gains and superior predictive capabilities of modern methods, especially DL, RL, and hybrid systems, over traditional methods. In Energy and carbon management, deep RL and predictive modeling by DeepMind achieved significant efficiency gains, such as a 30% reduction in data center cooling energy and a 20% increase in wind energy value, while advanced industrial controls cut CO_2 capture energy use by up to 24%. Transportation applications use large-scale traffic data and deep RL to optimize signal timing and leverage autonomous vehicles such as mobile traffic controllers, decreasing stops, emissions, and phantom traffic jams. For example, Google's Project Green Light reduced intersection emissions by 10%. Similarly, Industry sector benefited from optimization algorithms. For example, the adaptive multiscale CNNs and enhanced highway LSTM (ACEL) model outperformed traditional methods in industrial fault diagnosis. For buildings and cities, RL learning was applied to grid-interactive communities and HVAC systems to reduce peak loads and cut building energy use by around 913%. In Agriculture and Ecosystem Reservation, AI tools like FarmBeats and MegaDetector improved productivity and monitoring efficiency by substantial margins (up to 45% productivity and 90%

Table 11 Comparative performance and deployment profile of AI algorithms and representative climate tasks for climate change mitigation. Abbreviations: UQ = Uncertainty Quantification; MC = Model Complexity (L = Low, M = Medium, H = High).

Model family	Representative climate task	Best reported metric	UQ	MC	Key limitation
Classical ML					
Random forest / XGBoost	Carbon footprint estimation (Energy, industry)	87.4% accuracy (An et al., 2024)	Post-hoc (SHAP)	L	No temporal memory; poor on spatiotemporal sequence.
SVM	Solar/wind power forecasting (Energy)	Competitive on small data (Jang et al., 2016)	None, natively	L	Kernel selection sensitive; does not scale to large datasets.
Deep learning sequence models					
LSTM / GRU	Water demand forecasting (Ecosystem, energy)	Outperforms statistical baselines; RMSE 30% vs. ensemble (J. Zhao et al., 2021)	Post-hoc (MC dropout)	M	Overfits on short or single-season datasets; poor extrapolation.
Transformer	Extreme weather, hydroclimatic forecasting (Weather, ecosystem)	+31% over CNN baseline (Yang et al., 2023); 90% skill score (GraphCast)	Conformal prediction (emerging)	H	Very high data hunger; calibration degrades under distribution shift.
Deep learning spatial models					
CNNs	Fault detection, species classification, deforestation mapping (Industry, ecosystem)	94% anomaly detection; 96.88% mAP wildlife (Simões et al., 2023)	Post-hoc (saliency, Grad-CAM)	M	Spatial autocorrelation leakage; limited temporal memory.
GNN	Traffic flow prediction, global weather forecasting (Transport, weather)	Outperforms HRES on 90% of 1,380 targets (Lam, 2023)	None natively; ensemble variants exist	H	Requires graph topology; degrades when network structure changes.
Deep learning control and optimization					
Deep RL (DQN, PPO, SAC)	HVAC control, traffic signals, EV scheduling (Buildings, transport, energy)	Scheduling time 61% vs. standard (K. Zhou et al., 2022); GHG 10% reduction at intersections (Matias, 2025)	None natively; distributional RL emerging	H	Validated mostly in simulation; limitations in live system.
Hybrid and physics-informed					
CNN-LSTM hybrid	Industrial predictive maintenance, building energy (Industry, buildings)	86% fault classification (Le et al., 2021)	Post-hoc (SHAP)	M	Architecture tuning complex; dataset-specific.
PINN (physics-informed NN)	Hydrological modeling, CCS simulation (Ecosystem, energy)	Outperforms pure DL; geological storage analysis 40% faster (Punnam et al., 2023)	Residual loss as physical consistency check	M-H	Training instability; requires domain expertise.
Ensemble methods	Deforestation risk, climate downscaling (Ecosystem, weather)	RMSE 30% vs. single model (J. Zhao et al., 2021); 92% flood susceptibility (Bui et al., 2020)	Native (variance across members)	M	High memory.
Foundation / large-scale models					
Climate foundation model (ClimaX)	Global weather and climate projection (Weather)	Comparable to NWP at fraction of inference time (T. Nguyen et al., 2023)	Ensemble fine-tuning (emerging)	H	Very high training cost; limited fine-tuning data.

processing time reduction, respectively). Finally, Weather and disaster forecasting saw major leaps with GraphCast and LSTM-based flood forecasting, which delivered faster and more reliable predictions than conventional meteorological systems. These methods demonstrate AI's capacity to drive measurable sustainability improvements through optimized resource management and enhanced predictive accuracy.

5 Open Issues and Future Research Directions

Before diving into the detailed subsections, it is helpful to frame the principal open issues that currently limit the effective use of AI for climate change mitigation. First, data scarcity and heterogeneous data quality constrain model training and generalization, particularly for low-income regions and marginalized communities. Second, the opacity of many high performing AI models and weak UQ hinder trust by scientists, policymakers, and practitioners. Third, the computational and infrastructure demands of state-of-the-art AI, from resource-intensive training and inference processes to continuously powered data centers, create a carbon and resource footprint that can partially obstruct the mitigation gains. Fourth, ethical and equity concerns (algorithmic bias, privacy, unequal access, and potential misuse) threaten to amplify existing social and geographic inequalities if not explicitly addressed. Finally, policy, governance, and interdisciplinary coordination have not kept pace with technical advances, leaving gaps in standards, accountability, and cross-sector collaboration that are essential for safe, scalable deployment.

The systemic challenges at the intersection of AI and climate mitigation are interconnected and demand coordinated technical, institutional, and social strategies rather than isolated interventions. Effective responses require three critical pillars: (1) standardized climate datasets with interpretable infrastructures, which ensure fairness, seamless sharing, exchange, and interpretation; (2) wider adoption of explainable, uncertainty quantifying models and 'green AI' practices that minimize computational emissions; and (3) participatory design with frontline communities, co-created validation frameworks, and harmonized regulations that accelerate innovation while embedding equity and environmental safeguards. The following sections discuss root causes, evaluate existing approaches through comparative analysis, and spotlight actionable policy pathways and real-world case studies to bridge the gap between AIs transformative potential and its fairness, scalable, and low-carbon contribution to climate mitigation.

5.1 Open issues

5.1.1 Data scarcity, quality, and model transferability

Despite rapid advances in AI, high-quality climate and emissions data remain scarce, fragmented, and inconsistent. Three primary root causes drive this challenge: (1) Climate-relevant data originate from diverse sources, including satellites, ground stations, simulations, social media, and emerging IoT/drones, each characterized by unique resolutions, coverage limitations, and incompatible formats. (2) Developing nations frequently lack the digital infrastructure and funding necessary to effectively collect, process, or share data. (3) Critical datasets, such as utility energy records, are often proprietary or restricted, limiting their availability for research. Consequently, existing datasets suffer from critical gaps in spatial coverage, temporal resolution, and standardization. For instance, high-resolution meteorological models like the High-Resolution Rapid Refresh (HRRR) (NOAA, 2025) provide detailed insights but are limited to the United States, leaving vast global regions without comparable data. While ECMWF reanalysis v5 (ERA5) (Hersbach et al., 2020) offers consistent global

Table 12 Summary of state-of-the-art ML/DL applications for climate change mitigation categorized by sector, methodology, and performance outcomes (20172025).

Domain	Method	Contributions	Performance	Year
Energy and carbon management	Industrial control (Deepmind, 2025b)	Deep RL that autonomously controls cooling in hyperscale data centers.	Cut cooling energy use by 30% in Google data centers compared to human-operated baselines.	2018
	Wind power forecasting (Deepmind, 2025a)	DeepMind on turbine and weather data to predict 36-hour wind power output.	Raised wind energy value by 20% via improved hourly grid commitments.	2019
	CCS (Z. Zhang, Vo, Kum, Hong, & Lee, 2023)	Advanced waste-heat recovery integrated with high-capture-rate amine CO_2 absorption.	Cascade waste-heat recovery cuts CO_2 capture energy use by 12–24% vs. baseline or single-module setups.	2023
Industry	REINFORCE (Kool, Van Hoof, & Welling, 2018)	Transformer encoderdecoder with multi-head attention for combinatorial optimization.	Generalizes across diverse routing problems without task-specific tuning.	2018
	ACEL (S. Zhao, Duan, Roy, & Zhang, 2024)	Hybrid deep model tailored for nonstationary chemical and process control systems.	Outperforms CNNs, LSTM, autoencoders, DBNs, and KPCA+SVM on large-scale fault diagnosis.	2024
Agriculture	FarmBeats (Vasisht et al., 2017)	IoT+AI platform combining TV whitespace links, drone imagery, and sensors for precision farming.	Showed up to 45% higher productivity via precision irrigation and microclimate monitoring.	2017
	PlantVillage Nuru (Mrisho et al., 2020)	Offline mobile CV assistant for real-time crop disease and pest diagnosis.	Achieved 65–88% accuracy, surpassing extension agents (58%) and farmers (31%).	2020
Buildings and cities	HVAC control (Luo et al., 2022)	A deep RL for optimizing HVAC for real-time chiller plant control.	Reduced energy use by 9–13% in large buildings and campuses.	2022
	CityLearn v2 (Nweye et al., 2025)	RL-based control of grid-interactive communities.	RL agents improve flexibility and cut peak loads vs. rule-based controllers.	2024
Transportation	Flow (Kheterpal et al., 2018)	Deep RL framework where AVs act as mobile traffic controllers to smooth traffic.	Simulations show AVs can remove phantom jams and raise fuel efficiency.	2018
	Project Green Light (Matias, 2025)	Uses Google Maps data to model traffic and optimize signal timing without new hardware.	Reduced stops by up to 30% and intersection emissions by 10% in pilot cities.	2023
Ecosystem reservation	MegaDetector (Beery, 2023)	General object detector for animals, people, and vehicles in camera-trap images.	Removes 70–90% of empty images, cutting manual processing time and cost by up to 90%.	2019
	Dynamic World (Brown et al., 2022)	Near real-time DL model for 10 m global land-use/land-cover mapping.	Enables continuous land-change monitoring with >70% agreement to expert labels.	2022
Weather disaster forecasting	GraphCast (Lam, 2023)	GNN-based global weather model producing 10-day forecasts at 0.25° resolution.	Outperforms Hybrid Renewable Energy System (HRES) on 90% of variables and runs 10-day forecasts in <60 s.	2023
	Extreme Flood Forecasting (Nearing et al., 2024)	LSTM-based hydrology model using global streamflow data to predict extreme floods.	Provides 5-day forecasts with reliability comparable to 0-day GloFAS nowcasts.	2024

coverage, it does so at a coarse spatial resolution. On the other hand, localized sources (e.g., OpenAQ (Openaq, 2025) or Global precipitation measurement (GPM) satellite imagery (Huffman et al., 2015)) offer fine-grained detail but suffer from limited geographic scope. Furthermore, all major data sources require significant preprocessing before they can be utilized for model training, and no single dataset currently comprehensively addresses these spatial, temporal, and thematic gaps simultaneously. Table 13 provides a comparative analysis of key climate datasets in different aspects.

Table 13 Examples of climate and energy datasets used in AI models. No single dataset provides full, unbiased coverage, highlighting the need for integrating multiple sources.

Data source	Data type	Coverage	Access	Limitations
ERA5 (Hersbach et al., 2020)	Meteorological (temp, wind, rain)	Global, hourly (1979–now)	Free	Coarse (∼31 km); limited ground truth
GPM (Huffman et al., 2015)	Precipitation	Global (30-min, 0.1°)	Free	Clouds and orbits limit detail.
OpenAQ (Openaq, 2025)	Air quality (PM, NO_2, etc.)	∼100+ countries (variable)	Open API	Sparse in many regions; variable quality.
EDGAR emissions (Commision, 2025)	GHG by sector and country (annual)	Global, aggregated	Free	High uncertainty, dated reports.
IoT sensors	Local energy use, traffic, etc.	City or building-specific	Varies	Often private; low interoperability.

Data bias represents another critical challenge, originating from historical and structural inequalities embedded within climate datasets. Many essential data sources, such as air quality sensors and adaptive capacity indices, are either sparse or entirely absent in developing nations (Adams, Ide, Barnett, & Detges, 2018). For instance, pollutant monitoring networks and disaster response systems are frequently concentrated in urban centers. As the result, AI models trained on such skewed distributions risk systematically ignoring or underpredicting hazards in rural and low-income regions (McGovern et al., 2024). Beyond immediate prediction errors, a deeper and often overlooked consequence of this data disparity is the limited transferability of AI models across diverse geographical and climatic contexts. The majority of high-performing models reviewed in this survey were trained on data from North America, Europe, or East Asia, regions characterized by dense sensor networks, robust reanalysis products, and extensive historical records. However, directly applying these models to climatically and physically distinct regions introduces severe generalization risks in applications ranging from flood forecasting and groundwater recharge estimation to emission prediction and ecosystem monitoring. For example, a flood forecasting model trained on ERA5 reanalysis data for European catchment encodes physical relationships between precipitation, soil moisture, and runoff that are specific to temperate climates with well-assessed river systems. However, the model encounters fundamentally different dynamics, such as glacial melt contributions, monsoon-driven precipitation regimes, complex orographic effects, and sparse gauge networks, when deployed in the Himalayan basin (Shukla, Jain, & Kansal, 2021). These discrepancies highlight how models optimized for data-rich regions may fail catastrophically when transferred to data-scarce environments with distinct hydro-climatic regions.

5.1.2 Model interpretability and uncertainty quantification

Climate phenomena are inherently complex and highly non-linear. Table 14 compares different AI modeling paradigms used for climate change mitigation. Unlike traditional physics-based climate models, which derive outcomes from transparent and well-established physical equations, purely data-driven ML models do not explicitly encode these physical laws. DL approaches often prioritize optimizing millions of neural weights over preserving domain-specific constraints. Consequently, these complex AI models introduce significant transparency gaps in crucial climate applications, where opaque decision logic can erode trust among scientists, policymakers, and research communities. For instance, if a flood prediction system issues warnings based on false correlations with outdated river flow data rather than real-time rainfall inputs, the lack of interpretability could prevent early detection of these errors, potentially leading to catastrophic failures in emergency response (Maimuri, Altahir, Abdulameer, Rashid, & Al-Dujaili, 2025).

Uncertainty quantification (UQ) refers to the principled characterization of prediction confidence through methods such as ensemble forecasting, Bayesian DL, and conformal prediction intervals. In climate-critical applications, UQ is a critical. For example, a flood forecast with 90% accuracy is technically precise but practically dangerous if it ignores the 10% tail risk, the only zone where critical decisions are made.

Table 14 Summary of interpretability levels and applications for various climate-related modeling approaches.

Approach	Interpretability	Typical use case	Example tools/models
Physics-based models	High (based on equations)	Long-term climate projections, physics validation.	GCMs (CMIP), numerical weather models.
Physics-informed ML	Medium (constrained)	Hybrid forecasts and parameterization.	PINNs, ECMWFs AIFS (AI forecasting).
Ensemble methods	Moderate (some feature importance)	Emission scenarios, resource optimization.	Random forests, gradient boosting.
Foundation/ Generative DL	Low-Medium	Scenario generation, downscaling.	Diffusion models, GANs.
Pure ML/DL	Low (black-box)	Fast prediction (e.g., high-resolution forecasts).	CNNs, Transformers (GraphCast) on satellite/-precip data.

In critical tasks such as predicting droughts or estimating emission trajectories, stakeholders require not only accurate predictions but also an understanding of the underlying drivers. Explainable AI (XAI) (Minh, Wang, Li, & Nguyen, 2022) methods, such as SHapley Additive exPlanations (SHAP), counterfactual analysis, and saliency mapping, offer promising tools to uncover feature importance and the logic behind model decisions. However, despite their potential, these methods are frequently overlooked in climate change applications, even as the demand for trustworthy and accountable predictions grows increasingly urgent. Recent successes illustrate this potential: (1) XAI analysis revealed that a drought index model disproportionately weighted temperature anomalies (Dikshit & Pradhan, 2021), allowing scientists to recalibrate the system; and (2) a study on river floods (Choubin et al., 2025) demonstrated that quantifying the influence of individual climate variables significantly improved trust among hydrologists.

5.1.3 Energy consumption and infrastructure demands of AI

Training and deploying powerful AI models are highly energy-intensive processes that can potentially offset some of their intended climate benefits. Large DNNs with billions of parameters require vast amounts of electricity for both training and deployment that still comes from fossil-fuel-based grids (Berthelot, Caron, Jay, & Lefevre, 2024). Consequently, the carbon footprint of AI training generally scales with model size and dataset complexity. Empirical evidence emphasizes the magnitude of this challenge: training GPT-3 (175 billion parameters) consumed 1,287 megawatt-hours (MWh) of electricity and generated approximately 502552 metric tons of CO_2 equivalent (De Vries, 2023). In contrast, the training of Hugging Face's BLOOM model (176 billion parameters), executed on a French supercomputer powered largely by nuclear energy, consumed only 433 MWh and emitted just 25 metric tons of CO_2 equivalent (Workshop et al., 2022). This profound gap demonstrates that grid carbon intensity is a decisive factor in AI's environmental impact. Moreover, advances such as deeper architectures, ensemble methods, and higher-resolution datasets continue to accelerate computational demand.

After training, the ongoing operational phase where deployed models process user queries can cumulatively exceed training emissions over time. While inference per query consumes less energy than training, the sheer volume of requests compounds the impact rapidly. At current scales, inference for ChatGPT is estimated to consume approximately 150 MWh per day (Medium, 2025). According to a recent IEA report, global data centers consumed approximately 415 terawatt-hours (TWh) of electricity in 2024 (1.5% of total global demand), with projections indicating consumption could exceed 945 TWh by 2030, more than doubling current levels (IEA, 2025). Moreover, the continuous operation of data centers for inference and storage demands substantial electricity and millions of liters of water daily for cooling systems (Rong, Zhang, Xiao, Li, & Hu, 2016).

These rising workloads place increasing stress on electrical grids. Forecasts from the Lawrence Berkeley National Laboratory suggest that by 2028, over half of all electricity allocated to data centers will serve AI functions, potentially consuming energy equivalent to 22% of annual U.S. household consumption (L.B.N. Laboratory, 2025).

Consequently, although AI for climate mitigation is increasingly deployed to reduce emissions, it simultaneously carries a substantial carbon footprint unless the underlying infrastructure is powered predominantly by renewable energy. The environmental costs extend beyond energy use; specialized hardware such as graphics processing units (GPUs) and application-specific integrated circuits (ASICs) account for significant manufacturing emissions, resource-intensive extraction, and the accumulation of electronic waste.

Table 15 Summary of energy and resource consumption challenges in AI development and actionable strategies for carbon footprint reduction.

Component	Resource use	Mitigation strategies
Model training	Very high electricity; extensive GPU/TPU utilization.	Use efficient algorithms, model pruning, or smaller architectures; schedule training during off-peak hours; utilize carbon-free electricity sources.
Model inference	Persistent server load (scales with user volume).	Edge computing; batching predictions; dynamic scaling (turning off idle systems).
Data centers	Continuous power and water for cooling.	Immersion cooling; water recycling; siting in cool climates; renewable energy.
Supercomputing (HPC)	Large HPC clusters for climate simulations.	Co-design ML with HPC workflows; use low-energy processors, green data centers.

5.1.4 Governing AI in climate change mitigation domain

Currently, binding policies specifically governing the use of AI in climate domains are scarce. Existing legislation, such as the EU's AI Act (Union, 2023), emphasize fundamental rights and safety, with limited provisions regarding energy consumption. (Pagallo, Ciani Sciolla, & Durante, 2022) critically examined the legal consequences of this omission, highlighting the lack of environmental safeguards within the Act and offering recommendations for reform. In addition, major international climate frameworks like the Paris Agreement do not yet address AI tools at all. As a result, climate-focused AI projects operate within a fragmented patchwork of national regulations and voluntary norms, which leaves critical areas like data governance and environmental performance under-defined. In the absence of clear standards, private sector actors may overlook safety, equity, or energy efficiency unless mandated, while public institutions may hesitate to adopt AI solutions due to legal and ethical uncertainties. Three deployment-critical regulatory gaps stand out:

- Cross-border data sharing: Although shared river basins, such as the Mekong and Nile, generate hydrological data essential for AI-driven flood forecasting, no binding framework obliges upstream nations to share real-time sensor data with downstream communities that bear the greatest climate risk (Eddamiri et al., 2025). This lack of regulatory oversight undermines the development of equitable early warning systems.

- Carbon market integrity: As AI-estimated sequestration values increasingly determine carbon credit prices on voluntary markets, the integrity of these markets is at risk. Currently, no internationally standardized protocols govern acceptable estimation methods, required uncertainty disclosures, or audit procedures for AI-based carbon accounting (Committee, 2023).
- Liability in early warning systems: AI-based early warning systems operate under undefined liability systems. When an AI model issues a false negative for floods or heatwaves resulting in loss of life, legal accountability among developers, agencies, and governments remains unresolved in most jurisdictions. Such ambiguity serves as a barrier to both the deployment of life-saving tools and the rigorous disclosure of model limitations (Cowls et al., 2023).

Beyond regulatory gaps, data sovereignty presents a profound conflict largely ignored in previous studies. Satellite data covering forests and coastlines in developing nations is frequently collected by agencies such as NASA and ESA, processed abroad, and used to train models that inform international carbon markets, with minimal involvement from the monitored nations (Chander & Sun, 2023). Similarly, IoT and smart meter data from cities in the Global South are increasingly stored on foreign cloud infrastructure under foreign jurisdictions. Furthermore, indigenous ecological knowledge digitized for AI conservation models rarely confers intellectual property rights or financial benefits to the originating communities (Williamson, Provost, & Price, 2023). Addressing these inequities requires extending United Nations Framework Convention on Climate Change (UNFCCC) data-sharing principles to AI training datasets, investing in in-country compute infrastructure, and establishing participatory governance mechanisms that grant affected communities genuine authority over their data (Chander & Sun, 2023).

The ethical risks of ungoverned climate AI are most severe in regions with high climate vulnerability. AI risk models trained predominantly on North American and European data systematically underestimate hazards in Sub-Saharan Africa, South Asia, and Small Island Developing States, regions facing the most severe impacts, due to structural underrepresentation in training data (Adams et al., 2018). Moreover, while efficiency gains from AI-optimized energy and agriculture systems often accumulate to already-advantaged populations, AI-powered monitoring tools (e.g., for deforestation or poaching) can be repurposed to monitor and criminalize indigenous land use in contexts of contested tenure (Cowls et al., 2023). Governance responses must therefore extend beyond technical auditing to mandate community consent, participatory co-design, benefit-sharing agreements, and human rights impact assessments as preconditions for deployment.

To address these challenges, experts call for inclusive, multi-stakeholder governance frameworks that enforce transparency, fairness, and accountability. For instance, a UNFCCC technical panel recommends policies prioritizing these principles alongside collaborative standard-setting (Committee, 2023). Practical steps include aligning multi-stakeholder standards, fostering formal partnerships between AI researchers and geoscientists, and funding cross-disciplinary centers. While some nations have initiated seed funding and pilot programs, significantly greater international coordination is required to avoid fragmented rules, duplicated efforts, and barriers to scaling AI-driven mitigation. Without these governance advances, AI risks deepening rather than bridging the inequities that already characterize the global climate crisis.

5.2 Future research direction

5.2.1 Benchmarks, foundation models, and geographic transferability

Beyond domain-specific directions, our analysis of open issues reveals several critical research directions:

- Data scarcity and bias: Mitigating data scarcity and bias requires standardized, open benchmarks and shared simulation environments that cover underrepresented regions and sectors, enabling reproducible model comparison under realistic constraints (Kaack et al., 2022). The challenge of data transferability demands both technical and institutional responses. Technically, the field needs standard benchmarks that explicitly include data-scarce regions, standardized protocols for reporting out-of-distribution performance, and open-access pre-trained foundation models adaptable to local contexts. Institutionally, international data-sharing agreements, investment in sensor infrastructure in underrepresented regions, and capacity-building programs for local AI practitioners are essential to ensure climate AI does not replicate existing geographic inequities embedded in training data (Adams et al., 2018).
- Foundation models for climate AI: A transformative research priority for all considered domains is the development of large-scale, pre-trained foundation models that can be efficiently fine-tuned to domain-specific climate tasks. In atmospheric science, this approach has already been implemented: GraphCast (Lam, 2023) and Pangu-Weather produce global 10-day forecasts in under 60 seconds, outperforming operational NWP systems on 90% of verification targets, while ClimaX (T. Nguyen et al., 2023) extends this to multi-variable climate projection by pre-training on heterogeneous CMIP6 ensembles and fine-tuning to regional tasks with minimal data. In remote sensing and land-use, vision foundation models pre-trained on large satellite archives, such as those built on masked autoencoder frameworks applied to Sentinel and Landsat imagery, are beginning to enable zero- and few-shot land cover classification, deforestation detection, and crop mapping in data-scarce regions without task-specific retraining (Silvestro et al., 2022). In hydrology, the LSTM-based global flood forecasting system of (Nearing et al., 2024), trained on the CAMELS-DK multi-catchment dataset (J. Liu et al., 2024) and validated across thousands of ungauged watersheds, provides 5-day forecasts with reliability comparable to 0-day GloFAS nowcasts. Building on these examples, the field urgently needs foundation models trained on globally integrated datasets combining ERA5 reanalysis (Hersbach et al., 2020), satellite altimetry, GRACE groundwater observations, and in-situ gauge records, that can be fine-tuned to individual river systems, agricultural monitoring tasks, or ecosystem health indices using transfer learning and physics-informed constraints. This approach would directly address the transferability gap identified in Section 5.1.1 and provide the shared benchmarking infrastructure currently lacking across climate AI domains.

These research directions aim to directly tackle the systemic gaps identified in Section 5.1.1 by improving AI algorithms, infrastructure design, and governance mechanisms. They illustrate how future work can simultaneously improve technical performance, reduce the carbon footprint of AI itself, and strengthen the reliability and legitimacy of AI-enabled climate mitigation strategies. Finally, future AI for climate mitigation should adopt a structured data benchmark evaluation protocol with at least five dimensions: (1) spatial or temporal integrity of the train-test split; (2) validation across multiple sites, years, or operational contexts; (3) minority-class or tail-event performance reporting; (4) UQ beyond point estimates; and (5) public availability of code and data. This framework would enable not only a more honest synthesis of the state of the art but also provide actionable guidance for practitioners on which results are robust enough to inform deployment decisions (Kaack et al., 2022; Ladi et al., 2022).

5.2.2 Physics-informed and uncertainty-aware AI

A fundamentally distinct approach to the interpretability and reliability challenges described in Section 5.1.2 is the family of PINNs (Meng et al., 2025). Rather than treating interpretability as a post-hoc diagnostic issue, PINNs embed physical knowledge directly into the model architecture and loss function during training, constraining the solution space to outputs consistent with known governing equations. This architectural constraint simultaneously improves interpretability, reduces data requirements, and enhances generalization under novel climate conditions (S. Liu, Lu, Painter, Griffiths, & Pierce, 2023).

The applications of PINNs for climate-critical water applications are a representative example. In flood forecasting, PINNs trained on sparse gauge networks can interpolate hydraulically consistent flow fields across ungauged river reaches, filling spatial data gaps that hinder reliable inundation mapping in developing regions (B.J. Lee & Chang, 2026). Similarly, in groundwater modeling, physics-informed approaches embedding Darcy's law and the Richards equation enable recharge and depletion forecasts that respect aquifer geometry and hydraulic conductivity constraints, even with limited borehole observations (Y. Li, Sun, Fu, & Wei, 2025). Despite their promise, PINNs face open challenges requiring community attention: (1) training stability is more complex than for standard DL models; (2) performance is highly sensitive to collocation point distribution, loss weighting strategies, and network architecture; and (3) while they reduce data dependency, they still require sufficient observational data to anchor solutions, and performance degrades if the assumed governing equations incompletely represent physical processes. These issues require dedicated benchmark datasets for physics-informed modeling, standardized evaluation protocols testing both data-fitting accuracy and physics residual compliance, and closer collaboration among applied mathematicians, hydrologists, and AI researchers.

In addition, Section 5.1.2 highlighted the critical need for enhanced UQ and robust decision-making in high-stakes climate applications. Currently, many AI deployments in energy, transport, and urban planning rely on point forecasts or static scenario analyses that fail to fully integrate uncertainty into infrastructure design and policy decisions (S. Liu et al., 2023). Stochastic optimization models offer a promising trend. For instance, the network expansion framework proposed by (Giannelos, Konstantelos, Zhang, & Strbac, 2025) explicitly distinguishes between exogenous uncertainties (e.g., load growth, weather patterns) and endogenous uncertainties (e.g., consumer adoption of demand-side response). By adopting such distinct uncertainty classifications, planners can develop resilient expansion strategies that remain viable across a wider range of future climate and technological scenarios. Future research should prioritize three key directions: (1) Coupling probabilistic ML/DL models with stochastic planning frameworks to ensure forecast uncertainty is directly integrated into optimization constraints; (2) Systematically exploring how different uncertainty representations, such as ensembles, Bayesian models, and distributionally robust optimization, influence infrastructure investment decisions; and (3) Developing open benchmark problems where AI-based forecasters and planners can be rigorously compared under shared uncertainty assumptions. These efforts would directly address current gaps in trust and robustness for AI-supported climate decisions.

5.2.3 Green AI and scalable decarbonized infrastructure

Section 5.1.3 underscored the growing energy and carbon footprint of AI models and data centers themselves. A key research direction is "Green AI," which aims to decarbonize the full AI lifecycle, from model design to deployment and infrastructure planning. Beside common approaches like efficient model architectures and pruning techniques (Tmamna et al., 2024), this requires system-level optimization of where and when AI workloads are executed.

Recent work by (da Silva, Gamatié, Sassatelli, Poss, & Robert, 2022) illustrates this direction by showing how computing loads can be dynamically migrated across data center networks to locations with high renewable energy availability, complemented by on-site storage to smooth variability. Future research can extend such frameworks by: (i) co-optimizing model scheduling, hardware allocation, and renewable integration under explicit carbon constraints; (ii) embedding carbon-aware objectives directly into training and inference pipelines; and (iii) developing standardized reporting protocols so that AI-for-climate applications disclose their own energy use and emissions. These advances would turn AI infrastructure from a passive load into an actively optimized component of decarbonized energy systems.

The review of AI applications in energy management (Section 4.1) and buildings/cities (Section 4.2) reveals that current studies predominantly focus on optimizing single assets, such as individual buildings, heat pumps, or batteries, in isolation. A pressing future direction is to coordinate the optimization of diverse distributed assets to provide system-level flexibility, while simultaneously respecting local comfort constraints, equity considerations, and computational limits (Alanne & Sierla, 2022). Recent work by (Dong, Zhang, Zhang, Giannelos, & Strbac, 2024) demonstrates how the thermal flexibility of thousands of buildings can be effectively aggregated through a normalization and control framework. This approach enables coordinated space heating that enhances urban energy system flexibility without incurring prohibitive computational costs. By leveraging distributed reinforcement learning or hierarchical model predictive control, such methods can scale to city-district levels, successfully balancing peak demand reduction with user preferences.

Developing similar scalable coordination algorithms for other sectors, such as EV fleets, industrial heat pumps, and distributed renewable generation, is a critical priority for future mitigation strategies. In EV aggregation, game-theoretic or federated learning approaches could incentivize vehicle-to-grid participation while ensuring charging equity across neighborhoods (L. Zhou, Huo, Chen, Bo, & Li, 2025). For the industrial sector, hybrid PINNs offer a pathway to integrate complex process constraints with dynamic demand response signals. Future research should prioritize three key areas: (1) Privacy-preserving aggregation via differential privacy or secure multiparty computation; (2) Standardized benchmarks for cross-sector flexibility markets; and (3) Real-world pilots that integrate these coordination frameworks with stochastic weather forecasts to strengthen climate resilience.

5.2.4 Bridging mitigation and adaptation of AI for climate resilience

While the preceding sections primarily frame AI's role through the lens of emissions reduction and mitigation, the IPCC explicitly emphasizes that mitigation and adaptation must be deeply interconnected to achieve long-term climate stability (Calvin et al., 2023). AI plays a pivotal role in bridging these two pillars by moving beyond passive environmental monitoring to actively enabling transformative climate adaptation.

- Resilient infrastructure design: Current AI applications in buildings/cities (Section 4.1) and transportation (Section 4.4) are largely optimized for operational efficiency under current climate conditions. A critical but underexplored direction is utilizing AI to design infrastructure that remains functional and safe under projected future climate trajectories (Shehadeh et al., 2024). This requires shifting from static optimization to dynamic, scenario-aware design using CMIP6 ensembles to stress-test assets against 1.5-3 °C warming scenarios. In particular, energy systems face cascading disruptions during compound climate events, such as heatwaves that simultaneously reduce hydropower availability and spike cooling demand (Perera et al., 2020). GNNs are particularly well-suited for this task, as they can model the cascading vulnerability of interconnected infrastructure networks. Furthermore, RL agents can be trained to optimize infrastructure layout and investment allocation to minimize long-term climate risk across the full network, as demonstrated by deep RL approaches for resilient road network recovery under flooding hazards (Fan et al., 2023).
- Compound hazard forecasting: While Section 4.7 covers individual extreme weather events, the growing threat of compound hazards, where two or more extreme events co-occur or rapidly succeed one another, remains largely unaddressed in the reviewed literature. Climate warming is projected to substantially increase exposure to compound extremes (e.g., flood-heatwave combinations), with disproportionate impacts on vulnerable populations (Q. Zhao et al., 2024). Such events produce impacts greater than the sum of their individual parts. However, most AI forecasting systems are trained to predict single event types in isolation. Future research

must develop multi-hazard AI frameworks that model the joint probability distribution of co-occurring extremes, their physical interdependencies, and their cascading effects on human systems. Transformer-based architectures with multi-target output heads could simultaneously forecast the onset probability, intensity, and spatial footprint of multiple hazard types from shared atmospheric inputs. These systems would directly support the IPCC AR6 adaptation goal of building early warning systems capable of detecting compound risks before individual thresholds are breached (Calvin et al., 2023).

- Nature-Based Solutions (NBS) optimization: NBS simultaneously sequester carbon (contributing to mitigation) and buffer communities against climate extremes such as floods, heatwaves, and storm surges (contributing to adaptation). Although wildlife-focused conservation and trophic rewilding alone could enable the sequestration of up to 6.41 billion tons of CO_2 annually (Schmitz et al., 2023), the spatial deployment of NBS at scale remains a significant unsolved challenge. Moreover, declining forest ecosystem resilience under climate change threatens the long-term stability of these natural carbon sinks (Forzieri et al., 2022). AI can play a central role by applying multi-objective optimization algorithms, including RL and evolutionary strategies, to identify the placement and configuration of NBS that maximize co-benefits (carbon sequestration, urban cooling, flood attenuation, biodiversity, and equity) within land availability and cost constraints. Remote sensing-driven AI models, as demonstrated in the forest management and land-use applications reviewed in Section 4.6, provide the necessary spatial data foundation. In addition, PINNs embedding hydrological and ecological process equations could predict how proposed NBS configurations will perform under future climate scenarios, allowing planners to design nature-based interventions robust across the full range of projected climate futures. Integrating AI-optimized NBS planning into urban and regional development frameworks represents one of the most direct approaches to operationalizing IPCC adaptation strategies at the scale the climate crisis demands (Calvin et al., 2023).

In summary, these three sample goals move AI beyond simple efficiency customization toward driving deep, systemic adaptation. To achieve this, experts from climate science, engineering, and social sciences need to work together under inclusive governance. Researchers should view the intersection of climate mitigation and adaptation as the primary frontier for AI innovation, where it can make the greatest impact on global resilience (Hintz et al., 2026).

5.2.5 Governance, equity, and participatory AI development

The governance of AI in climate domains represents one of the most critical yet under-developed research frontiers. Despite the rapid scaling of AI deployment for energy systems, disaster forecasting, and conservation, binding policies specifically governing the intersection of AI and climate remain scarce. Existing legislation, such as the EU AI Act (Union, 2023), prioritizes fundamental rights and safety with minimal provisions regarding energy consumption or climate equity, a gap whose legal and environmental consequences have been critically examined (Pagallo et al., 2022).

Major international climate frameworks including the Paris Agreement do not yet address AI, leaving climate-focused AI projects operating within a fragmented patchwork of national regulations and voluntary norms. Without enforceable standards, private actors may deprioritize safety, equity, and energy efficiency, while public institutions may hesitate to adopt AI solutions due to unresolved legal uncertainty. Three critical regulatory gaps demand immediate attention:

1. Cross-border data sharing: No binding framework obliges upstream nations (e.g., in the Mekong or Nile basins) to share real-time hydrological data essential for downstream flood forecasting, leaving vulnerable communities unprotected (Eddamiri et al., 2025).
2. Carbon market integrity: As AI estimates drive carbon credit pricing, the lack of standardized protocols for estimation methods, uncertainty disclosure, and auditing threatens market reliability (Committee, 2023).
3. Liability in early warning systems: Undefined legal accountability for false negatives in life-critical models inhibits both deployment and transparent reporting of model limitations (Cowls et al., 2023).

A second frontier largely absent from prior governance literature is data sovereignty. Satellite and IoT data from the Global South are frequently extracted, processed abroad, and used for international markets with minimal local involvement or benefit (Chander & Sun, 2023; Williamson et al., 2023). This requires extending UNFCCC data principles to AI datasets, investing in local computing infrastructure, and granting communities genuine authority over their data. Ethical risks are most severe where climate vulnerability is highest. Models trained on Euro-American data systematically underestimate hazards in Sub-Saharan Africa, South Asia, and Small Island Developing States (SIDS) (Adams et al., 2018; McGovern et al., 2024). Moreover, while efficiency gains often favor advantaged populations, monitoring tools can be repurposed to observe indigenous communities (Cowls et al., 2023). Governance must therefore mandate community consent, participatory co-design, and human rights impact assessments as preconditions for deployment.

Future research should prioritize four directions: (1) Establish a UNFCCC working group to define binding standards for carbon accounting, data sharing, and liability; (2) Extend regional data-sharing frameworks to climate AI datasets; (3) Mandate national environmental and human rights impact assessments paired with local capacity building; and (4) Develop regulatory sandboxes and participatory design protocols that empower frontline communities to co-define targets and validate models, transforming governance from a compliance check into an upstream design constraint (Committee, 2023; Cowls et al., 2023).

6 Conclusion

This systematic review analyzed 280 peer-reviewed studies (2015–2025) to evaluate the methodological development, empirical performance, and practical applicability of AI in climate change mitigation and adaptation. The analysis demonstrates that ML/DL architectures significantly enhance predictive accuracy, operational efficiency, and decision-support capacity for the seven key climate-impact domains. Based on comprehensive bibliometric screening, critical evaluations, and cross-domain synthesis, the primary findings are summarized below:

- Domain and geographic distribution: Research output varies significantly by domain and region. Energy and Carbon Management represents the largest share (21%), followed by Transportation (15%), Agriculture (14%), and Buildings and Cities (14%). Ecosystem Conservation, Weather and Disaster Forecasting, and Industry each account for approximately 12–13%. Geographically, Asia (35%), North America (26%), and Europe (22%) dominate the literature, while climate-vulnerable regions, including Africa, South America, and Oceania, collectively contribute less than 7%, revealing a critical representation gap.
- Methodological trends and technical limitations: DL architectures (CNNs, RNNs/LSTMs, Transformers) dominate forecasting and monitoring tasks. However, supervised models frequently struggle with inference under non-stationary climate regions. On the other hand, hybrid and physics-informed approaches (e.g., PINNs, differentiable hydrological models) demonstrate superior physical consistency and transferability. However, they remain overlooked due to computational complexity and implementation difficulties. Finally, the literature exhibits inconsistent research methods, such as inadequate spatiotemporal cross-validation, unreported uncertainty quantification, dataset leakage, and a lack of open benchmarks for cross-regional evaluation.
- Generalizability and data ecosystem challenges: Model transferability remains a systemic bottleneck. Performances of algorithms trained on data-rich often degrade sharply when deployed in data-scarce or climatically distinct environments. This limitation is combined with fragmented data ecosystems, proprietary restrictions, and the lack of coordinated, multi-jurisdictional validation protocols.
- Socio-technical and governance gaps: Technical performance metrics dominate the literature, while socio-technical dimensions, including algorithmic bias, community co-design, data sovereignty, and the environmental footprint of AI training, are systematically underreported. Responsible deployment requires explicit integration of equity frameworks, transparent uncertainty communication, and governance mechanisms that prioritize climate-vulnerable populations.
- Priority future directions: Future research trends in AI for climate change mitigation and adaptation include: (i) development of open, standardized benchmark datasets spanning diverse climatic and socioeconomic contexts; (ii) scalable, physics-informed and hybrid architectures that balance accuracy with interpretability and extrapolation robustness; (iii) rigorous out-of-distribution validation and uncertainty-aware reporting standards; and (iv) governance-aligned AI frameworks that bridge technical innovation with climate adaptation.

This review emphasizes that while AI has matured into a powerful enabler of climate mitigation and adaptation-oriented applications, its full potential remains constrained by methodological fragmentation, geographic bias, and governance gaps. To foster climate-resilient, equitable, and scientifically robust development, future AI systems require coordinated investment in open science, cross-disciplinary collaboration, and policy-aligned deployment standards. By adopting the evaluation criteria, algorithm selection guidance, and quality assessment frameworks introduced in this review, researchers and practitioners can systematically navigate methodological trade-offs, mitigate deployment risks, and accelerate the transition from experimental AI to operational, context-aware climate solutions.

Table 16: List of abbreviations used in this survey

Abbreviation	Meaning
AI	Artificial Intelligence
ANN	Artificial Neural Network
BEMS	Building Energy Management System
BESS	Battery Energy Storage System
CCS	Carbon Capture and Storage
CH_4	Methane
CMIP6	Coupled Model Intercomparison Project Phase 6
CNN	Convolutional Neural Network
CNNs	Convolutional Neural Network
CO_2	Carbon Dioxide
CO_2e	Carbon Dioxide Equivalent
CV	Computer Vision
DL	Deep Learning
ECMWF	European Centre for Medium-Range Weather Forecasts
EO	Earth Observation
ERA5	ECMWF Reanalysis v5
EV	Electric Vehicle
FAO	Food and Agriculture Organization of the United Nations
GA	Genetic Algorithm
GHG	Greenhouse Gas
GIS	Geographic Information System
GNN	Graph Neural Network
GRU	Gated Recurrent Unit
HVAC	Heating, Ventilation, and Air Conditioning
HRES	Hybrid Renewable Energy Systems
IEA	International Energy Agency
IoT	Internet of Things
IPCC	Intergovernmental Panel on Climate Change
LIME	Local Interpretable Model-Agnostic Explanations
LSTM	Long Short-Term Memory
ML	Machine Learning
MLP	Multilayer Perceptron
MPC	Model Predictive Control
MODIS	Moderate Resolution Imaging Spectroradiometer
MSE	Mean Squared Error
NASA	National Aeronautics and Space Administration

Table 16: List of abbreviations used in this survey

Abbreviation	Meaning
NDVI	Normalized Difference Vegetation Index
NOAA	National Oceanic and Atmospheric Administration
NWP	Numerical Weather Prediction
PPAs	Power Purchase Agreements
PSO	Particle Swarm Optimization
PV	Photovoltaic
RF	Random Forest
RL	Reinforcement Learning
RMSE	Root Mean Squared Error
RNN	Recurrent Neural Network
RS	Remote Sensing
SCADA	Supervisory Control and Data Acquisition
SVM	Support Vector Machine
UNFCCC	United Nations Framework Convention on Climate Change
WRF	Weather Research and Forecasting (model)
XGBoost	eXtreme Gradient Boosting

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Conflict of interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Author contribution

L. Minh Dang: Writing original draft, Writing review & editing, Methodology, Conceptualization. Sufyan Danish: Investigation, Data curation. Muhammad Fayaz: Formal analysis, Conceptualization. Gul E Arzu: Visualization, Validation. Andy Nguyen: Validation. Hyoung-Kyu Song: Formal analysis, Funding acquisition. Hyeonjoon Moon: Supervision.

References

Abbass, K., Qasim, M.Z., Song, H., Murshed, M., Mahmood, H., Younis, I. (2022). A review of the global climate change impacts, adaptation, and sustainable mitigation measures. *Environmental science and pollution research*, *29*(28), 42539–42559,

Abdelaty, M., Doriguzzi-Corin, R., Siracusa, D. (2021). Daics: A deep learning solution for anomaly detection in industrial control systems. *IEEE Transactions on Emerging Topics in Computing*, *10*(2), 1117–1129,

Abdulameer, L., Al Maimuri, N., Nama, A., Rashid, F., Al-Dujaili, A. (2025). The role of artificial intelligence in managing sustainable water resources: a review of smart solution implementations. *Water Conserv Manag*, *9*(2), 181–191,

Abdulameer, L., Al-Maimuri, N.M.L., Nama, A.H., Rashid, F.L., Mohammed, H.I., Al-Dujaili, A.N.G. (n.d.). Review of artificial intelligence applications in dams and water resources: current trends and future directions. *management services*, *11*, 13,

Adams, C., Ide, T., Barnett, J., Detges, A. (2018). Sampling bias in climate–conflict research. *Nature Climate Change*, *8*(3), 200–203,

Aderyani, F.R., Mousavi, S.J., Jafari, F. (2022). Short-term rainfall forecasting using machine learning-based approaches of pso-svr, lstm and cnn. *Journal of Hydrology*, *614*, 128463,

Adewoyin, R.A., Dueben, P., Watson, P., He, Y., Dutta, R. (2021). Tru-net: a deep learning approach to high resolution prediction of rainfall. *Machine Learning*, *110*, 2035–2062,

Adil, L., Eckstein, D., Künzel, V., Schäfer, L. (2025). Climate risk index 2025.

Afroz (2025). *Solar power generation forecast.* (https://www.kaggle.com/code/pythonafroz/solar-power-generation-forecast, accessed 2025-05-17)

Agency, E.E. (2025). *Greenhouse gas emissions from transport in Europe.* (https://www.eea.europa.eu/en/analysis/indicators/greenhouse-gas-emissions-from-transport, accessed 2025-05-17)

Agency, T.I.E. (2025). *Renewables 2024.* (https://www.iea.org/reports/renewables-2024, accessed 2025-06-07)

Agency, U.S.E.P. (2025). *Transportation Sector Emissions.* (https://www.epa.gov/ghgemissions/transportation-sector-emissions, accessed 2025-05-17)

Ahire, P.R., Hanchate, R., Varadarajan, V. (2024). Indigenous knowledge in smart agriculture. *Advanced technologies for smart agriculture* (pp. 241–258). River Publishers.

Ai, G., Zuo, X., Chen, G., Wu, B. (2022). Deep reinforcement learning based dynamic optimization of bus timetable. *Applied Soft Computing*, *131*, 109752,

Akilan, T., & Baalamurugan, K. (2024). Automated weather forecasting and field monitoring using gru-cnn model along with iot to support precision agriculture. *Expert systems with applications*, *249*, 123468,

Alanne, K., & Sierla, S. (2022). An overview of machine learning applications for smart buildings. *Sustainable Cities and Society*, *76*, 103445,

Alemazkoor, N., Tootkaboni, M., Nateghi, R., Louhghalam, A. (2022). Smart-meter big data for load forecasting: An alternative approach to clustering. *IEEE access*, *10*, 8377–8387,

Ali, U., Bano, S., Shamsi, M.H., Sood, D., Hoare, C., Zuo, W., ... O'Donnell, J. (2024). Urban building energy performance prediction and retrofit analysis using data-driven machine learning approach. *Energy and Buildings*, *303*, 113768,

Alibabaei, K., Gaspar, P.D., Assunção, E., Alirezazadeh, S., Lima, T.M. (2022). Irrigation optimization with a deep reinforcement learning model: Case study on a site in portugal. *Agricultural Water Management*, *263*, 107480,

Alizadeh, O. (2022). Advances and challenges in climate modeling. *Climatic Change*, *170*(1), 18,

Al-Waked, R., Nasif, M.S., Groenhout, N., Partridge, L. (2017). Energy performance and co2 emissions of hvac systems in commercial buildings. *Buildings*, *7*(4), 84,

Alzubaidi, L., Zhang, J., Humaidi, A.J., Al-Dujaili, A., Duan, Y., Al-Shamma, O., ... Farhan, L. (2021). Review of deep learning: concepts, cnn architectures, challenges, applications, future directions. *Journal of big Data*, *8*(1), 53, Amiri, Z., Heidari, A., Navimipour, N.J. (2024). Comprehensive survey of artificial intelligence techniques and strategies for climate change mitigation. *Energy*, 132827,

An, N., Huang, C., Shen, Y., Wang, J., Yu, Z., Fu, J., ... Yao, J. (2024). Efficient data-driven prediction of household carbon footprint in china with limited features. *Energy Policy*, *185*, 113926,

Anbarasan, M., Muthu, B., Sivaparthipan, C., Sundarasekar, R., Kadry, S., Krishnamoorthy, S., ... others (2020). Detection of flood disaster system based on iot, big data and convolutional deep neural network. *Computer Communications*, *150*, 150–157,

Anthony, L.F.W., Kanding, B., Selvan, R. (2020). Carbontracker: Tracking and predicting the carbon footprint of training deep learning models. *arXiv preprint arXiv:2007.03051*, ,

Arunthavanathan, R., Khan, F., Ahmed, S., Imtiaz, S. (2021). A deep learning model for process fault prognosis. *Process Safety and Environmental Protection*, *154*, 467–479,

Aslam, S., Aung, P.P., Rafsanjani, A.S., Majeed, A.P. (2025). Machine learning applications in energy systems: current trends, challenges, and research directions. *Energy Informatics*, *8*(1), 1–39,

Banerjee, D., Ganguly, S., Kushwaha, S. (2024). Forecasting future groundwater recharge from rainfall under different climate change scenarios using comparative analysis of deep learning and ensemble learning techniques. *Water Resources Management*, *38*(11), 4019–4037,

Bar, S., Parida, B.R., Pandey, A.C. (2020). Landsat-8 and sentinel-2 based forest fire burn area mapping using machine learning algorithms on gee cloud platform over uttarakhand, western himalaya. *Remote Sensing Applications: Society and Environment*, *18*, 100324,

Bardoutsos, A., Filios, G., Katsidimas, I., Krousarlis, T., Nikoletseas, S., Tzamalis, P. (2020). A multidimensional human-centric framework for environmental intelligence: Air pollution and noise in smart cities. *2020 16th international conference on distributed computing in sensor systems (dcoss)* (pp. 155–164).

Bashir, T., Wang, H., Tahir, M., Zhang, Y. (2025). Wind and solar power forecasting based on hybrid cnn-abilstm, cnn-transformer-mlp models. *Renewable Energy*, *239*, 122055,

Bassiouni, M.M., Chakrabortty, R.K., Sallam, K.M., Hussain, O.K. (2024). Deep learning approaches to identify order status in a complex supply chain. *Expert Systems with Applications*, *250*, 123947,

BBC (2025). *On board the driverless lorries hoping to transform China's transport industry.* (https://www.bbc.com/news/articles/c5ykel5dr62o, accessed 2025-06-08)

Beery, S. (2023). The megadetector: Large-scale deployment of computer vision for conservation and biodiversity monitoring. *California Institute of Technology, Pasadena, CA, USA*, ,

Ben Welle, T.H.T., Anna Kustar, & Albuquerque, C. (2025). *Post-Pandemic, Public Transport Needs to Get Back on Track to Meet Global Climate Goals.* (https://www.wri.org/insights/current-state-of-public-transport-climate-goals, accessed 2025-05-17)

Berthelot, A., Caron, E., Jay, M., Lefevre, L. (2024). Estimating the environmental impact of generative-ai services using an lca-based methodology. *Procedia CIRP*, *122*, 707–712,

Bogaerts, T., Masegosa, A.D., Angarita-Zapata, J.S., Onieva, E., Hellinckx, P. (2020). A graph cnn-lstm neural network for short and long-term traffic forecasting based on trajectory data. *Transportation Research Part C: Emerging Technologies*, *112*, 62–77,

Brown, C.F., Brumby, S.P., Guzder-Williams, B., Birch, T., Hyde, S.B., Mazzariello, J., . . . others (2022). Dynamic world, near real-time global 10 m land use land cover mapping. *Scientific data*, *9*(1), 251,

Bui, D.T., Hoang, N.-D., Martínez-Álvarez, F., Ngo, P.-T.T., Hoa, P.V., Pham, T.D., . . . Costache, R. (2020). A novel deep learning neural network approach for predicting flash flood susceptibility: A case study at a high frequency tropical storm area. *Science of The Total Environment*, *701*, 134413, Calvin, K., Dasgupta, D., Krinner, G., Mukherji, A., Thorne, P.W., Trisos, C., ... others (2023). Ipcc, 2023: Climate change 2023: Synthesis report. contribution of working groups i, ii and iii to the sixth assessment report of the intergovernmental panel on climate change [core writing team, h. lee and j. romero (eds.)]. ipcc, geneva, switzerland. *(No Title)*, ,

Camci, E., Kripalani, D.R., Ma, L., Kayacan, E., Khanesar, M.A. (2018). An aerial robot for rice farm quality inspection with type-2 fuzzy neural networks tuned by particle swarm optimization-sliding mode control hybrid algorithm. *Swarm and evolutionary computation*, *41*, 1–8,

Chai, B., & Li, P. (2023). An ensemble method for monitoring land cover changes in urban areas using dense landsat time series data. *ISPRS Journal of Photogrammetry and Remote Sensing*, *195*, 29–42,

Chandel, N.S., Jat, D., Chakraborty, S.K., Upadhyay, A., Subeesh, A., Chouhan, P., ... Dubey, K. (2025). Deep learning assisted real-time nitrogen stress detection for variable rate fertilizer applicator in wheat crop. *Computers and Electronics in Agriculture*, *237*, 110545,

Chander, A., & Sun, H. (2023). *Data sovereignty: From the digital silk road to the return of the state.* Oxford University Press.

Chandriah, K.K., & Naraganahalli, R.V. (2021). Rnn/lstm with modified adam optimizer in deep learning approach for automobile spare parts demand forecasting. *Multimedia Tools and Applications*, *80*(17), 26145–26159,

Chao, M., Maimai, W., Hanzhang, L., Zhibo, C., Xiaohui, C. (2023). A spatio-temporal neural network learning system for city-scale carbon storage capacity estimating. *IEEE Access*, *11*, 31304–31322,

Chattopadhyay, A., Nabizadeh, E., Hassanzadeh, P. (2020). Analog forecasting of extreme-causing weather patterns using deep learning. *Journal of Advances in Modeling Earth Systems*, *12*(2), e2019MS001958,

Chen, C., Fu, H., Zheng, Y., Tao, F., Liu, Y. (2023). The advance of digital twin for predictive maintenance: The role and function of machine learning. *Journal of Manufacturing Systems*, *71*, 581–594, Chen, C., Wang, C., Liu, B., He, C., Cong, L., Wan, S. (2023). Edge intelligence empowered vehicle detection and image segmentation for autonomous vehicles. *IEEE Transactions on Intelligent Transportation Systems*, *24*(11), 13023–13034,

Chen, J., Li, J., Chen, W., Wang, Y., Jiang, T. (2020). Anomaly detection for wind turbines based on the reconstruction of condition parameters using stacked denoising autoencoders. *Renewable Energy*, *147*, 1469–1480,

Chen, J., Tang, P., Rakstad, T., Patrick, M., Zhou, X. (2020). Augmenting a deep-learning algorithm with canal inspection knowledge for reliable water leak detection from multispectral satellite images. *Advanced Engineering Informatics*, *46*, 101161,

Chen, J., Zhang, D., Nanehkaran, Y.A. (2021). Research of power load prediction based on boost clustering. *Soft Computing*, *25*, 6401–6413,

Chen, L., Chen, Z., Zhang, Y., Liu, Y., Osman, A.I., Farghali, M., … others (2023). Artificial intelligence-based solutions for climate change: a review. *Environmental Chemistry Letters*, *21*(5), 2525–2557,

Chen, L., Han, B., Wang, X., Zhao, J., Yang, W., Yang, Z. (2023). Machine learning methods in weather and climate applications: A survey. *Applied Sciences*, *13*(21), 12019,

Chen, R., Wang, X., Zhang, W., Zhu, X., Li, A., Yang, C. (2019). A hybrid cnn-lstm model for typhoon formation forecasting. *GeoInformatica*, *23*, 375–396,

Chen, S., Zhu, X., Chen, K., Liu, Z., Li, P., Liang, X., … Du, Z. (2023). Applying deep learning-based regional feature recognition from macro-scale image to assist energy saving and emission reduction in industrial energy systems. *Journal of Advanced Research*, *46*, 189–197,

Cheng, Y., Zhu, H., Wu, J., Shao, X. (2018). Machine health monitoring using adaptive kernel spectral clustering and deep long short-term memory recurrent neural networks. *IEEE Transactions on Industrial Informatics*, *15*(2), 987–997, Choubin, B., Jaafari, A., Henareh, J., Karimi, O., Hosseini, F.S. (2025). Explainable artificial intelligence (xai) for interpreting predictive models and key variables in flood susceptibility. *Results in Engineering*, 105976,

Codevilla, F., Müller, M., López, A., Koltun, V., Dosovitskiy, A. (2018). End-to-end driving via conditional imitation learning. *2018 ieee international conference on robotics and automation (icra)* (pp. 4693–4700).

Comission, E. (2025). *Reducing emissions from the shipping sector.* (https://climate.ec.europa.eu/eu-action/transport-decarbonisation/reducing-emissions-shipping-sector_en, accessed 2025-06-03)

Commision, E. (2025). *Emissions Database for Global Atmospheric Research.* (https://data.jrc.ec.europa.eu/collection/edgar, accessed 2025-06-08)

Commission, E. (2025). *GHG emissions of all world countries.* (https://edgar.jrc.ec.europa.eu/report_2024, accessed 2025-07-23)

Committee, T.E. (2023). *AI for Climate action: advancing mitigation and adaptation in developing countries.* (https://unfccc.int/ttclear/tec/AI4climate.html, accessed 2025-06-07)

Copernicus (2025a). *Sentinel-2.* (https://dataspace.copernicus.eu/explore-data/data-collections/sentinel-data/sentinel-2, accessed 2025-05-17)

Copernicus (2025b). *Sentinel-5P.* (https://dataspace.copernicus.eu/explore-data/data-collections/sentinel-data/sentinel-5p, accessed 2025-05-17)

Cordeiro-Costas, M., Villanueva, D., Eguía-Oller, P., Granada-Álvarez, E. (2023). Intelligent energy storage management trade-off system applied to deep learning predictions. *Journal of energy storage*, *61*, 106784,

Cordts, M., Omran, M., Ramos, S., Rehfeld, T., Enzweiler, M., Benenson, R., … Schiele, B. (2016). The cityscapes dataset for semantic urban scene understanding. *Proceedings of the ieee conference on computer vision and pattern recognition* (pp. 3213–3223).

Cowls, J., Tsamados, A., Taddeo, M., Floridi, L. (2023). The ai gambit: leveraging artificial intelligence to combat climate changeopportunities, challenges, and recommendations. *Ai & Society*, 1–25,

Dang, L.M., Danish, S., Khan, A., Alam, N., Fayaz, M., Nguyen, D.K., … Moon, H. (2024). An efficient zero-labeling segmentation approach for pest monitoring on smartphone-based images. *European Journal of Agronomy*, *160*, 127331, Dang, L.M., Nguyen, L.Q., Nam, J., Nguyen, T.N., Lee, S., Song, H.-K., Moon, H. (2024). Fifth generation district heating and cooling: A comprehensive survey. *Energy Reports*, *11*, 1723–1741,

Dang, L.M., Sagar, A.S., Bui, N.D., Nguyen, L.V., Nguyen, T.-H. (2025). Attention-guided marine debris detection with an enhanced transformer framework using drone imagery. *Process Safety and Environmental Protection*, *197*, 107089,

Dang, L.M., Shin, J., Li, Y., Tightiz, L., Nguyen, T.N., Song, H.-K., Moon, H. (2023). Toward explainable heat load patterns prediction for district heating. *Scientific Reports*, *13*(1), 7434,

Dang, L.M., Wang, H., Li, Y., Nguyen, L.Q., Nguyen, T.N., Song, H.-K., Moon, H. (2023). Lightweight pixel-level semantic segmentation and analysis for sewer defects using deep learning. *Construction and Building Materials*, *371*, 130792,

Dang, L.M., Wang, H., Li, Y., Nguyen, T.N., Moon, H. (2022). Defecttr: End-to-end defect detection for sewage networks using a transformer. *Construction and Building Materials*, *325*, 126584,

da Silva, M.D.M., Gamatié, A., Sassatelli, G., Poss, M., Robert, M. (2022). Optimization of data and energy migrations in mini data centers for carbon-neutral computing. *IEEE Transactions on Sustainable Computing*, *8*(1), 68–81,

Deepmind (2025a). *Machine learning can boost the value of wind energy.* (https://deepmind.google/blog/machine-learning-can-boost-the-value-of-wind-energy/, accessed 2025-12-07)

Deepmind (2025b). *Safety-first AI for autonomous data centre cooling and industrial control.* (https://deepmind.google/blog/safety-first-ai-for-autonomous-data-centre-cooling-and-industrial-control/, accessed 2025-12-07)

Defard, T., Setkov, A., Loesch, A., Audigier, R. (2021). Padim: a patch distribution modeling framework for anomaly detection and localization. *International conference on pattern recognition* (pp. 475–489).

de Knegt, H.J., Eikelboom, J.A., van Langevelde, F., Spruyt, W.F., Prins, H.H. (2021). Timely poacher detection and localization using sentinel animal movement. *Scientific reports*, *11*(1), 4596, Deng, L., Guo, S., Yin, J., Zeng, Y., Chen, K. (2022). Multi-objective optimization of water resources allocation in han river basin (china) integrating efficiency, equity and sustainability. *Scientific reports*, *12*(1), 798,

Deng, M., Wang, X., Li, D., Menassa, C.C. (2022). Digital id framework for human-centric monitoring and control of smart buildings. *Building simulation* (Vol. 15, pp. 1709–1728).

Deng, Z., Wang, B., Xu, Y., Xu, T., Liu, C., Zhu, Z. (2019). Multi-scale convolutional neural network with time-cognition for multi-step short-term load forecasting. *IEEE Access*, *7*, 88058–88071,

de Souza, C.V.F., Barcellos, P.d.C.L., Crissaff, L., Cataldi, M., Miranda, F., Lage, M. (2022). Visualizing simulation ensembles of extreme weather events. *Computers & Graphics*, *104*, 162–172,

De Vries, A. (2023). The growing energy footprint of artificial intelligence. *Joule*, *7*(10), 2191–2194,

Dikshit, A., & Pradhan, B. (2021). Explainable ai in drought forecasting. *Machine Learning with Applications*, *6*, 100192,

Ding, C., Ke, J., Levine, M., Zhou, N. (2024). Potential of artificial intelligence in reducing energy and carbon emissions of commercial buildings at scale. *Nature Communications*, *15*(1), 5916,

Dogan, S., Barua, P.D., Kutlu, H., Baygin, M., Fujita, H., Tuncer, T., Acharya, U.R. (2022). Automated accurate fire detection system using ensemble pretrained residual network. *Expert Systems with Applications*, *203*, 117407,

Dong, Z., Zhang, X., Zhang, L., Giannelos, S., Strbac, G. (2024). Flexibility enhancement of urban energy systems through coordinated space heating aggregation of numerous buildings. *Applied Energy*, *374*, 123971,

Duan, J., Yi, Z., Shi, D., Lin, C., Lu, X., Wang, Z. (2019). Reinforcement-learning-based optimal control of hybrid energy storage systems in hybrid ac–dc microgrids. *IEEE Transactions on Industrial Informatics*, *15*(9), 5355–5364, Dulin, S., Smith, M., Ellinport, B., Trump, B., Keenan, J.M., Linkov, I. (2025). Quantifying the compounding effects of natural hazard events: a case study on wildfires and floods in california. *npj Natural Hazards*, *2*(1), 40,

Eakin, C.M., Sweatman, H.P., Brainard, R.E. (2019). The 2014–2017 global-scale coral bleaching event: insights and impacts. *Coral Reefs*, *38*(4), 539–545,

ECMWF (2025). *ECMWF Reanalysis v5 (ERA5).* (https://www.ecmwf.int/en/forecasts/dataset/ecmwf-reanalysis-v5, accessed 2025-05-17)

Eddamiri, S., Bassine, F.Z., Hakam, O., Kambiet, P.L.K., Chehbouni, A. (2025). Applications of artificial intelligence for forecasting and managing extremes. *Climate change and rainfall extremes in africa* (pp. 91–113). Elsevier.

Elsisi, M., Tran, M.-Q., Mahmoud, K., Lehtonen, M., Darwish, M.M. (2021). Deep learning-based industry 4.0 and internet of things towards effective energy management for smart buildings. *Sensors*, *21*(4), 1038,

Emami, P., Sahu, A., Graf, P. (2023). Buildingsbench: A large-scale dataset of 900k buildings and benchmark for short-term load forecasting. *Advances in Neural Information Processing Systems*, *36*, 19823–19857,

EMDAT (2025). *EM-DAT - The international disaster database.* (https://www.emdat.be/, accessed 2025-05-17)

EPA (2025). *Sources of Greenhouse Gas Emissions.* (https://www.epa.gov/ghgemissions/sources-greenhouse-gas-emissions, accessed 2025-07-30)

Esa (2025). *Simulated dioxide plumes.* (https://www.esa.int/ESA_Multimedia/Images/2020/07/Simulated_data_showing_carbon_dioxide_plumes, accessed 2025-05-17)

Fan, X., Zhang, X., Wang, X., Yu, X. (2023). A deep reinforcement learning model for resilient road network recovery under earthquake or flooding hazards. *Journal of Infrastructure Preservation and Resilience*, *4*(1), 8,

Fan, X., Zhang, X., Yu, X..B. (2021). Machine learning model and strategy for fast and accurate detection of leaks in water supply network. *Journal of Infrastructure Preservation and Resilience*, *2*, 1–21, FAO (2024). *2024 breaks climate records / Early warning systems and climate services are crucial for building resilience in agrifood systems.* (https://www.fao.org/climate-change/news/news-detail/2024-breaks-climate-records.-early-warning-systems-and-climate-services-crucial-for-building-resilience-in-agrifood-systems---wmo-report/en, accessed 2025-07-30)

FAO (2025a). *Climate Smart Agriculture Sourcebook.* (https://www.fao.org/climate-smart-agriculture-sourcebook/en/, accessed 2025-05-17)

FAO (2025b). *FAO land-use data.* (https://www.fao.org/statistics/highlights-archive/highlights-detail/land-statistics-and-indicators-(2000-2021).-global--regional-and-country-trends/en, accessed 2025-05-17)

Fayaz, M., Dang, L.M., Moon, H. (2024). Enhancing land cover classification via deep ensemble network. *Knowledge-Based Systems*, *305*, 112611,

Fayaz, M., Dang, L.M., Moon, H. (2025). Dlan: A dual attention network for effective land cover classification in remote sensing. *Knowledge-Based Systems*, 113620,

Feng, X., Wen, A., Li, L., Wu, T., Yan, S. (2025). Comparing uav and satellites accuracy in simulating fine-scale alpine grassland heterogeneity in periglacial environment. *Applied Ecology and Environmental Research*, *23*(5), 10293–10313,

Forzieri, G., Dakos, V., McDowell, N.G., Ramdane, A., Cescatti, A. (2022). Emerging signals of declining forest resilience under climate change. *Nature*, *608*(7923), 534–539,

Frame, J.M., Kratzert, F., Klotz, D., Gauch, M., Shalev, G., Gilon, O., ... Nearing, G.S. (2022). Deep learning rainfall–runoff predictions of extreme events. *Hydrology and Earth System Sciences*, *26*(13), 3377–3392,

Gan, S., Fu, J., Zhao, G., Chan, P., He, Y. (2024). Short-term prediction of tropical cyclone track and intensity via four mainstream deep learning techniques. *Journal of Wind Engineering and Industrial Aerodynamics*, *244*, 105633,

Gao, S., & Wang, Y. (2023). Explainable deep learning powered building risk assessment model for proactive hurricane response. *Risk analysis*, *43*(6), 1222–1234, Gao, Y., Ruan, Y., Fang, C., Yin, S. (2020). Deep learning and transfer learning models of energy consumption forecasting for a building with poor information data. *Energy and Buildings*, *223*, 110156,

Gavahi, K., Abbaszadeh, P., Moradkhani, H. (2021). Deepyield: A combined convolutional neural network with long short-term memory for crop yield forecasting. *Expert Systems with Applications*, *184*, 115511,

GBF, M.G.B.F. (2022). *Kunming-montreal global biodiversity framework.*

Geng, J., Shen, S., Cheng, C., Dai, K. (2022). A hybrid spatiotemporal convolution-based cellular automata model (st-ca) for land-use/cover change simulation. *International Journal of Applied Earth Observation and Geoinformation*, *110*, 102789,

Ghgsat (2025). *DATA.SAT.* (https://www.ghgsat.com/en/products-services/data-sat/, accessed 2025-05-17)

Giannelos, S., Konstantelos, I., Zhang, X., Strbac, G. (2025). A stochastic optimization model for network expansion planning under exogenous and endogenous uncertainty. *Electric Power Systems Research*, *248*, 111894,

Grönquist, P., Yao, C., Ben-Nun, T., Dryden, N., Dueben, P., Li, S., Hoefler, T. (2021). Deep learning for post-processing ensemble weather forecasts. *Philosophical Transactions of the Royal Society A*, *379*(2194), 20200092,

gtfs (2025). *General Transit Feed Specification.* (https://gtfs.org/resources/data/, accessed 2025-05-17)

Guo, J., Yun, S., Meng, Y., He, N., Ye, D., Zhao, Z., . . . Yang, L. (2023). Prediction of heating and cooling loads based on light gradient boosting machine algorithms. *Building and Environment*, *236*, 110252,

Guo, K., Hu, Y., Qian, Z., Liu, H., Zhang, K., Sun, Y., . . . Yin, B. (2020). Optimized graph convolution recurrent neural network for traffic prediction. *IEEE Transactions on Intelligent Transportation Systems*, *22*(2), 1138–1149,

Guo, Q., He, Z., Wang, Z. (2024). Monthly climate prediction using deep convolutional neural network and long short-term memory. *Scientific Reports*, *14*(1), 17748, Guo, Y., Zhang, F., Chang, S., Li, Z., Li, Z. (2024). Research on a multiobjective cooperative operation scheduling method for agricultural machinery across regions with time windows. *Computers and Electronics in Agriculture*, *224*, 109121,

Gupta, A., Badr, Y., Negahban, A., Qiu, R.G. (2021). Energy-efficient heating control for smart buildings with deep reinforcement learning. *Journal of Building Engineering*, *34*, 101739,

Hafiz, F., Awal, M., de Queiroz, A.R., Husain, I. (2020). Real-time stochastic optimization of energy storage management using deep learning-based forecasts for residential pv applications. *IEEE Transactions on Industry Applications*, *56*(3), 2216–2226,

Han, C., & Zhang, Q. (2021). Optimization of supply chain efficiency management based on machine learning and neural network. *Neural Computing and Applications*, *33*(5), 1419–1433,

Hao, H., Wang, Y., Chen, J. (2024). Empowering scenario planning with artificial intelligence: A perspective on building smart and resilient cities. *Engineering*, ,

Harrou, F., Kadri, F., Sun, Y. (2020). Forecasting of photovoltaic solar power production using lstm approach. *Advanced statistical modeling, forecasting, and fault detection in renewable energy systems*, *3*, ,

Haurum, J.B., & Moeslund, T.B. (2021). Sewer-ml: A multi-label sewer defect classification dataset and benchmark. *Proceedings of the ieee/cvf conference on computer vision and pattern recognition* (pp. 13456–13467).

Hemavathi, S., & Shinisha, A. (2022). A study on trends and developments in electric vehicle charging technologies. *Journal of energy storage*, *52*, 105013,

Hernandez-Mejia, J.L., Imhof, M., Pyrcz, M.J. (2024). Anomaly detection for geological carbon sequestration monitoring. *International Journal of Greenhouse Gas Control*, *136*, 104188,

Hersbach, H., Bell, B., Berrisford, P., Hirahara, S., Horányi, A., Muñoz-Sabater, J., . . . others (2020). The era5 global reanalysis. *Quarterly journal of the royal meteorological society*, *146*(730), 1999–2049, Hess, P., & Boers, N. (2022). Deep learning for improving numerical weather prediction of heavy rainfall. *Journal of Advances in Modeling Earth Systems*, *14*(3), e2021MS002765,

Hewage, P., Trovati, M., Pereira, E., Behera, A. (2021). Deep learning-based effective fine-grained weather forecasting model. *Pattern Analysis and Applications*, *24*(1), 343–366,

Hintz, M.J., Gross, M., Creutzig, F., Kaack, L.H. (2026). Practical implementation of artificial intelligence for climate change mitigation in cities–priorities, collaborations and challenges. *Energy Research & Social Science*, *131*, 104498,

Ho, L., & Goethals, P. (2022). Machine learning applications in river research: Trends, opportunities and challenges. *Methods in ecology and evolution*, *13*(11), 2603–2621,

Howe, P.D. (2021). Extreme weather experience and climate change opinion. *Current Opinion in Behavioral Sciences*, *42*, 127–131,

Huang, K., Wei, K., Li, F., Yang, C., Gui, W. (2022). Lstm-mpc: A deep learning based predictive control method for multimode process control. *IEEE Transactions on Industrial Electronics*, *70*(11), 11544–11554,

Huang, L., Kang, J., Wan, M., Fang, L., Zhang, C., Zeng, Z. (2021). Solar radiation prediction using different machine learning algorithms and implications for extreme climate events. *Frontiers in Earth Science*, *9*, 596860,

Huang, W., Shi, Y., Yang, Y., Li, Z., Ke, J., Liang, Y., Wang, J. (2024). Research on flood risk prediction of substation based on temporal fusion transformer. *2024 6th international conference on energy, power and grid (icepg)* (pp. 386–390).

Huffman, G.J., Bolvin, D.T., Braithwaite, D., Hsu, K., Joyce, R., Xie, P., Yoo, S.-H. (2015). Nasa global precipitation measurement (gpm) integrated multi-satellite retrievals for gpm (imerg). *Algorithm theoretical basis document (ATBD) version*, *4*(26), 30,

Hultgren, A., Carleton, T., Delgado, M., Gergel, D.R., Greenstone, M., Houser, T., . . . others (2025). Impacts of climate change on global agriculture accounting for adaptation. *Nature*, *642*(8068), 644–652, IEA (2025). *Energy demand from AI.* (https://www.iea.org/reports/energy-and-ai/energy-demand-from-ai, accessed 2025-12-07)

Inceyol, Y., & Cay, T. (2022). Comparison of traditional method and genetic algorithm optimization in the land reallocation stage of land consolidation. *Land Use Policy*, *115*, 105989,

Informatics, C. (2025). *Climate Informatics.* (https://www.climateinformatics.org/, accessed 2025-06-07)

Islam, F.S. (2025). Artificial intelligence-driven optimization of nature-based carbon sequestration: A scalable architecture for urban climate resilience. *International Journal of Environment and Climate Change*, *15*(7), 252–277,

Issaoui, Y., Khiat, A., Bahnasse, A., Ouajji, H. (2021). An advanced lstm model for optimal scheduling in smart logistic environment: E-commerce case. *IEEE Access*, *9*, 126337–126356,

Jacques-Dumas, V., Ragone, F., Borgnat, P., Abry, P., Bouchet, F. (2022). Deep learning-based extreme heatwave forecast. *Frontiers in Climate*, *4*, 789641,

Jain, P., Barber, Q.E., Taylor, S.W., Whitman, E., Castellanos Acuna, D., Boulanger, Y., ... others (2024). Drivers and impacts of the record-breaking 2023 wildfire season in canada. *Nature Communications*, *15*(1), 6764,

Jang, H.S., Bae, K.Y., Park, H.-S., Sung, D.K. (2016). Solar power prediction based on satellite images and support vector machine. *IEEE Transactions on Sustainable Energy*, *7*(3), 1255–1263,

Ji, J., He, J., Lei, M., Wang, M., Tang, W. (2024). Spatio-temporal transformer network for weather forecasting. *IEEE Transactions on Big Data*, ,

Jia, L., Yang, F., Chen, Y., Peng, L., Leng, H., Zu, W., ... Zhao, M. (2024). Prediction of wetland soil carbon storage based on near infrared hyperspectral imaging and deep learning. *Infrared Physics & Technology*, *139*, 105287, Jin, W., Zhang, W., Hu, J., Chen, J., Weng, B., Gao, J., Huang, T. (2023). Transformer for sub-seasonal extreme high temperature probabilistic forecasting over eastern china. *Theoretical and Applied Climatology*, *151*(1), 65–80,

Kaack, L.H., Donti, P.L., Strubell, E., Kamiya, G., Creutzig, F., Rolnick, D. (2022). Aligning artificial intelligence with climate change mitigation. *Nature Climate Change*, *12*(6), 518–527,

Kaggle (2025). *Uber movement data.* (https://www.kaggle.com/datasets/vaishalij/san-francisco-caltrain-uber-movement-data, accessed 2025-05-17)

Kahl, S., Wood, C.M., Eibl, M., Klinck, H. (2021). Birdnet: A deep learning solution for avian diversity monitoring. *Ecological Informatics*, *61*, 101236,

Kalusivalingam, A.K., Sharma, A., Patel, N., Singh, V. (2022). Enhancing supply chain resilience through ai: Leveraging deep reinforcement learning and predictive analytics. *International Journal of AI and ML*, *3*(9), ,

Karanth, S., Benefo, E.O., Patra, D., Pradhan, A.K. (2023). Importance of artificial intelligence in evaluating climate change and food safety risk. *Journal of Agriculture and Food Research*, *11*, 100485,

Kashyap, P.K., Kumar, S., Jaiswal, A., Prasad, M., Gandomi, A.H. (2021). Towards precision agriculture: Iot-enabled intelligent irrigation systems using deep learning neural network. *IEEE Sensors Journal*, *21*(16), 17479–17491,

Kavya, M., Mathew, A., Shekar, P.R., et al. (2023). Short term water demand forecast modelling using artificial intelligence for smart water management. *Sustainable Cities and Society*, *95*, 104610,

Ke, Q., Siłka, J., Wieczorek, M., Bai, Z., Woźniak, M. (2022). Deep neural network heuristic hierarchization for cooperative intelligent transportation fleet management. *IEEE Transactions on Intelligent Transportation Systems*, *23*(9), 16752–16762,

Khaki, S., Wang, L., Archontoulis, S.V. (2020). A cnn-rnn framework for crop yield prediction. *Frontiers in Plant Science*, *10*, 1750, Khayyam, H., Naebe, M., Milani, A.S., Fakhrhoseini, S.M., Date, A., Shabani, B., ... Jazar, R.N. (2021). Improving energy efficiency of carbon fiber manufacturing through waste heat recovery: A circular economy approach with machine learning. *Energy*, *225*, 120113,

Kheterpal, N., Vinitsky, E., Wu, C., Kreidieh, A., Jang, K., Parvate, K., Bayen, A. (2018). Flow: Open source reinforcement learning for traffic control.

Kikstra, J.S., Nicholls, Z.R., Smith, C.J., Lewis, J., Lamboll, R.D., Byers, E., ... others (2022). The ipcc sixth assessment report wgiii climate assessment of mitigation pathways: from emissions to global temperatures. *Geoscientific Model Development*, *15*(24), 9075–9109,

Kim, M.-K., Yoo, T.-A., Chung, J.-B. (2025). Toward sustainable generative ai: A scoping review of carbon footprint and environmental impacts across training and inference stages. *arXiv preprint arXiv:2511.17179*, ,

Kong, F., Li, J., Jiang, B., Wang, H., Song, H. (2021). Integrated generative model for industrial anomaly detection via bidirectional lstm and attention mechanism. *IEEE Transactions on Industrial Informatics*, *19*(1), 541–550,

Kong, W., Dong, Z.Y., Jia, Y., Hill, D.J., Xu, Y., Zhang, Y. (2017). Short-term residential load forecasting based on lstm recurrent neural network. *IEEE transactions on smart grid*, *10*(1), 841–851,

Kong, X., & Ge, Z. (2021). Deep learning of latent variable models for industrial process monitoring. *IEEE Transactions on Industrial Informatics*, *18*(10), 6778–6788,

Konstantakopoulos, I.C., Barkan, A.R., He, S., Veeravalli, T., Liu, H., Spanos, C. (2019). A deep learning and gamification approach to improving human-building interaction and energy efficiency in smart infrastructure. *Applied energy*, *237*, 810–821,

Kool, W., Van Hoof, H., Welling, M. (2018). Attention, learn to solve routing problems! *arXiv preprint arXiv:1803.08475*, , Kow, P.-Y., Hsia, I.-W., Chang, L.-C., Chang, F.-J. (2022). Real-time image-based air quality estimation by deep learning neural networks. *Journal of Environmental Management*, *307*, 114560,

Küçük, Ç., Giannakos, A., Schneider, S., Jann, A. (2024). Transformer-based nowcasting of radar composites from satellite images for severe weather. *Artificial Intelligence for the Earth Systems*, *3*(2), e230041,

Laboratory, L.B.N. (2025). *2024 United States Data Center Energy Usage Report.* (https://escholarship.org/uc/item/32d6m0d1, accessed 2025-12-07)

Laboratory, N.N.S.S. (2025). *Multi-Radar/Multi-Sensor System (MRMS).* (https://www.nssl.noaa.gov/projects/mrms/, accessed 2025-05-17)

Ladi, T., Jabalameli, S., Sharifi, A. (2022). Applications of machine learning and deep learning methods for climate change mitigation and adaptation. *Environment and Planning B: Urban Analytics and City Science*, *49*(4), 1314–1330,

Lam, R. (2023). Graphcast: Ai model for faster and more accurate global weather forecasting. *DeepMind. November*, *14*, 2023,

Lam, R., Sanchez-Gonzalez, A., Willson, M., Wirnsberger, P., Fortunato, M., Alet, F., ... others (2023). Learning skillful medium-range global weather forecasting. *Science*, *382*(6677), 1416–1421,

Lara-Benítez, P., Carranza-García, M., Luna-Romera, J.M., Riquelme, J.C. (2020). Temporal convolutional networks applied to energy-related time series forecasting. *applied sciences*, *10*(7), 2322,

Le, M., Nguyen, D.K., Dao, V.-D., Vu, N.H., Vu, H.H.T., et al. (2021). Remote anomaly detection and classification of solar photovoltaic modules based on deep neural network. *Sustainable Energy Technologies and Assessments*, *48*, 101545,

Lee, B.J., & Chang, Y.-S. (2026). A modular coupled physics-informed neural network framework for urban flood prediction. *Journal of Water and Climate Change*, *17*(2), 426–439,

Lee, S.-H., Han, K.-J., Lee, K., Lee, K.-J., Oh, K.-Y., Lee, M.-J. (2020). Classification of landscape affected by deforestation using high-resolution remote sensing data and deep-learning techniques. *Remote Sensing*, *12*(20), 3372,

Li, C., Chen, S., Ye, M. (2024). Adaptive high-frequency transformer for diverse wildlife re-identification. *European conference on computer vision* (pp. 296–313).

Li, K., Pan, J., Xiong, W., Xie, W., Ali, T. (2022). The impact of 1.5 c and 2.0 c global warming on global maize production and trade. *Scientific Reports*, *12*(1), 17268,

Li, L., Zhang, Y., Wang, B., Feng, P., He, Q., Shi, Y., … others (2023). Integrating machine learning and environmental variables to constrain uncertainty in crop yield change projections under climate change. *European Journal of Agronomy*, *149*, 126917,

Li, P., Yu, Y., Huang, D., Wang, Z.-H., Sharma, A. (2023). Regional heatwave prediction using graph neural network and weather station data. *Geophysical Research Letters*, *50*(7), e2023GL103405,

Li, X., Liang, X., Wang, X., Wang, R., Shu, L., Xu, W. (2023). Deep reinforcement learning for optimal rescue path planning in uncertain and complex urban pluvial flood scenarios. *Applied Soft Computing*, *144*, 110543,

Li, X., Ma, L., Chen, P., Xu, H., Xing, Q., Yan, J., … Cheng, Y. (2022). Probabilistic solar irradiance forecasting based on xgboost. *Energy Reports*, *8*, 1087–1095,

Li, Y., Sun, Q., Fu, Y., Wei, J. (2025). Solving the richards infiltration equation by coupling physics-informed neural networks with hydrus-1d. *Scientific Reports*, *15*(1), 18649,

Li, Y., Wang, H., Dang, L.M., Sadeghi-Niaraki, A., Moon, H. (2020). Crop pest recognition in natural scenes using convolutional neural networks. *Computers and Electronics in Agriculture*, *169*, 105174,

Li, Y., Wang, H., Dang, L.M., Song, H.-K., Moon, H. (2023). Attention-guided multiscale neural network for defect detection in sewer pipelines. *Computer-Aided Civil and Infrastructure Engineering*, *38*(15), 2163–2179, Li, Z., Ma, J., Tan, Y., Guo, C., Li, X. (2023). Combining physical approaches with deep learning techniques for urban building energy modeling: A comprehensive review and future research prospects. *Building and Environment*, *246*, 110960,

Liang, X., Wang, T., Yang, L., Xing, E. (2018). Cirl: Controllable imitative reinforcement learning for vision-based self-driving. *Proceedings of the european conference on computer vision (eccv)* (pp. 584–599).

Lin, H., & Tang, C. (2021). Analysis and optimization of urban public transport lines based on multiobjective adaptive particle swarm optimization. *IEEE Transactions on Intelligent Transportation Systems*, *23*(9), 16786–16798,

Lin, K., Zhao, R., Xu, Z., Zhou, J. (2018). Efficient large-scale fleet management via multi-agent deep reinforcement learning. *Proceedings of the 24th acm sigkdd international conference on knowledge discovery & data mining* (pp. 1774–1783).

Liu, H., Wang, L., Shi, Y., Wang, X., Chang, F., Wu, Y. (2023). A deep learning-based method for detecting granular fertilizer deposition distribution patterns in centrifugal variable-rate spreader fertilization. *Computers and Electronics in Agriculture*, *212*, 108107,

Liu, J., Koch, J., Stisen, S., Troldborg, L., Højberg, A.L., Thodsen, H., ... Schneider, R.J. (2024). Camels-dk: Hydrometeorological time series and landscape attributes for 3330 catchments in denmark. *Earth System Science Data Discussions*, *2024*, 1–30,

Liu, J., Liu, G., Zhao, H., Zhao, J., Qiu, J., Dong, Z.Y. (2023). A real-time carbon emission estimation framework for industrial parks with non-intrusive load monitoring. *Sustainable Energy Technologies and Assessments*, *60*, 103482,

Liu, J., Zhou, Y., Yang, H., Wu, H. (2022). Uncertainty energy planning of net-zero energy communities with peer-to-peer energy trading and green vehicle storage considering climate changes by 2050 with machine learning methods. *Applied Energy*, *321*, 119394,

Liu, R., Zayed, T., Xiao, R., Hu, Q. (2025). Time-transformer for acoustic leak detection in water distribution network. *Journal of Civil Structural Health Monitoring*, *15*(3), 759–775, Liu, S., Lu, D., Painter, S.L., Griffiths, N.A., Pierce, E.M. (2023). Uncertainty quantification of machine learning models to improve streamflow prediction under changing climate and environmental conditions. *Frontiers in Water*, *5*, 1150126,

Liu, T., Tan, Z., Xu, C., Chen, H., Li, Z. (2020). Study on deep reinforcement learning techniques for building energy consumption forecasting. *Energy and Buildings*, *208*, 109675,

Liu, W., Li, R., Cao, J., Huang, C., Zhang, F., Zhang, M. (2024). Mapping high-resolution xco2 concentrations in china from 2015 to 2020 based on spatiotemporal ensemble learning model. *Ecological Informatics*, *83*, 102806,

Liu, Y., Lu, Q., Yu, Z., Chen, Y., Yang, Y. (2024). Reinforcement learning-enhanced adaptive scheduling of battery energy storage systems in energy markets. *Energies (19961073)*, *17*(21), ,

Luo, J., Paduraru, C., Voicu, O., Chervonyi, Y., Munns, S., Li, J., … others (2022). Controlling commercial cooling systems using reinforcement learning. *arXiv preprint arXiv:2211.07357*, ,

Ma, D., Li, X., Lin, B., Zhu, Y., Yue, S. (2023). A dynamic intelligent building retrofit decision-making model in response to climate change. *Energy and Buildings*, *284*, 112832,

Ma, M., Xie, P., Teng, F., Wang, B., Ji, S., Zhang, J., Li, T. (2023). Histgnn: Hierarchical spatio-temporal graph neural network for weather forecasting. *Information Sciences*, *648*, 119580,

Maimuri, N.M.A., Altahir, A.A.R., Abdulameer, L., Rashid, F.L., Al-Dujaili, A.N. (2025). Smart rubber balloon dam for coastal hurricane and tsunami protection: A renewable energy-powered system with hydrodynamic design and adaptive control. *International Journal of Mathematical, Engineering and Management Sciences*, *10*(6), 2286,

Maldonado-Correa, J., Martín-Martínez, S., Artigao, E., Gómez-Lázaro, E. (2020). Using scada data for wind turbine condition monitoring: A systematic literature review. *Energies*, *13*(12), 3132, Manchella, K., Haliem, M., Aggarwal, V., Bhargava, B. (2021). Passgoodpool: Joint passengers and goods fleet management with reinforcement learning aided pricing, matching, and route planning. *IEEE Transactions on Intelligent Transportation Systems*, *23*(4), 3866–3877,

Manzocco, L., Ignat, A., Anese, M., Bot, F., Calligaris, S., Valoppi, F., Nicoli, M.C. (2015). Efficient management of the water resource in the fresh-cut industry: Current status and perspectives. *Trends in Food Science & Technology*, *46*(2), 286–294,

Marques, T., Carreira, S., Miragaia, R., Ramos, J., Pereira, A. (2024). Applying deep learning to real-time uav-based forest monitoring: Leveraging multi-sensor imagery for improved results. *Expert Systems with Applications*, *245*, 123107,

Marsh, J.I., Hu, H., Gill, M., Batley, J., Edwards, D. (2021). Crop breeding for a changing climate: Integrating phenomics and genomics with bioinformatics. *Theoretical and Applied Genetics*, *134*(6), 1677–1690,

Marshall, M., Belgiu, M., Boschetti, M., Pepe, M., Stein, A., Nelson, A. (2022). Field-level crop yield estimation with prisma and sentinel-2. *ISPRS journal of photogrammetry and remote sensing*, *187*, 191–210,

Marusov, A., Grabar, V., Maximov, Y., Sotiriadi, N., Bulkin, A., Zaytsev, A. (2024). Long-term drought prediction using deep neural networks based on geospatial weather data. *Environmental Modelling & Software*, *179*, 106127,

Masoumi, Z., Coello Coello, C.A., Mansourian, A. (2020). Dynamic urban land-use change management using multi-objective evolutionary algorithms. *Soft Computing*, *24*, 4165–4190,

Mathew, V., Kurian, C.P., Augustine, N. (2023). Climate-responsive machine learning-based control of switchable glazing towards human-centric lighting. *Solar Energy*, *260*, 49–60,

Matias, Y. (2025). *Project Green Lights work to reduce urban emissions using AI.* (https://blog.google/outreach-initiatives/sustainability/google-ai-reduce-greenhouse-emissions-project-greenlight/, accessed 2025-05-17)

Mazzarino, P.R., Macii, A., Bottaccioli, L., Patti, E. (2023). A multi-agent framework for smart grid simulations: Strategies for power-to-heat flexibility management in residential context. *Sustainable Energy, Grids and Networks*, *34*, 101072,

McGovern, A., Bostrom, A., McGraw, M., Chase, R.J., Gagne, D.J., Ebert-Uphoff, I., ... Schumacher, A. (2024). Identifying and categorizing bias in ai/ml for earth sciences. *Bulletin of the American Meteorological Society*, *105*(3), E567–E583,

Medium (2025). *The Electricity Bill Nobody Can Pay:The Mathematics of an AI Collapse.* (https://ai.plainenglish.io/the-electricity-bill-nobody-can-pay-the-mathematics-of-an-ai-collapse-061df2f3079f, accessed 2025-12-07)

Mendeley (2025). *Mismatching Faults of Photovoltaic Modules.* (https://data.mendeley.com/datasets/xjs42j8dtf/2, accessed 2025-05-17)

Meng, C., Griesemer, S., Cao, D., Seo, S., Liu, Y. (2025). When physics meets machine learning: A survey of physics-informed machine learning. *Machine Learning for Computational Science and Engineering*, *1*(1), 20,

Miao, Z., Yu, X., Li, N., Zhang, Z., He, C., Li, Z., ... Sun, T. (2023). Efficient tomato harvesting robot based on image processing and deep learning. *Precision Agriculture*, *24*(1), 254–287,

Minh, D., Wang, H.X., Li, Y.F., Nguyen, T.N. (2022). Explainable artificial intelligence: a comprehensive review. *Artificial Intelligence Review*, *55*(5), 3503–3568,

Mo, F., Jiao, X., Li, X., Du, Y., Yao, Y., Meng, Y., Ding, S. (2024). A novel multi-step ahead solar power prediction scheme by deep learning on transformer structure. *Renewable Energy*, *230*, 120780,

Modi (2025). *Wind power forecasting.* (https://www.kaggle.com/code/paridhimodi/easy-wind-power-forecasting/notebook, accessed 2025-05-17)

Mohammadi, M.G., Mahmoud, D., Elbestawi, M. (2021). On the application of machine learning for defect detection in l-pbf additive manufacturing. *Optics & Laser Technology*, *143*, 107338,

Molęda, M., Małysiak-Mrozek, B., Ding, W., Sunderam, V., Mrozek, D. (2023). From corrective to predictive maintenancea review of maintenance approaches for the power industry. *Sensors*, *23*(13), 5970,

Mrisho, L.M., Mbilinyi, N.A., Ndalahwa, M., Ramcharan, A.M., Kehs, A.K., McCloskey, P.C., ... Legg, J.P. (2020). Accuracy of a smartphone-based object detection model, plantvillage nuru, in identifying the foliar symptoms of the viral diseases of cassava–cmd and cbsd. *Frontiers in plant science*, *11*, 590889,

Mtibaa, F., Nguyen, K.-K., Azam, M., Papachristou, A., Venne, J.-S., Cheriet, M. (2020). Lstm-based indoor air temperature prediction framework for hvac systems in smart buildings. *Neural Computing and Applications*, *32*, 17569–17585,

Müller, J., Mitesser, O., Schaefer, H.M., Seibold, S., Busse, A., Kriegel, P., ... others (2023). Soundscapes and deep learning enable tracking biodiversity recovery in tropical forests. *Nature communications*, *14*(1), 6191,

Muzaffar, S., & Afshari, A. (2019). Short-term load forecasts using lstm networks. *Energy Procedia*, *158*, 2922–2927,

Nasa (2025). *Orbiting Carbon Observatory-2.* (https://ocov2.jpl.nasa.gov/, accessed 2025-05-17)

Nations, U. (2025a). *Global Set of Climate Change Statistics and Indicators.* (https://unstats.un.org/unsd/envstats/climatechange.cshtml, accessed 2025-05-17)

Nations, U. (2025b). *Sustainably manage forests, combat desertification, halt and reverse land degradation, halt biodiversity loss'.* (https://www.un.org/sustainabledevelopment/biodiversity/, accessed 2025-08-17)

Nayak, G.H., Alam, M.W., Avinash, G., Kumar, R.R., Ray, M., Barman, S., ... others (2024). Transformer-based deep learning architecture for time series forecasting. *Software Impacts*, *22*, 100716,

Nearing, G., Cohen, D., Dube, V., Gauch, M., Gilon, O., Harrigan, S., ... others (2024). Global prediction of extreme floods in ungauged watersheds. *Nature*, *627*(8004), 559–563,

Neun, M., Eichenberger, C., Martin, H., Spanring, M., Siripurapu, R., Springer, D., ... Hochreiter, S. (2023). *Traffic4cast at neurips 2022 – predict dynamics along graph edges from sparse node data: Whole city traffic and eta from stationary* *vehicle detectors.*

Nevavuori, P., Narra, N., Lipping, T. (2019). Crop yield prediction with deep convolutional neural networks. *Computers and electronics in agriculture*, *163*, 104859,

Nguyen, H.D., Tran, K.P., Thomassey, S., Hamad, M. (2021). Forecasting and anomaly detection approaches using lstm and lstm autoencoder techniques with the applications in supply chain management. *International Journal of Information Management*, *57*, 102282,

Nguyen, L.Q., Shin, J., Ryu, S., Dang, L.M., Park, H.Y., Lee, O.N., Moon, H. (2023). Innovative cucumber phenotyping: A smartphone-based and data-labeling-free model. *Electronics*, *12*(23), 4775,

Nguyen, T., Brandstetter, J., Kapoor, A., Gupta, J.K., Grover, A. (2023). Climax: A foundation model for weather and climate. *arXiv preprint arXiv:2301.10343*, ,

Nguyen, T., Shah, R., Bansal, H., Arcomano, T., Maulik, R., Kotamarthi, R., … Grover, A. (2024). Scaling transformer neural networks for skillful and reliable medium-range weather forecasting. *Advances in Neural Information Processing Systems*, *37*, 68740–68771,

Nile, B.K., Al-Saadi, R.J.M., Abdulameer, L., Al Maimuri, N.M., Al-Dujaili, A.N. (2025). Climate change impacts on river hydraulics: a global synthesis of hydrological shifts, ecological consequences, and adaptive strategies. *Water Conservation Science and Engineering*, *10*(2), 48,

Noaa (2025). *The High-Resolution Rapid Refresh (HRRR).* (https://rapidrefresh.noaa.gov/hrrr/, accessed 2025-05-17)

NOAA (2025). *The High-Resolution Rapid Refresh (HRRR).* (https://rapidrefresh.noaa.gov/hrrr/, accessed 2025-06-08)

noaa (2025). *Next Generation Weather Radar (NEXRAD).* (https://www.ncei.noaa.gov/products/radar/next-generation-weather-radar/, accessed 2025-05-17)

NUTRITION, I.S.E. (2018). Innovation with a purpose: The role of technology innovation in accelerating food systems transformation.

Nvidia (2025). *End-to-End Solutions for Autonomous Vehicles.* (https://developer.nvidia.com/drive, accessed 2025-05-17)

Nweye, K., Kaspar, K., Buscemi, G., Fonseca, T., Pinto, G., Ghose, D., … others (2025). Citylearn v2: energy-flexible, resilient, occupant-centric, and carbon-aware management of grid-interactive communities. *Journal of Building Performance Simulation*, *18*(1), 17–38,

of Melbourne, T.U. (2025). *The World's New Climate Projections CMIP6 Visualisation Tool.* (https://cmip6.science.unimelb.edu.au/, accessed 2025-05-17)

Olu-Ajayi, R., Alaka, H., Sulaimon, I., Sunmola, F., Ajayi, S. (2022). Building energy consumption prediction for residential buildings using deep learning and other machine learning techniques. *Journal of Building Engineering*, *45*, 103406,

Openaq (2025). *OpenAQ data.* (https://openaq.org/, accessed 2025-06-08)

Ordoñez, J.G., Barco-Jiménez, J., Pantoja, A., Revelo-Fuelagán, J., Candelo-Becerra, J.E. (2024). Comprehensive analysis of mpc-based energy management strategies for isolated microgrids empowered by storage units and renewable energy sources. *Journal of Energy Storage*, *94*, 112127,

Organization, W.M. (2025). *Global climate predictions show temperatures expected to remain at or near record levels in coming 5 years.* (https://wmo.int/news/media-centre/global-climate-predictions-show-temperatures-expected-remain-or-near-record-levels-coming-5-years, accessed 2025-05-17)

Oroojlooyjadid, A., Nazari, M., Snyder, L.V., Takáč, M. (2022). A deep q-network for the beer game: Deep reinforcement learning for inventory optimization. *Manufacturing & Service Operations Management*, *24*(1), 285–304,

Ou, C., Zhu, H., Shardt, Y.A., Ye, L., Yuan, X., Wang, Y., Yang, C. (2022). Quality-driven regularization for deep learning networks and its application to industrial soft sensors. *IEEE Transactions on Neural Networks and Learning Systems*, ,

Pagallo, U., Ciani Sciolla, J., Durante, M. (2022). The environmental challenges of ai in eu law: lessons learned from the artificial intelligence act (aia) with its drawbacks. *Transforming Government: People, Process and Policy*, *16*(3), 359–376, Pan, B., Anderson, G.J., Goncalves, A., Lucas, D.D., Bonfils, C.J., Lee, J. (2022). Improving seasonal forecast using probabilistic deep learning. *Journal of Advances in Modeling Earth Systems*, *14*(3), e2021MS002766,

Panahi, M., Jaafari, A., Shirzadi, A., Shahabi, H., Rahmati, O., Omidvar, E., ... Bui, D.T. (2021). Deep learning neural networks for spatially explicit prediction of flash flood probability. *Geoscience Frontiers*, *12*(3), 101076,

Parisi, P., Arca, S., Ciulla, M., Morodei, F., Palozzo, W., Di Profio, P., D'Alessandro, E. (2024). Toward 2050: Critical analysis of energy and economic requirements of carbon capture and storage in post combustion capture. *Spe europec featured at eage conference and exhibition?* (p. D011S002R003).

Paudel, D., De Wit, A., Boogaard, H., Marcos, D., Osinga, S., Athanasiadis, I.N. (2023). Interpretability of deep learning models for crop yield forecasting. *Computers and Electronics in Agriculture*, *206*, 107663,

PeMS (2025). *Caltrans Performance Measurement System (PeMS).* (https://pems.dot.ca.gov/, accessed 2025-05-17)

Pereira, L., Costa, D., Ribeiro, M. (2022). A residential labeled dataset for smart meter data analytics. *Scientific Data*, *9*(1), 134,

Perera, A.T., Nik, V.M., Chen, D., Scartezzini, J.-L., Hong, T. (2020). Quantifying the impacts of climate change and extreme climate events on energy systems. *Nature Energy*, *5*(2), 150–159,

Petri, I., Rezgui, Y., Ghoroghi, A., Alzahrani, A. (2023). Digital twins for performance management in the built environment. *Journal of industrial information integration*, *33*, 100445,

Pichler, M., & Hartig, F. (2023). Machine learning and deep learninga review for ecologists. *Methods in Ecology and Evolution*, *14*(4), 994–1016,

Ponnoprat, D. (2021). Short-term daily precipitation forecasting with seasonally-integrated autoencoder. *Applied Soft Computing*, *102*, 107083,

Punnam, P.R., Dutta, A., Krishnamurthy, B., Surasani, V.K. (2023). Study on utilization of machine learning techniques for geological co2 sequestration simulations.

Materials Today: Proceedings, *72*, 378–385,

Rahimi, E., & Jung, C. (2024). Global trends in climate suitability of bees: Ups and downs in a warming world. *Insects*, *15*(2), 127,

Rai, K.K. (2022). Integrating speed breeding with artificial intelligence for developing climate-smart crops. *Molecular biology reports*, *49*(12), 11385–11402,

Raziel, B. (2025). *How AI Is Helping Big Fleet Operators Cut Greenhouse Gas Emissions.* (https://www.forbes.com/sites/zengernews/2023/09/15/how-ai-is-helping-big-fleet-operators-cut-greenhouse-gas-emissions/, accessed 2025-05-17)

Ren, J., Yu, Z., Gao, G., Yu, G., Yu, J. (2022). A cnn-lstm-lightgbm based short-term wind power prediction method based on attention mechanism. *Energy Reports*, *8*, 437–443,

Roberge, V., Brooks, K., Tarbouchi, M. (2024). Parallel algorithm on multicore processor and graphics processing unit for the optimization of electric vehicle recharge scheduling. *Electronics*, *13*(9), 1783,

Rocchetta, R., Bellani, L., Compare, M., Zio, E., Patelli, E. (2019). A reinforcement learning framework for optimal operation and maintenance of power grids. *Applied energy*, *241*, 291–301,

Rong, H., Zhang, H., Xiao, S., Li, C., Hu, C. (2016). Optimizing energy consumption for data centers. *Renewable and Sustainable Energy Reviews*, *58*, 674–691,

Rubio-Loyola, J., & Paul-Fils, W.R.S. (2022). Applied machine learning in industry 4.0: case-study research in predictive models for black carbon emissions. *Sensors*, *22*(10), 3947,

Saha, S., Saha, M., Mukherjee, K., Arabameri, A., Ngo, P.T.T., Paul, G.C. (2020). Predicting the deforestation probability using the binary logistic regression, random forest, ensemble rotational forest, reptree: A case study at the gumani river basin, india. *Science of the Total Environment*, *730*, 139197, Salloom, T., Kaynak, O., He, W. (2021). A novel deep neural network architecture for real-time water demand forecasting. *Journal of Hydrology*, *599*, 126353,

Sami, M., Khan, S.Q., Khurram, M., Farooq, M.U., Anjum, R., Aziz, S., ... Sadak, F. (2022). A deep learning-based sensor modeling for smart irrigation system. *Agronomy*, *12*(1), 212,

Scher, S. (2018). Toward data-driven weather and climate forecasting: Approximating a simple general circulation model with deep learning. *Geophysical Research Letters*, *45*(22), 12–616,

Schmaranzer, D., Braune, R., Doerner, K.F. (2021). Multi-objective simulation optimization for complex urban mass rapid transit systems. *Annals of Operations Research*, *305*(1), 449–486,

Schmitz, O.J., Sylvén, M., Atwood, T.B., Bakker, E.S., Berzaghi, F., Brodie, J.F., ... others (2023). Trophic rewilding can expand natural climate solutions. *Nature Climate Change*, *13*(4), 324–333,

Schrotter, G., & Hürzeler, C. (2020). The digital twin of the city of zurich for urban planning. *PFG–Journal of Photogrammetry, Remote Sensing and Geoinformation Science*, *88*(1), 99–112,

Seydi, S.T., Saeidi, V., Kalantar, B., Ueda, N., Halin, A.A. (2022). Fire-net: A deep learning framework for active forest fire detection. *Journal of Sensors*, *2022*(1), 8044390,

Shafiq, M., Bhavani, N., Ramesh, J.V.N., Veeresha, R., Talasila, V., Alfurhood, B.S. (2024). Thermal modeling and machine learning for optimizing heat transfer in smart city infrastructure balancing energy efficiency and climate impact. *Thermal Science and Engineering Progress*, *54*, 102868,

Shahid, F., Zameer, A., Muneeb, M. (2021). A novel genetic lstm model for wind power forecast. *Energy*, *223*, 120069,

Shang, W.-L., Song, X., Xiang, Q., Chen, H., Elhajj, M., Bi, H., ... Ochieng, W. (2025). The impact of deep reinforcement learning-based traffic signal control on emission reduction in urban road networks empowered by cooperative vehicle-infrastructure systems. *Applied Energy*, *390*, 125884,

Shehadeh, A., Alshboul, O., Tamimi, M. (2024). Integrating climate change predictions into infrastructure degradation modelling using advanced markovian frameworks to enhanced resilience. *Journal of Environmental Management*, *368*, 122234,

Shen, P., Gao, X., Lu, S., Zhang, Y., Zheng, X., Santamouris, M. (2026). How ai shapes the future landscape of sustainable building design with climate change challenges? *Advanced Science*, e23238,

Shi, X., Gao, Z., Lausen, L., Wang, H., Yeung, D.-Y., Wong, W.-k., Woo, W.-c. (2017). Deep learning for precipitation nowcasting: A benchmark and a new model. *Advances in neural information processing systems*, *30*, ,

Shivaprakash, K.N., Swami, N., Mysorekar, S., Arora, R., Gangadharan, A., Vohra, K., … Kiesecker, J.M. (2022). Potential for artificial intelligence (ai) and machine learning (ml) applications in biodiversity conservation, managing forests, and related services in india. *Sustainability*, *14*(12), 7154,

Shook, J., Gangopadhyay, T., Wu, L., Ganapathysubramanian, B., Sarkar, S., Singh, A.K. (2021). Crop yield prediction integrating genotype and weather variables using deep learning. *Plos one*, *16*(6), e0252402,

Shukla, S., Jain, S.K., Kansal, M.L. (2021). Hydrological modelling of a snow/glacier-fed western himalayan basin to simulate the current and future streamflows under changing climate scenarios. *Science of the Total Environment*, *795*, 148871,

Siebert, S., Burke, J., Faures, J.-M., Frenken, K., Hoogeveen, J., Döll, P., Portmann, F.T. (2010). Groundwater use for irrigation–a global inventory. *Hydrology and earth system sciences*, *14*(10), 1863–1880,

Silvestro, D., Goria, S., Sterner, T., Antonelli, A. (2022). Improving biodiversity protection through artificial intelligence. *Nature sustainability*, *5*(5), 415–424, Simões, F., Bouveyron, C., Precioso, F. (2023). Deepwild: Wildlife identification, localisation and estimation on camera trap videos using deep learning. *Ecological Informatics*, *75*, 102095,

Sing, S.L., Kuo, C., Shih, C., Ho, C., Chua, C.K. (2021). Perspectives of using machine learning in laser powder bed fusion for metal additive manufacturing. *Virtual and Physical Prototyping*, *16*(3), 372–386,

Singh, D., Jain, N., Jain, P., Kayal, P., Kumawat, S., Batra, N. (2020). Plantdoc: A dataset for visual plant disease detection. *Proceedings of the 7th acm ikdd cods and 25th comad* (pp. 249–253).

Su, B., Chen, H., Zhou, Z. (2021). Baf-detector: An efficient cnn-based detector for photovoltaic cell defect detection. *IEEE Transactions on Industrial Electronics*, *69*(3), 3161–3171,

Su, D., Kong, H., Qiao, Y., Sukkarieh, S. (2021). Data augmentation for deep learning based semantic segmentation and crop-weed classification in agricultural robotics. *Computers and Electronics in Agriculture*, *190*, 106418,

Su, H., Wu, L., Jiang, J.H., Pai, R., Liu, A., Zhai, A.J., ... DeMaria, M. (2020). Applying satellite observations of tropical cyclone internal structures to rapid intensification forecast with machine learning. *Geophysical Research Letters*, *47*(17), e2020GL089102,

Suleman, M.A.R., & Shridevi, S. (2022). Short-term weather forecasting using spatial feature attention based lstm model. *IEEE Access*, *10*, 82456–82468,

Sun, P., Hu, Y., Lan, J., Tian, L., Chen, M. (2019). Tide: Time-relevant deep reinforcement learning for routing optimization. *Future Generation Computer Systems*, *99*, 401–409,

Sun, P., Kretzschmar, H., Dotiwalla, X., Chouard, A., Patnaik, V., Tsui, P., ... others (2020). Scalability in perception for autonomous driving: Waymo open dataset. *Proceedings of the ieee/cvf conference on computer vision and pattern recognition* (pp. 2446–2454).

Sun, Y., Li, J., Xu, X., Shi, Y. (2022). Adaptive multi-lane detection based on robust instance segmentation for intelligent vehicles. *IEEE Transactions on Intelligent Vehicles*, *8*(1), 888–899, Tarmanini, C., Sarma, N., Gezegin, C., Ozgonenel, O. (2023). Short term load forecasting based on arima and ann approaches. *Energy Reports*, *9*, 550–557,

Tautz-Weinert, J., & Watson, S.J. (2017). Using scada data for wind turbine condition monitoring–a review. *IET Renewable Power Generation*, *11*(4), 382–394,

TechCrunch (2025). *Avalo uses machine learning to accelerate the adaptation of crops to climate change'.* (https://techcrunch.com/2021/08/25/avalo-uses-machine-learning-to-accelerate-the-adaptation-of-crops-to-climate-change/, accessed 2025-08-17)

Tesla (2025). *Tesla Autopilot and Full Self-Driving (Supervised).* (https://www.tesla.com/support/autopilot, accessed 2025-05-17)

Tian, J., Xiong, R., Shen, W., Lu, J. (2021). State-of-charge estimation of lifepo4 batteries in electric vehicles: A deep-learning enabled approach. *Applied Energy*, *291*, 116812,

Tian, Z., Li, S., Wang, Y., Wang, X. (2018). Wind power prediction method based on hybrid kernel function support vector machine. *Wind Engineering*, *42*(3), 252–264,

Tien, P.W., Wei, S., Liu, T., Calautit, J., Darkwa, J., Wood, C. (2021). A deep learning approach towards the detection and recognition of opening of windows for effective management of building ventilation heat losses and reducing space heating demand. *Renewable Energy*, *177*, 603–625,

Tightiz, L., Dang, L.M., Yoo, J. (2023). Novel deep deterministic policy gradient technique for automated micro-grid energy management in rural and islanded areas. *Alexandria Engineering Journal*, *82*, 145–153,

Tmamna, J., Ayed, E.B., Fourati, R., Gogate, M., Arslan, T., Hussain, A., Ayed, M.B. (2024). Pruning deep neural networks for green energy-efficient models: A survey. *Cognitive Computation*, *16*(6), 2931–2952,

Torres-Barrán, A., Alonso, Á., Dorronsoro, J.R. (2019). Regression tree ensembles for wind energy and solar radiation prediction. *Neurocomputing*, *326*, 151–160, Tran, H.M., Tsai, F.-J., Lee, Y.-L., Chang, J.-H., Chang, L.-T., Chang, T.-Y., ... others (2023). The impact of air pollution on respiratory diseases in an era of climate change: A review of the current evidence. *Science of the Total Environment*, *898*, 166340,

Tzachor, A., Devare, M., King, B., Avin, S., Ó hÉigeartaigh, S. (2022). Responsible artificial intelligence in agriculture requires systemic understanding of risks and externalities. *Nature Machine Intelligence*, *4*(2), 104–109,

UCI (2025). *Forest Fires dataset.* (https://archive.ics.uci.edu/dataset/162/forest+fires, accessed 2025-05-17)

UNEP (2025). *ENERGY EFFICIENCY FOR BUILDINGS.* (https://www.unep.org/topics/energy/buildings, accessed 2025-05-17)

Union, E. (2023). *The EU Artificial Intelligence Act.* (https://artificialintelligenceact.eu/, accessed 2025-06-07)

USGS (2025). *Landsat Data Access.* (https://www.usgs.gov/landsat-missions/landsat-data-access, accessed 2025-05-17)

Vasisht, D., Kapetanovic, Z., Won, J., Jin, X., Chandra, R., Sinha, S., ... Stratman, S. (2017). {FarmBeats}: an {IoT} platform for {Data-Driven} agriculture. *14th usenix symposium on networked systems design and implementation (nsdi 17)* (pp. 515–529).

Verma, A., Ranga, V., Vishwakarma, D.K. (2023). Forecasting of satellite based carbon-monoxide time-series data using a deep learning approach. *2023 4th international conference on innovative trends in information technology (icitiit)* (pp. 1–4).

Walter, T., & Couzin, I.D. (2021). Trex, a fast multi-animal tracking system with markerless identification, and 2d estimation of posture and visual fields. *Elife*, *10*, e64000,

Wambugu, N., Chen, Y., Xiao, Z., Wei, M., Bello, S.A., Junior, J.M., Li, J. (2021). A hybrid deep convolutional neural network for accurate land cover classification. *International Journal of Applied Earth Observation and Geoinformation*, *103*, 102515,

Wang, F., & Tian, D. (2022). On deep learning-based bias correction and downscaling of multiple climate models simulations. *Climate dynamics*, *59*(11), 3451–3468, Wang, H., Li, B., Xue, Z., Fan, S., Liu, X. (2024). Powerformer: A temporal-based transformer model for wind power forecasting. *Energy Reports*, *11*, 736–744,

Wang, H., Li, Y., Dang, L.M., Moon, H. (2022). An efficient attention module for instance segmentation network in pest monitoring. *Computers and Electronics in Agriculture*, *195*, 106853,

Wang, H., Nguyen, T.-H., Nguyen, T.N., Dang, M. (2024). Pd-tr: End-to-end plant diseases detection using a transformer. *Computers and Electronics in Agriculture*, *224*, 109123,

Wang, H.-M., Peng, X., He, X. (2024). Forecasting fierce floods with transferable ai in data-scarce regions. *The Innovation*, *5*(4), ,

Wang, J., Hadjikakou, M., Hewitt, R.J., Bryan, B.A. (2022). Simulating large-scale urban land-use patterns and dynamics using the u-net deep learning architecture. *Computers, Environment and Urban Systems*, *97*, 101855,

Wang, J., Swartz, C.L., Huang, K. (2023). Deep learning-based model predictive control for real-time supply chain optimization. *Journal of Process Control*, *129*, 103049,

Wang, J., Yin, X., Liu, Y., Cai, W. (2023). Optimal design of combined operations of wind power-pumped storage-hydrogen energy storage based on deep learning. *Electric Power Systems Research*, *218*, 109216,

Wang, J.Q., Du, Y., Wang, J. (2020). Lstm based long-term energy consumption prediction with periodicity. *energy*, *197*, 117197,

Wang, R., Keyantuo, P., Zeng, T., Sandoval, J., Vishwanath, A., Borhan, H., Moura, S. (2024). Robust routing for a mixed fleet of heavy-duty trucks with pickup and delivery under energy consumption uncertainty. *Applied Energy*, *368*, 123407,

Wang, W., Wang, Z., Zhou, Z., Deng, H., Zhao, W., Wang, C., Guo, Y. (2021). Anomaly detection of industrial control systems based on transfer learning. *Tsinghua Science and Technology*, *26*(6), 821–832, Wang, X., Ma, Y., Wang, Y., Jin, W., Wang, X., Tang, J., ... Yu, J. (2020). Traffic flow prediction via spatial temporal graph neural network. *Proceedings of the web conference 2020* (pp. 1082–1092).

Wang, Y., Limmer, S., Olhofer, M., Emmerich, M., Bäck, T. (2021). Automatic preference based multi-objective evolutionary algorithm on vehicle fleet maintenance scheduling optimization. *Swarm and Evolutionary Computation*, *65*, 100933,

Wang, Y., Ma, X., Qian, P. (2018). Wind turbine fault detection and identification through pca-based optimal variable selection. *IEEE Transactions on Sustainable Energy*, *9*(4), 1627–1635,

Weyn, J.A., Durran, D.R., Caruana, R., Cresswell-Clay, N. (2021). Sub-seasonal forecasting with a large ensemble of deep-learning weather prediction models. *Journal of Advances in Modeling Earth Systems*, *13*(7), e2021MS002502,

WF (2025). *LIVING PLANET REPORT 2024.* (https://livingplanet.panda.org/en-GB/, accessed 2025-07-23)

Williamson, B., Provost, S., Price, C. (2023). Operationalising indigenous data sovereignty in environmental research and governance. *Environment and planning F*, *2*(1-2), 281–304,

Wisser, D., Ozkan, S., Lanzoni, L., Tempio, G., Tubiello, F., Uwizeye, A., ... others (2023). Pathways towards lower emissions. *Pathways towards lower emissions–a global assessment of the greenhouse gas emissions and mitigation options from livestock agrifood systems.* Food and Agriculture Organization (FAO).

WMO (2025a). *State of the Global Climate 2024.* (https://wmo.int/publication-series/state-of-global-climate-2024, accessed 2025-07-23)

WMO (2025b). *UN Report: Natures Dangerous Decline 'Unprecedented'; Species Extinction Rates 'Accelerating'.* (https://www.un.org/sustainabledevelopment/blog/2019/05/nature-decline-unprecedented-report/, accessed 2025-07-23)

WMO (2025c). *WMO report documents spiralling weather and climate impacts.* (https://wmo.int/news/media-centre/wmo-report-documents-spiralling-weather-and-climate-impacts, accessed 2025-06-07)

Workshop, B., Scao, T.L., Fan, A., Akiki, C., Pavlick, E., Ilić, S., ... others (2022). Bloom: A 176b-parameter open-access multilingual language model. *arXiv preprint arXiv:2211.05100*, , Wu, C.-l., He, H.-d., Song, R.-f., Zhu, X.-h., Peng, Z.-r., Fu, Q.-y., Pan, J. (2023). A hybrid deep learning model for regional o3 and no2 concentrations prediction based on spatiotemporal dependencies in air quality monitoring network. *Environmental pollution*, *320*, 121075,

Xi, L., Shu, Q., Sun, Y., Huang, J., Song, H. (2023). Carbon storage estimation of mountain forests based on deep learning and multisource remote sensing data. *Journal of Applied Remote Sensing*, *17*(1), 014510–014510,

Xi, Z., Hopkinson, C., Rood, S.B., Peddle, D.R. (2020). See the forest and the trees: Effective machine and deep learning algorithms for wood filtering and tree species classification from terrestrial laser scanning. *ISPRS Journal of Photogrammetry and Remote Sensing*, *168*, 1–16,

Xiang, L., Yang, X., Hu, A., Su, H., Wang, P. (2022). Condition monitoring and anomaly detection of wind turbine based on cascaded and bidirectional deep learning networks. *Applied Energy*, *305*, 117925,

Yan, H., Cui, Z., Chen, X., Ma, X. (2022). Distributed multiagent deep reinforcement learning for multiline dynamic bus timetable optimization. *IEEE Transactions on Industrial Informatics*, *19*(1), 469–479,

Yang, H., Zhang, Z., Liu, X., Jing, P. (2023). Monthly-scale hydro-climatic forecasting and climate change impact evaluation based on a novel dcnn-transformer network. *Environmental Research*, *236*, 116821,

Yao, J., Chang, Z., Han, T., Tian, J. (2024). Semi-supervised adversarial deep learning for capacity estimation of battery energy storage systems. *Energy*, *294*, 130882,

Yi, Z., Liu, X.C., Wei, R., Chen, X., Dai, J. (2022). Electric vehicle charging demand forecasting using deep learning model. *Journal of Intelligent Transportation Systems*, *26*(6), 690–703,

Yoo, H., Kim, B., Kim, J.W., Lee, J.H. (2021). Reinforcement learning based optimal control of batch processes using monte-carlo deep deterministic policy gradient with phase segmentation. *Computers & Chemical Engineering*, *144*, 107133, You, J., Ampomah, W., Sun, Q., Kutsienyo, E.J., Balch, R.S., Dai, Z., ... Zhang, X. (2020). Machine learning based co-optimization of carbon dioxide sequestration and oil recovery in co2-eor project. *Journal of Cleaner Production*, *260*, 120866,

Yu, F., Chen, H., Wang, X., Xian, W., Chen, Y., Liu, F., ... Darrell, T. (2020). Bdd100k: A diverse driving dataset for heterogeneous multitask learning. *Proceedings of the ieee/cvf conference on computer vision and pattern recognition* (pp. 2636–2645).

Yu, J., Zheng, Y., Wang, X., Li, W., Wu, Y., Zhao, R., Wu, L. (2021). Fastflow: Unsupervised anomaly detection and localization via 2d normalizing flows. *arXiv preprint arXiv:2111.07677*, ,

Zahedi, A., Shafei, A.M., Shamsi, M. (2023). Application of hybrid robotic systems in crop harvesting: kinematic and dynamic analysis. *Computers and Electronics in Agriculture*, *209*, 107724,

Zhang, G., Chang, F., Jin, J., Yang, F., Huang, H. (2024). Multi-objective deep reinforcement learning approach for adaptive traffic signal control system with concurrent optimization of safety, efficiency, and decarbonization at intersections. *Accident Analysis & Prevention*, *199*, 107451,

Zhang, J., Chen, F., Cui, Z., Guo, Y., Zhu, Y. (2020). Deep learning architecture for short-term passenger flow forecasting in urban rail transit. *IEEE Transactions on Intelligent Transportation Systems*, *22*(11), 7004–7014,

Zhang, K., Tang, B., Deng, L., Liu, X. (2021). A hybrid attention improved resnet based fault diagnosis method of wind turbines gearbox. *Measurement*, *179*, 109491,

Zhang, W., Yu, Y., Qi, Y., Shu, F., Wang, Y. (2019). Short-term traffic flow prediction based on spatio-temporal analysis and cnn deep learning. *Transportmetrica A: Transport Science*, *15*(2), 1688–1711,

Zhang, Y., Chouinard, L.E., Power, G.J., Conciatori, D., Sasai, K., Bah, A.S. (2023). Multi-objective optimization for the sustainability of infrastructure projects under the influence of climate change. *Sustainable and Resilient Infrastructure*, *8*(5), 492–513, Zhang, Z., Kayacan, E., Thompson, B., Chowdhary, G. (2020). High precision control and deep learning-based corn stand counting algorithms for agricultural robot. *Autonomous Robots*, *44*(7), 1289–1302,

Zhang, Z., Vo, D.-N., Kum, J., Hong, S.-H., Lee, C.-H. (2023). Enhancing energy efficiency of chemical absorption-based co2 capture process with advanced waste-heat recovery modules at a high capture rate. *Chemical Engineering Journal*, *472*, 144918,

Zhao, H., Liu, H., Hu, W., Yan, X. (2018). Anomaly detection and fault analysis of wind turbine components based on deep learning network. *Renewable energy*, *127*, 825–834,

Zhao, J., Guo, Z., Guo, Y., Lin, W., Zhu, W. (2021). A self-organizing forecast of day-ahead wind speed: Selective ensemble strategy based on numerical weather predictions. *Energy*, *218*, 119509,

Zhao, Q., Gao, L., Meng, Q., Zhu, M. (2024). Climate warming will exacerbate unequal exposure to compound flood-heatwave extremes. *Earth's Future*, *12*(12), e2024EF005179,

Zhao, S., Duan, Y., Roy, N., Zhang, B. (2024). A deep learning methodology based on adaptive multiscale cnn and enhanced highway lstm for industrial process fault diagnosis. *Reliability engineering & system safety*, *249*, 110208,

Zheng, H., Wu, J., Li, R., Song, Y. (2025). The role of artificial intelligence in renewable energy development: Insights from less developed economies. *Energy Economics*, *146*, 108551,

Zhong, Y., & Li, Y. (2024). Statistical evaluation of sustainable urban planning: Integrating renewable energy sources, energy-efficient buildings, and climate resilience measures. *Sustainable Cities and Society*, *101*, 105160,

Zhong, Z., Hu, W., Zhao, X. (2024). Rethinking electric vehicle smart charging and greenhouse gas emissions: Renewable energy growth, fuel switching, and efficiency improvement. *Applied Energy*, *361*, 122904, Zhong, Z., Sun, A.Y., Yang, Q., Ouyang, Q. (2019). A deep learning approach to anomaly detection in geological carbon sequestration sites using pressure measurements. *Journal of hydrology*, *573*, 885–894,

Zhou, J., Cui, G., Hu, S., Zhang, Z., Yang, C., Liu, Z., … Sun, M. (2020). Graph neural networks: A review of methods and applications. *AI open*, *1*, 57–81,

Zhou, J., Lu, X., Xiao, Y., Tang, J., Su, J., Li, Y., … Dou, D. (2024). Sdwpf: a dataset for spatial dynamic wind power forecasting over a large turbine array. *Scientific Data*, *11*(1), 649,

Zhou, K., Zhou, K., Yang, S. (2022). Reinforcement learning-based scheduling strategy for energy storage in microgrid. *Journal of Energy Storage*, *51*, 104379,

Zhou, L., Huo, D., Chen, J., Bo, B., Li, H. (2025). Federated reinforcement learning with constrained markov decision processes and graph neural networks for fair and grid-constrained coordination of large-scale electric vehicle charging networks. *Scientific Reports*, *15*(1), 39593,

Zhu, L., Husny, Z.J.B.M., Samsudin, N.A., Xu, H., Han, C. (2023). Deep learning method for minimizing water pollution and air pollution in urban environment. *Urban Climate*, *49*, 101486,

Zhu, L., Song, R., Sun, S., Li, Y., Hu, K. (2022). Land use/land cover change and its impact on ecosystem carbon storage in coastal areas of china from 1980 to 2050. *Ecological Indicators*, *142*, 109178,

Zhu, Z., & Zhao, H. (2021). A survey of deep rl and il for autonomous driving policy learning. *IEEE Transactions on Intelligent Transportation Systems*, *23*(9), 14043–14065,

Zimmerling, C., Poppe, C., Stein, O., Kärger, L. (2022). Optimisation of manufacturing process parameters for variable component geometries using reinforcement learning. *Materials & Design*, *214*(110), 423,

Zou, Y., Lou, S., Xia, D., Lun, I.Y., Yin, J. (2021). Multi-objective building design optimization considering the effects of long-term climate change. *Journal of Building Engineering*, *44*, 102904,

Declaration of interests

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