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Deep learning for sustainable development: cross-disciplinary applications and responsible AI

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Abstract. Global climate change, energy shortages, food security crises, and urban sprawl pose multifaceted governance challenges for sustainable development. Leveraging its capacity for hierarchical representation learning from high-dimensional, heterogeneous data, deep learning has emerged as a core digital technology enabler for advancing the Sustainable Development Goals (SDGs). Employing a systematic literature review methodology and drawing on open-access publications from Google Scholar (2018-2026), this paper examines deep learning applications across four key domains: climate action, sustainable energy, smart agriculture, and smart cities. Through four comparative tables analyzing model suitability, data types, application outcomes, and challenges, the study identifies key bottlenecks in technology deployment from a "Responsible AI" perspective. It identifies three major industry trends: the large-scale deployment of physics-AI hybrid modeling, the growing dominance of deep reinforcement learning in energy dispatch, and the integration of federated learning with edge Artificial Intelligence (AI) for distributed ecological monitoring. Current implementation efforts remain constrained by four critical issues: regional data divides, a lack of model interpretability, algorithmic bias, and the high carbon footprint associated with large-scale models. By outlining corresponding optimization pathways, this paper provides a theoretical framework and practical guidance for green AI and sustainable digital governance.

Keywords: deep learning, sustainable development, UN SDGs, responsible AI

1. Introduction

The 2030 Agenda for Sustainable Development establishes 17 Sustainable Development Goals (SDGs) spanning climate, clean energy, food security, liveable cities, and ecological conservation. However, frequent extreme weather events, a reliance on fossil fuels, the vulnerability of smallholder agriculture, and growing urban pollution continue to exacerbate the limitations of traditional governance approaches. Conventional methods for environmental monitoring, resource allocation, and agricultural management—which rely on manual data collection and linear models—are incapable of processing the massive volumes of multimodal spatiotemporal data generated by satellite remote sensing, IoT sensors, and climate simulations. Deep learning addresses these limitations through capabilities such as automated feature extraction and nonlinear modeling. Although research confirms that AI can positively support 128 specific SDG targets, issues such as the environmental cost of computation, data silos, and algorithmic bias can hinder progress on 58 other targets, giving rise to an "AI–sustainability paradox."

Existing reviews exhibit significant limitations: while Toderas provided a comprehensive overview of AI applications in sustainable development, the study did not specify the application scenarios for underlying network architectures such as Convolutional Neural Network (CNNs), Graph Neural Networks (GNNs), and Transformers [1]; similarly, some reviews on Earth observation have focused exclusively on satellite image processing, overlooking the value of deep reinforcement learning and federated learning in system scheduling and distributed monitoring. Overall, the current literature largely consists of studies focused on specific sub-fields; there is a notable research gap in systematic reviews that span the four major sustainability domains, integrate underlying models, and address both practical implementation and ethical constraints.

This study employs a literature review methodology, utilizing Google Scholar as the primary database to select 112 articles published between 2018 and 2026. It constructs a comprehensive framework encompassing "underlying architecture," "multi-source data," "cross-domain applications," and "risk governance." By comparing model suitability, data source characteristics, application outcomes, and technical challenges, the study summarizes key industry trends and proposes optimization strategies to address the dilemmas of responsible AI.

At the theoretical level, this paper transcends the limitations of existing single-domain reviews by constructing a comprehensive analytical framework for deep learning-enabled sustainable development, thereby filling a gap in cross-disciplinary research. At the practical level, it offers guidance on model selection and data fusion for environmental regulators, new energy enterprises, digital agricultural platforms, and urban planning departments; simultaneously, it proposes technical and policy improvements for green AI and the governance of algorithmic ethics, facilitating the equitable global deployment of digital monitoring systems for the SDGs.

2. Deep learning infrastructure and data systems for sustainable development

2.1. Core deep learning architectures adapted for sustainability scenarios

2.1.1. Convolutional Neural Networks (CNNs): core tools for spatial imagery monitoring

By leveraging local receptive fields and weight sharing, CNNs are well-suited for processing 2D remote sensing imagery from satellites and drones for tasks such as image segmentation, object detection, and land-cover change detection. When applied to Sentinel-2 satellite imagery, CNNs enable precise classification of forests, croplands, and deserts, accounting for 40% of remote sensing classification applications. Architectures such as U-Net and residual CNNs address the vanishing gradient problem in deep networks and are widely used for flood boundary extraction, carbon source identification, and urban green space mapping; eliminating the need for manual feature engineering, they are ideal for the batch processing of large-scale Earth observation data.

2.1.2. RNNs and LSTMs: modeling time-series environmental data

LSTM and GRU networks address the limitations of traditional RNNs regarding long-term temporal dependencies, making them suitable for continuous time-series data from meteorological, soil, and power sensors. For instance, LSTM models integrating 72 hours of solar irradiance and wind speed data to predict photovoltaic power output have demonstrated a 30% accuracy improvement over linear regression; in agriculture, LSTM models processing multi-year soil moisture time-series data enable the assessment of agricultural vulnerability to drought and flooding [2]. However, these models have limited parallel computing capabilities and incur high computational costs when processing long time-series data, often leading to their combination with CNNs to construct hybrid spatiotemporal models.

2.1.3. Large-scale vision transformers: a new paradigm for multimodal remote sensing fusion

Self-attention mechanisms overcome the limitations of CNNs regarding local feature extraction, enabling the simultaneous capture of global spatial correlations and multi-band spectral information within images. Remote Sensing Vision Transformers (RSViT) fuse visible light and infrared satellite data to rectify spectral distortions associated with CNNs, while large-scale climate models leverage Transformers to simulate phenomena such as sea-level rise and extreme rainstorm evolution. However, these models are characterized by massive parameter counts and high energy consumption during training, making large-scale deployment challenging in low-income regions [3].

2.1.4. Graph Neural Networks (GNN): modeling spatially interconnected systems

GNNs represent entities such as farmlands, power grids, road networks, and ecological reserves as graph nodes, thereby capturing the spatial interdependencies of irregular geographic units. In the sustainable energy sector, GNNs are employed for power grid load flow calculations and the coordinated scheduling of distributed photovoltaic clusters [4]. In agriculture, they model the dynamics of water and nutrient flows as well as the spread of pests and diseases across regional plots. In urban governance, they characterize spatial couplings within transportation networks and among air quality monitoring stations, serving as a core architecture for cross-regional system optimization.

2.1.5. Generative Adversarial Networks (GANs): tools for small-sample data augmentation

Labeled samples for disasters and equipment defects are scarce in the sustainability sector; GANs generate synthetic samples to augment datasets, thereby reducing the costs associated with field data collection. In the photovoltaic industry, GANs generate samples of hotspots and cracks to facilitate automated inspections, while in ecology, they synthesize images of landslides and desertification to improve disaster recognition accuracy. Although diffusion models can simulate future urban ecological configurations, the generated samples exhibit geographic-spectral discrepancies and require calibration against real-world observational data [5].

2.1.6. Multi-architecture collaborative fusion: a mainstream industry trend

A single architecture cannot simultaneously handle three types of heterogeneous data—image, time-series, and geospatial network data—making hybrid multi-model architectures the industry consensus. Mainstream combinations include CNN-LSTM spatiotemporal models, GNN-Transformer global correlation models, and GAN-CNN frameworks for few-shot data augmentation. Physics-AI hybrid modeling couples physical equations governing climate, power systems, and crop growth, thereby addressing the lack of logical grounding inherent in purely data-driven models.

Table 1 summarizes the core advantages, compatible data types, typical application scenarios, and primary limitations of the five architectures discussed above, providing an intuitive reference for model selection across various sustainability-related contexts.

Table 1. Comparison of five deep learning architectures for sustainability scenarios [1, 3-5]

Model type	Core Advantages	Compatible Data Types	Typical Application Scenarios	Main Limitations
CNN	Image feature extraction, high-precision segmentation	2D satellite and UAV remote sensing imagery	Carbon source identification, forest monitoring, PV defect detection	Unable to capture long-term temporal dependencies; weak global long-range correlation
LSTM/RNN	Captures long-term temporal dependencies	Meteorological and power time-series data from sensors	PV output forecasting, drought temporal early warning	Low parallel computing efficiency; high computational cost for long sequences
Transformer	Global self-attention, multi-modal fusion capability	Multi-spectral satellite imagery + meteorological time-series hybrid data	Global extreme climate simulation, multi-scale remote sensing modeling	Large parameter scale; extremely high carbon emissions during training
GNN	Modeling of irregular geospatial correlations	Graph structure data of power grids, farmland and urban road networks	Power grid dispatch, pest spread modeling, air quality interpolation	Slow training speed for large-scale graph data
GAN	Few-shot data augmentation, scene simulation generation	Scarce disaster and defect samples	Virtual remote sensing sample generation, urban ecological simulation	Geospatial and spectral authenticity bias in generated samples

2.2. Three core data networks supporting sustainability research

Three types of core data networks—satellite and remote sensing networks, IoT sensor networks, and global climate and Earth observation datasets—underpin the global advancement of sustainability research. Table 2 systematically outlines these three core data networks supporting deep learning research in sustainability. By comparing them across four dimensions—representative data sources, spatial resolution, temporal update frequency, and core application areas—the table clearly illustrates the technical characteristics and operational boundaries of each data system, providing a reference for data selection in multimodal data fusion research.

2.2.1. Satellite and remote sensing observation data

The EU's Sentinel, the US's Landsat, and China's Gaofen satellites provide free, global, multi-temporal, and multispectral imagery, serving as core data sources for macro-scale ecological and climate monitoring [3]. Sentinel-2 offers a 10-meter resolution and provides monthly updates on vegetation and land surface temperature, while Landsat's long-term datasets enable the tracking of desertification and deforestation over nearly five decades. Unmanned Aerial Vehicles (UAVs) provide centimeter-level, micro-scale imagery, establishing a multi-scale observation system that combines "macro-scale satellite" and "micro-scale UAV" capabilities [6].

2.2.2. IoT sensor networks

Sensors deployed across farmlands, buildings, and urban areas collect time-series data—such as temperature, humidity, soil nutrients, PM2.5 levels, and power loads—in real time, forming a distributed data acquisition network. Edge devices locally preprocess the data before uploading it to the cloud, thereby reducing transmission energy consumption and supporting the decentralized training paradigm of federated learning [5].

2.2.3. Global climate and earth observation datasets

The CMIP6 climate simulation archive and datasets on global soil and carbon emission statistics—comprising historical meteorological data, greenhouse gas levels, and ecological parameters—are utilized for long-term climate change projections and carbon sink estimation. These datasets incorporate physical prior constraints that mitigate prediction errors inherent in purely data-driven models, serving as indispensable foundational resources for physics-AI hybrid modeling [7].

Table 2. Characteristics and application scopes of three major data sources for sustainable development [3, 6, 7]

Data Category	Representative Data Sources	Spatial Resolution	Temporal Update Frequency	Core Application Fields
Satellite Remote Sensing Data	Sentinel-2, Landsat 8/9	10 m – 30 m	Every 10-30 days	Global carbon accounting, forest monitoring, urban green space mapping
IoT Sensor Data	Farmland soil moisture terminals, air quality monitoring terminals	Meter-level point measurements	Hourly real-time updates	Load forecasting, precision irrigation, dynamic urban pollution monitoring
Climate Simulation Datasets	CMIP6, Global Soil Database	Hundred-kilometer grid	Annual historical archive	Extreme climate projection, agro-climatic vulnerability assessment

3. Landscape of deep learning applications across sustainability domains

3.1. Climate action and ecological environmental protection (SDG 13, SDG 15)

Climate and ecology represent the sectors where deep learning was first adopted and is best supported by data; applications fall into three main categories: emissions monitoring, long-term ecological monitoring, and disaster emergency response. CNN-based satellite imagery analysis identifies industrial carbon sources and forest carbon sinks, enabling grid-based carbon emission accounting; Transformer-based large-scale climate models provide 7-14-day early warnings for typhoons and heatwaves, achieving a 25% improvement in accuracy over traditional numerical models; and deep reinforcement learning optimizes the energy consumption of carbon capture equipment. U-Net quantifies annual deforestation areas, LSTM tracks the expansion of desertification, and GNNs assess the cascading ecological impacts of watershed pollution; the FAO utilizes these technologies for global annual forest surveys, significantly reducing the costs associated with field assessments [3]. Image segmentation algorithms rapidly delineate the boundaries of floods and landslides, while AI early-warning systems can reduce the risk of disaster-related casualties by 18%-22%.

3.2. Sustainable energy systems (SDG 7)

Deep learning addresses challenges such as the intermittency of renewable energy sources, the complexity of grid dispatch, and energy waste in buildings, covering five key application areas: power generation forecasting, equipment inspection, grid optimization, building energy efficiency, and solid waste recycling. A hybrid CNN-LSTM model integrates satellite solar irradiance data and meteorological time-series data, keeping the prediction error for wind and solar power output within 5%; GANs generate samples of photovoltaic defects, enabling automated inspections that reduce O&M costs by 40%. Deep reinforcement learning solves optimal power flow problems in the grid, achieving an accuracy two orders of magnitude higher than linear models; GNNs rapidly pinpoint overloaded transmission lines [4]; and reinforcement learning controls HVAC and lighting systems in smart buildings, reducing energy consumption by 20%-30%. CNN-based visual sorting systems enhance solid waste recycling efficiency, while time-series models optimize the layout of waste collection sites.

3.3. Smart agriculture and food security (SDG 2, SDG 6)

Precision agriculture leverages deep learning to achieve stable yields, water conservation, and reduced agrochemical use. CNN-based analysis of drone imagery achieves over 95% accuracy in detecting pests and diseases, thereby curbing overuse of chemical fertilizers and pesticides. Multimodal fusion models integrate satellite-derived vegetation indices with soil sensor data, achieving an R^2 of 0.83 in crop yield modeling. Graph Neural Networks (GNNs) enable the mapping of the spatial distribution of smallholder farms, facilitating the targeted allocation of digital agricultural resources and narrowing the agricultural technology gap between developed and developing nations. LSTM models assess the long-term impact of extreme weather on crops to identify agricultural vulnerability zones, while multimodal monitoring—combining satellite data and IoT—enables precision irrigation on demand, resulting in a 25% reduction in water consumption in agricultural fields [6].

3.4. Sustainable urban development (SDG 11)

Smart cities leverage AI to address air pollution, the urban heat island effect, and traffic congestion. Graph Neural Networks (GNNs) integrate the spatial relationships between monitoring stations to perform city-wide spatial interpolation of PM2.5 and ozone concentration maps; Convolutional Neural Networks (CNNs) extract data on urban green spaces and water bodies from satellite imagery, quantifying per capita ecological space to inform urban planning [5]. Image segmentation techniques automatically extract road network boundaries, while reinforcement learning optimizes traffic signal timing to reduce vehicular carbon emissions; additionally, generative AI facilitates the creation of coupled urban-ecological simulation models to assess the impact of new buildings and green spaces on heat islands and air quality, thereby guiding low-carbon urban planning.

3.5. Development trends in cross-domain general-purpose technologies

Synthesizing implementation cases across four major fields, existing research identifies three key development trends: First, physics–AI hybrid modeling has become mainstream. By coupling fundamental physical laws with data-driven models, this method ensures fitting accuracy while reinforcing the physical consistency of outputs. It effectively addresses issues inherent in pure deep learning models—such as poor generalization and the tendency to produce results that violate physical laws—thereby reducing cross-region transfer errors by over 15% [3]. For instance, in predicting extreme precipitation on high plateaus, a solution integrating numerical atmospheric dynamic equations with large-scale climate Transformer models retains the constraints of underlying physical laws while leveraging deep learning's ability to extract complex nonlinear features; this yields significantly higher prediction accuracy than traditional numerical models in areas with sparse weather stations and markedly reduces accuracy degradation during cross-basin transfer.

Second, multimodal data fusion has become standard practice. Heterogeneous data—including satellite remote sensing imagery, IoT time-series monitoring data, and geospatial graph structures—is fed into hybrid architecture models. Feature-level fusion allows these data types to complement each other's informational shortcomings, effectively eliminating the limitations of single data sources and significantly enhancing model robustness in complex scenarios [6]. For example, in county-level crop yield estimation, a multimodal model integrating satellite multispectral imagery, field soil temperature and humidity time-series data, and spatial correlation data for farmland plots achieves significantly better yield fitting results than unimodal models relying solely on satellite data; furthermore, it maintains stable predictive capabilities even when satellite data is missing due to adverse weather conditions.

Third, the combination of federated learning and edge AI enables decentralized monitoring. By leveraging edge computing devices to perform local model training at the data collection point and uploading only model update parameters to the central node—without sharing sensitive raw data regarding agricultural production or urban living environments—this approach reduces bandwidth and energy costs for data transmission and is well-suited for developing regions characterized by weak network infrastructure and high demands for data privacy [8]. For instance, in pest and disease monitoring scenarios for small-scale rice-growing areas in Southeast Asia, a federated learning framework coordinates edge monitoring nodes at the village and township levels; farmers' raw production and imagery data remain local throughout the process, with only model weights being synchronized. The model resulting from collaborative training demonstrates significantly higher recognition accuracy than models trained locally on single nodes, while completely eliminating the privacy risks associated with centralized storage of agricultural data [9].

Table 3 provides a comprehensive overview of deep learning applications across four key sustainability domains, identifying the corresponding UN Sustainable Development Goals and mainstream model technology pathways for each. It also quantifies the practical outcomes of implementing these technologies—such as improved energy efficiency, cost reductions, and emission reductions—based on data synthesized from representative research literature in the respective fields [1, 3-5].

Table 3. Summary of key deep learning applications and emissions reduction/efficiency gains across four sustainability domains

Application Domain	Corresponding SDG Goals	Main Model Combinations	Quantitative Application Effects
Climate and Ecological Conservation	SDG 13, SDG 15	CNN + Transformer + LSTM	25% improvement in extreme disaster warning accuracy; 60% reduction in manual costs for forest monitoring
Sustainable Energy Systems	SDG 7	CNN-LSTM + GNN + reinforcement learning	PV output prediction error ≤ 5%; 20%–30% reduction in overall building energy consumption
Smart Agriculture and Food Security	SDG 2, SDG 6	CNN + GAN + LSTM	30% reduction in pesticide and fertilizer use; 25% reduction in farmland water consumption
Sustainable Smart Cities	SDG 11	GNN + generative AI	15% reduction in carbon emissions from idling urban vehicles; full-coverage pollution monitoring with no blind spots

4. Discussion: core challenges and future optimization directions from the perspective of responsible AI

4.1. Four core bottlenecks in leveraging deep learning for sustainable development

4.1.1. Data scarcity in low-resource regions creating a digital sustainability divide

Regions such as Africa, Southeast Asia, and Latin America lack subscriptions to high-resolution satellite imagery and large-scale IoT device deployments, resulting in an extreme shortage of annotated environmental datasets. Supervised learning relies on vast quantities of labeled samples, and data gaps lead directly to significant drops in model accuracy; furthermore, existing datasets are predominantly collected from temperate zones in Europe and North America, leading to a 12%–18% increase in prediction errors when models are applied to tropical or arid regions, thereby preventing the equitable global distribution of AI-driven sustainability benefits [9].

4.1.2. Black-box nature of models and lack of interpretability and data transparency

CNNs, Transformers, and deep reinforcement learning models are typical "black-box" models; the specific features driving their outputs cannot be clearly identified. For instance, in the context of regional carbon trading quota allocation, a deep learning-based accounting model can directly generate allocation results for various industries but fails to clearly break down the weighted contributions of key factors—such as industrial point-source emissions, road traffic emissions, and carbon sink offsets from forestland—to the final outcome. Consequently, regulatory bodies struggle to trace the accounting rationale or verify compliance, rendering the algorithmic output unsuitable as formal evidence for official administrative decision-making. Policy decisions on carbon trading, ecological law enforcement, and agricultural subsidies require traceable algorithmic foundations, yet black-box model outputs lack the validity required for official governance evidence. Furthermore, the processes for remote sensing and sensor data acquisition and calibration lack transparency; biases in raw data propagate through to the model, leading to distorted governance decisions [8].

4.1.3. Algorithmic ethics and fairness risks

There is a significant regional bias in the training datasets, with energy and agriculture samples from developed countries accounting for over 70% of the total; consequently, model optimization favors the needs of developed regions while overlooking the demands of smallholder farmers and low-income communities. Furthermore, carbon emission accounting models rely heavily on commercial satellite data, underestimating emissions from rural lifestyles and small-scale agriculture, which leads to an imbalance in the allocation of climate governance resources. Underlying this bias is a deeper issue of data sovereignty asymmetry: while mainstream global projects in agricultural remote sensing, ecological monitoring, and climate modeling routinely collect raw data on land use, crop production, and carbon emissions from developing regions—such as Africa, Southeast Asia, and Latin America—the development, iteration, patenting, and commercialization of core models are predominantly led by research institutions and enterprises in developed countries. Developing nations struggle not only to participate in rule-setting and governance decisions regarding these models but also to access technological outcomes tailored to local smallholder farming practices and ecological characteristics. In some instances, they are even required to pay for monitoring tools trained on their own domestic data, creating an inverted pattern where data resources flow out of developing countries while technological benefits concentrate in developed ones, thereby widening the digital divide in global sustainable governance. Additionally, remote sensing monitoring involves land property rights and farmers' operational privacy; the cross-border transmission and centralized storage of such data entail risks regarding data security and privacy infringement [10].

4.1.4. Large models and the "green AI" paradox

Training massive vision and climate Transformers consume substantial computational power; the carbon emissions from a single full training run are equivalent to the annual emissions of a hundred household cars, while also consuming vast amounts of water for cooling. Since data centers largely rely on fossil fuels for power, the expansion of AI computing capacity paradoxically exacerbates greenhouse gas emissions, and hardware turnover generates significant electronic waste, creating an inherent contradiction where "AI addresses environmental issues while simultaneously causing pollution" [11].

Table 4 systematically summarizes the four core challenges mentioned above, presenting them across four dimensions: challenge classification, core manifestations, affected regions and groups, and negative impacts on sustainable development. It comprehensively covers obstacles spanning data barriers, technical limitations, ethical risks, and environmental costs, with conclusions that align with the consensus found in existing research [8-11].

Table 4. Four core challenges of responsible AI and their respective scopes of impact

Challenge Category	Core Manifestation	Affected Regions / Groups	Negative Impacts on Sustainable Development
Regional Data Scarcity	Lack of labeled observation datasets in low-income countries	Smallholder farmers and environmental authorities in Africa, Southeast Asia and Latin America	Lack of regional SDGs monitoring capacity and widening development gaps
Lack of Model Interpretability	Black-box models cannot provide valid basis for decision-making	Carbon regulatory agencies, ecological law enforcement departments and agricultural policy institutions	AI outputs cannot be adopted as formal official governance policies
Algorithmic Fairness and Ethical Bias	Datasets are biased toward samples from developed regions	Farmers in developing countries and low-income urban residents	Uneven allocation of climate and agricultural support resources
High-Carbon Pollution from AI Computing	Excessive energy consumption and carbon emissions from large model training	Global AI R&D institutions across all fields	Offsets emission reduction benefits brought by AI and aggravates environmental burden

4.2. Pathways for improving responsible AI for sustainable development

To address four major bottlenecks, implementation and optimization strategies are proposed across four layers: data, technology, ethics, and computing power:

First, overcome data scarcity through few-shot and unsupervised learning. Employ transfer learning—leveraging pre-trained remote sensing models from Europe and the US followed by fine-tuning with small local datasets—to reduce annotation costs; use GANs to generate synthetic samples for dataset augmentation; and establish a global, free platform for sharing SDG observation data, providing low-income nations with access to raw satellite and meteorological data [9].

Second, enhance transparency by integrating Explainable AI (XAI) technologies. Incorporate attention visualization and feature weight analysis modules into CNNs and GNNs to intuitively display the core observation indicators influencing prediction results; establish end-to-end data traceability standards that fully document data collection, calibration, and cleaning processes to satisfy carbon regulation and ecological audit requirements [8].

Third, construct a fair and privacy-preserving algorithmic governance framework. Incorporate samples from diverse global regions to eliminate geographic bias; widely adopt federated learning and edge computing so that raw monitoring data never leaves the collection terminal, thereby preventing privacy leaks for farmers and citizens; and introduce fairness assessment standards for sustainable AI that include regional equity as a model performance metric [10].

Fourth, reduce the environmental footprint of computing power through lightweight, green AI. Develop compact, lightweight neural networks that cut computational consumption by 70% while maintaining equivalent accuracy; transition data centers to clean energy sources such as solar and wind power and utilize water-recycling cooling systems; and establish carbon emission accounting standards for AI models, prioritizing the deployment of low-carbon, lightweight inference models [11].

5. Conclusion

This paper conducts a systematic literature review to synthesize relevant studies from Google Scholar (2018-2026) and establishes a comprehensive analytical framework for deep learning-enabled sustainable development. Four quantitative comparison tables are provided to clearly illustrate key patterns across four dimensions: model suitability, data sources, application outcomes, and technical challenges. The study confirms that five fundamental architectures—CNN, LSTM, Transformer, GNN, and GAN—are respectively suited for scenarios involving spatial imagery, time-series data, multimodal data, geographic networks, and small-sample augmentation. Trends toward cross-domain integration include physics-AI hybrid modeling, multimodal data fusion, and federated edge-based distributed monitoring. Furthermore, deep learning significantly enhances resource utilization efficiency and environmental monitoring accuracy across the four key sectors of climate, energy, agriculture, and urban systems, directly supporting the implementation of the 17 UN Sustainable Development Goals (SDGs).

At the theoretical level, this paper moves beyond the limitations of existing single-domain reviews by refining the theoretical framework of "foundational technologies—cross-domain applications—ethical constraints," thereby filling a gap in cross-disciplinary integrated research. At the practical level, it quantitatively compares the applicability boundaries of various models and data types through tables, offering clear technical selection strategies for digital governance in the industry and delivering value for both industrial implementation and policy formulation.

This study has two limitations: first, the literature coverage is constrained, leaving room for expansion into further areas; second, the methodology relies solely on qualitative synthesis and tabular statistics rather than a large-scale quantitative meta-analysis, resulting in a lack of comparative quantitative analysis across different model performance metrics. Future research will expand database searches and incorporate a broader range of sources for meta-analysis, while also conducting field-based case studies in low-income countries to refine localization strategies for responsible AI.

Overall, deep learning serves as a pivotal digital tool for advancing global sustainable development; however, unlocking its full potential requires the integration of lightweight, green computing power, explainable algorithms, and equitable ethical governance frameworks. Balancing technological efficacy with environmental and social costs is essential to achieving a mutually reinforcing synergy between AI and sustainable development, thereby providing long-term digital support for the 2030 Agenda for Sustainable Development.

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