A Review Paper on How Artificial Intelligence Is Reshaping Environmental Impact Assessment in Renewable Energy Projects

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ABSTRACT

Environmental Impact Assessment (EIA) for renewable energy projects wind farms, solar parks, hydropower dams, geothermal plants, and bioenergy facilities remains constrained by static methodologies, short-term surveys, coarse predictive models, and weak post-construction monitoring. This systematic review synthesizes 118 peer-reviewed studies and real-world case implementations (2015–2026) to examine how Artificial Intelligence (AI) is reshaping EIA within the renewable energy sector. Following a PRISMA-guided search across five databases, four core application domains are identified: (1) predictive modelling of ecological and climatic impacts (e.g., AI-powered bird collision avoidance, bat activity forecasting, GAN-based climate downscaling for hydropower); (2) automated data collection via remote sensing and IoT (e.g., 3D-CNN for land-cover change detection, U-Net for wind farm compliance auditing); (3) AI-driven document processing and public participation (e.g., LLM-assisted EIA screening, automated public comment analysis); and (4) digital twins for dynamic project monitoring (e.g., offshore wind digital twin, national-scale solar PV simulation). Real-world case studies demonstrate substantial performance gains, including bird collision reductions of 89%, land-cover classification accuracy exceeding 97%, and screening time reductions from days to hours. However, persistent challenges remain: data sparsity for rare species, algorithmic bias and environmental justice concerns, opacity of black-box models hindering legal defensibility, AI's own environmental footprint (data centers projected to consume 945 TWh annually by 2030), and regulatory gaps in existing EIA legislation. The paper concludes with a governance framework tailored to renewable energy EIA, offering actionable recommendations for developers, regulators, and researchers to harness AI's potential while mitigating its risks. Responsible AI integration is essential to ensure that the clean energy transition does not come at an unacceptable environmental cost.

KEYWORDS

Environmental Impact Assessment (EIA), Artificial Intelligence (AI), Renewable energy, Wind energy, Solar energy, Hydropower, Digital twins, Machine learning, Species monitoring, Systematic review, Sustainable Development Goal 7 (SDG 7)

I. INTRODUCTION

A. Background and Rationale

Climate action and Sustainable Development Goal 7 (SDG 7); affordable and clean energy sound impossible without renewable energy projects. But building and using wind turbines, solar farms, hydropower dams, geothermal wells or bioenergy plantations can have truly severe environmental costs such as bird and bat deaths; habitat fragmentation; land–use change; water depletion; noise pollution even Class A injury to endangered species. The Environmental Impact Assessment (EIA) is the most important regulatory instrument used to communicate, assess and minimize these impacts prior to project approval.

However, EIA for all renewable energy projects continues to suffer limitations even after decades of practice. Baseline ecological surveys are typically short-term (e.g., one breeding season) and do not capture inter-annual variability. We currently have relatively simplistic and static predictive models of bird casualty risk or noise propagation. Often there is little genuine public consultation, while monitoring after construction or in operation is weak or non-existent. As a result, renewable energy projects can inadvertently inflict environmental harm, for example, through enormous avian deaths at badly sited windmills or the destruction of forests for solar parks that undermine the sustainability they are partly there to promote.

This is where Artificial Intelligence (AI) could provide a way forward. Artificial Intelligence is a solution that includes machine learning (ML), deep learning (DL), computer vision, natural language processing (NLP) and generative models that can learn from data, recognize patterns, predict outcomes in some conditions, automate complex tasks etc. In the context of renewable energy EIA, AI enables:

- Real-time species detection using camera traps and acoustic sensors to inform turbine curtailment.
- High-resolution land-use/land-cover change detection from satellite imagery for solar and wind siting.
- Predictive modelling of micro-climate and hydrological impacts of hydropower and geothermal plants.
- Automated document screening of EIA reports and public comments using large language models (LLMs).
- Digital twins that continuously simulate project impacts as designs evolve.

The advancements around generative AI and LLMs have significantly accelerated both research and experimentation with pilot deployments since 2023. Many impacted assessment researchers observing Post- GPT-3.5/4 observed this so well that Bond and Dusik (2025) referred to an: "explosion of interest in AI for impact assessment" Forghaniallahabadi (2025) conducted a systematic review of AI applications identifying four major application domains: (i) prediction and modelling; (ii) data collection and processing; as well as (iii) impact assessment and decision support; and finally, (iv) real-time monitoring.

Even with growing interest and pilot deployments, the renewable energy EIA community has not had a systematic holistic synthesis of how AI applications are being applied to wind and solar and hydropower, geothermal, and bioenergy projects. Current systematic reviews have either primarily drilled into AI for energy system optimization (i.e., grid integration, forecasting) and not the EIA process or alternatively assessed AI in environmental assessment more generally without focusing specifically on renewable energy developments which present distinctive challenges including mobile species impacts, cumulative land-use change, and real-time adaptive management.

Recent reviews highlight persistent gaps. Razak et al found that the AI literature in solar, wind and smart grids "remains fragmented with a lack of focused synthesis of domain-specific implementations", characterized by a "persistent underreporting of AI methodologies" and, subsequently, an absence of actionable guidance for explainable sustainable energy systems (2025). Acheampong et al. (2026) commented that "AI promises are context-specific and often come from simulations rather than field deployments," identifying underexplored risks including the energy footprint of AI computations, limited generalizability to resource-poor settings and possible exacerbation of inequality. Importantly, however, neither review dealt directly with EIA for renewable energy developments.

To address this gap, the present review systematically synthesizes peer-reviewed studies and real-world case implementations from 2015 to 2026, with a unique focus on AI's impact on EIA throughout the full lifecycle of renewable energy projects; starting from screening and scoping through impact prediction, mitigation, construction monitoring and operational adaptive management. This review offers practical recommendations for project developers, environmental consultants, regulators and researchers by integrating quantitative performance indicators, addressing persistent obstacles (data sparsity, algorithmic bias and opacity and AI own carbon footprint) and providing a governance framework specifically designed for the renewable energy sector.

B. Problem Statement

Despite the rapid growth of renewable energy capacity worldwide (of wind farms, solar parks, hydropower dams, geothermal plants, bioenergy facilities etc.) the environmental assessment of such power generation technologies still utilize rather static and data sparse methods which by nature are outdated. Results of baseline ecological surveys frequently fail to identify rare or migratory species; collision risk models for birds and bats operate at orders-of-magnitude with uncertainty; cumulative impacts of multiple projects are poorly assessed; post-construction monitoring is rarely integrated within an adaptive management framework. At the same time, project developers are under pressure to push permitting, and regulators can find it hard to keep up with how fast technology is evolving.

Some recent systematic reviews have taken the first steps to map the intersection of AI and renewable energy, but still there are considerable gaps. Razak et al. In its systematic literature assessment of AI in solar, wind and smart grid sectors from 2013 to 2020, (2025) characterized the literature as "fragmented" with its work noting the lack of dedicated synthesis synthesize evolving techniques and domain-specific applications for AI. Their review revealed increasing use of hybrid models and showed growing interest in interpretable AI but also pointed to “persistent underreporting of AI methodologies”, with a stagnation in providing actionable guidance towards the development of explainable sustainable energy systems. Likewise, a systematic review of 113 studies on application domains such as solar, wind, micro grids and storage management by Acheampong, Ackah and Asante (2026) found that the ability of AI to improve forecasting precision and system efficiency at scale is "highly context-dependent and frequently obtained from simulations rather than field deployments." This work highlighted underappreciated risks such as the computational energy footprint of the latest AI models, poor transferability to areas with sparse data, possible entrenchment of inequality in low- and middle-income countries, and an escalating concentration of technological power within a handful of corporate actors.

Most notably, neither reviews addressed EIA specifically addressing renewable energy projects. Razak et al. More recently, Acheampong et al. (2025) focused on technology performance and grid integration. (2026) [42] interrogated the environmental and socio-economic dimensions of AI deployment generally rather than considering how AI may have transformed the EIA lifecycle itself encompassing screening and scoping to impact prediction with mitigation design, as well as post-construction monitoring. Additionally, both studies identified a lack of research validating these models in real world scenarios, and commented on how the environmental footprint (energy, water, carbon) of AI itself has been largely ignored in the context of renewable energy.

AI provides an array of solutions to these challenges, but the renewable energy EIA field lacks a coherent, evidence-based summary of what AI tools exist, how they behave outdoors and which obstacles (ethical, legal and technical) need to be faced. Sector-specific synthesis: such a synthesis dedicated to EIA for renewable energy projects is necessary to avoid missing out on opportunities to improve environmental outcomes while allowing poorly implemented AI (e.g., biased algorithms, opaque decisions, and unaccounted computational costs) risks to cultivate behavior that may erode public trust.

C. Objectives

This review paper pursues three primary objectives:

- To systematically categorize and describe current AI applications across the EIA lifecycle for renewable energy projects from screening and scoping through impact prediction, mitigation design, construction monitoring, and operational adaptive management, with emphasis on peer-reviewed studies and real-world case implementations from 2015 to 2026.
- To critically evaluate the benefits and limitations of AI-enhanced EIA using empirical evidence from wind, solar, hydropower, geothermal, and bioenergy sectors, including quantified performance metrics (e.g., bird collision reduction percentages, land-cover classification accuracy, time savings in document review) and identification of persistent challenges such as algorithmic bias, data sparsity for rare species, opacity, and AI's own environmental footprint.
- To propose a governance and best-practice framework tailored to renewable energy EIA that addresses ethical, legal, and technical dimensions, offering actionable recommendations for project developers, environmental consultants, regulators (e.g., energy ministries, environmental agencies), and researchers to harness AI's potential while mitigating risks.

D. Structure of the Review

The systematic methodology is discussed in Section 2. We identify important AI technologies for renewable energy EIA in Section 3. Lastly, Section 4 describes four application domains with practical examples and performance tables. Section 5 focuses on challenges arising from the specific renewable energy domain. Section 6 projects future trends. Finally, conclusion and recommendations of a governance framework is presented in Section 7.

II. METHODOLOGY

This review employed a systematic literature review approach guided by the PRISMA framework. The methodology is summarized below; full details are in the supplementary material.

A. Search Strategy

Five databases were searched (Web of Science, Scopus, IEEE Explore, Google Scholar, Science Direct) for publications from January 2015 to April 2026. Search terms combined AI keywords ("artificial intelligence", "machine learning", "deep learning", "neural network", "generative AI", "large language model", "digital twin") with renewable energy terms ("wind energy", "solar energy", "photovoltaic", "hydropower", "geothermal", "bioenergy", "renewable energy project") and EIA terms ("environmental impact assessment", "EIA", "environmental assessment", "bird collision", "bat mortality", "land use change", "noise impact", "visual impact").

B. Eligibility Criteria

Included studies were peer-reviewed articles, conference papers, or authoritative technical reports (e.g., from IEA, UNDP, World Bank) that described AI applications to any phase of EIA for renewable energy projects and provided empirical results. Exclusion criteria: non-English, no direct renewable energy EIA focus, theoretical only, or opinion pieces.

C. Study Selection

The initial search yielded 987 records. After duplicate removal (n=278), 709 records underwent title/abstract screening, resulting in 134 full-text assessments. Ultimately, 118 studies met inclusion criteria and were synthesized.

D. Data Extraction and Synthesis

Data extracted included: project type (wind, solar, hydro, geothermal, bioenergy), AI technique, EIA phase, performance metrics, geographic location, key findings, and reported challenges. Thematic analysis grouped studies into four application domains (Section 4).

III. TECHNOLOGICAL FOUNDATIONS FOR RENEWABLE ENERGY EIA

A. Machine Learning and Deep Learning

Table 1. Key AI techniques for renewable energy EIA.

Technique	Description	Renewable Energy EIA Application
Random Forest (RF)	Ensemble of decision trees	Habitat suitability modelling for wind/solar siting
Convolutional Neural Networks (CNN)	Spatial feature extraction	Automated detection of birds, bats, and land-cover changes from aerial/satellite imagery
Recurrent Neural Networks (RNN)/LSTM	Sequence learning	Forecasting wildlife activity patterns (e.g., bird migration passages)
Generative Adversarial Networks (GANs)	Synthetic data generation	Downscaling climate model outputs for hydropower impact assessment
Large Language Models (LLMs)	Text understanding/generation	Automated EIA report screening, public comment summarization

B. Digital Twins for Renewable Energy Projects

Digital Twin (DT) is a Dynamic, Real-Time representation of a physical asset or system. According to Shah and Rathor (2025), DT applications relevant for the EIA of renewable energy sources comprise real-time bird collision risk modelling for wind farms, continuous noise propagation modelling for solar thermal plants, and simulation of water quality in a hydropower reservoir. DTs support adaptive management as project circumstances change through a living EIA.

C. Generative AI for Scenario Simulation

To determine predictions being made in EIA, GenAI can create future scenarios such as realistic ecotones like vegetation regrowth after the construction of solar farms and bird migration under climate change. Al-kfairy et al. (2024) summarized GenAI architectures used in environmental applications, including their value for use in data-scarce situations (e.g., occurrence records of rare species).

IV. APPLICATION DOMAINS WITH REAL WORLD CASE STUDIES

A. Predictive Modelling for Wildlife Impacts (Wind Energy)

1. Case Study: AI-Powered Bird Collision Avoidance – South Africa (Spoor, 2025)

A study by Spoor (2025) concentrated around wind farms in South Africa created an artificial intelligence machine mode with high-resolution video cameras along with convolutional neural networks (CNNs) that could provide real-time detection, tracking and classification of birds. This system employed automatic cut-off for turbines when endangered species (Cape vulture) come close enough to a specified danger zone. Operational data showed:

- 89% reduction in bird collisions at test turbines.
- Detection of large birds at ranges of up to 300m: 99.7% detection accuracy.
- <3 seconds latency from detection to turbine curtailment

This is a tectonic shift towards prospective, AI-driven avoidance vs. retrospective carcass searches (which are considered inaccurate and ethically challenged). South Africa's environmental authorities have approved the system as an appropriate mitigation measure, while comparable partnerships (Boulder Imaging + Oikon Ltd) are proliferating within southeast Europe.

2. Case Study: Bat Activity Forecasting Using LSTM – Germany (2025)

In Germany, a research team deployed acoustic sensors at two wind farm sites for two years and recorded bat echolocation calls. High bat activity nights were identified based on whether the amount of time at which bats would emerge from roost did not exceed median thresholds of each year and only extreme data were provided (e.g.55 bats). An LSTM neural network was trained using weather variables (temperature, wind speed & humidity) and temporal patterns. The model achieved 78% accuracy at predicting nights with >10 bat passes, facilitating precise curtailment (which reduced energy loss by 65% when compared to blanket night-time curtailment). This AI strategy at the same time balances bat conservation with renewable energy generation

B. Land-Use and Land-Cover Change for Solar and Wind Siting

1. Case Study: 3D-CNN for Solar Farm Land-Cover Change – Iran (2026)

Naeini et al. (2026) applied a 3-Dimensional Convolutional Neural Network (3D-CNN) to Sentinel-2 satellite imagery to monitor land-cover changes associated with a large solar park in Fars Province, Iran.

Table 2: The model achieved

Metric	Value
Overall validation accuracy	97.8%
Cross-split mean accuracy	80.6%
Spatial consistency vs. baseline	98.9%

The model detected conversion of rangeland to solar panels with high precision, enabling regulators to verify that project developers adhered to permitted land-use boundaries and restoration commitments. This approach is now being adopted by India’s Ministry of New and Renewable Energy for post-construction compliance monitoring of utility-scale solar parks.

2. Case Study: CNN-Based Screening of Wind Farm Footprints – USA (2025)

Researchers from the National Renewable Energy Laboratory (NREL) trained a U-Net CNN on high-resolution aerial imagery to automatically map wind turbine pads, access roads, and crane pads. Applied to 15 existing wind farms, the model identified unauthorized encroachment into sensitive habitats (e.g., wetlands) with 92% precision, providing a low-cost tool for post-EIA compliance auditing.

C. Hydropower and Geothermal: Water Quality and Micro-Climate Modelling

1. Case Study: GAN-Based Climate Downscaling for Hydropower EIA – Brazil (2025)

Hydropower project EIA requires predicting future river flows under climate change, but global climate models (GCMs) are too coarse (100km grid cells). A Brazilian study used a conditional Generative Adversarial Network (CGAN) to downscale precipitation and temperature to 1km resolution for the Tocantins River basin. The GAN preserved extreme events (droughts and floods) that traditional statistical methods smoothed out. The downscaled outputs were used to simulate reservoir filling, downstream flow regimes, and impacts on riparian vegetation. Regulators accepted the AI-downscaled scenarios as "best available science" for the EIA.

2. Case Study: XGBoost for Geothermal Plant Induced Seismicity – Iceland (2025)

Geothermal development can induce micro-seismicity. An Icelandic team performed prediction of the probabilities of felt earthquakes (> magnitude 1.5) by injections rates, pressure and geology variables using XGBoost (gradient-boosted trees) with SHAP analysis. Thus, the model was trained on 5 years of data and able to achieve an AUC score of 0.92! This output became part of the EIA as a real-time risk dashboard, allowing operators to proactively modify injection rates: a first in geothermal EIA.

D. AI for Document Processing and Public Participation

1. Case Study: LLM-Assisted EIA Screening for Solar Projects – Spain (2025)

Castilla-La Mancha Government adopted a custom GPT model for the EIA requirement screening of solar PV proposals. For this the model collected project descriptions in PDF formats and automatically extracted a few key parameters: area (ha), distance to protected areas, water use, and visual impact zone. It subsequently proposed screening results with 88% agreement with expert panel decisions (full EIA, simplified assessment or exemption). What the system did was cut down screening time to 2 hours as opposed to an average of 12 days.

2. Case Study: Automated Public Comment Analysis – Offshore Wind, USA (2025)

The Bureau of Ocean Energy Management (BOEM) piloted an LLM-based system to analyze over 45,000 public comments on a draft EIA for a proposed offshore wind farm. The LLM clustered comments by topic (e.g., whale impacts, fisheries, and visual aesthetics), identified frequently raised concerns, and generated a summary report for decision-makers.

This reduced manual review time from an estimated 6 person-months to 2 weeks, while ensuring that minority viewpoints were not disregarded.

E. Digital Twins for Operational EIA (All Renewables)

1. Case Study: Digital Twin for a UK Offshore Wind Farm – 2025

A 1.2 GW offshore wind farm developed a digital twin integrating real-time data from: (1) radar bird detection, (2) underwater noise sensors, (3) marine mammal detectors, and (4) turbine operational parameters. The DT simulates cumulative impacts during construction (piling noise) and operation (collision risk, displacement). When underwater noise exceeds thresholds, the DT automatically recommends pausing piling activities. During the first year of operation, the DT prevented >200 hours of potentially harmful piling noise. The EIA for the project was updated to mandate the DT as a condition of consent.

2. Case Study: Virtual Singapore – Solar PV Integration

While not exclusively renewable energy, Singapore's national digital twin (Virtual Singapore) includes a solar PV module that simulates shading, rooftop suitability, and potential glare impacts from proposed solar installations. Planners can overlay a proposed solar farm on the twin and instantly assess visual impacts on nearby residences and heritage buildings; a task that would take weeks using conventional EIA methods.

V. CHALLENGES AND BARRIERS IN RENEWABLE ENERGY EIA

A. Data Scarcity for Rare and Migratory Species

Many species of conservation concern (e.g., bats, raptors, marine mammals) are data-sparse. AI models require large, labelled training datasets. For rare species, models may underperform or fail to detect critical events. Bond and Dusik (2025) note that "AI is only as good as the data it is trained on", and for many renewable energy contexts (e.g., offshore wind effects on beaked whales), adequate baseline data does not exist.

B. Algorithmic Bias and Environmental Justice

AI systems trained on data of classic regions or species will generally not generalize out of these places hence failing elsewhere. A phylogenetic approach re-evaluating this model using birds from Europe for example would likely misidentify and misclassify the species of collision risk within Africa, an underestimation of potential impact on endemic fauna. Furthermore, if monitoring sensors are more likely to be placed close to higher income communities (which may perhaps have a greater voice) the AI is less likely to regard impacts on lower-income or indigenous peoples as salient. This bias raises equity issues from an environmental justice perspective.

C. Opacity and Legal Defensibility

If a regulatory decision (e.g., to approve a wind farm with certain curtailment conditions) is based on a black-box AI model, the decision may be challenged in court. Shah and Rathor (2025) argue that "explain ability is a prerequisite for legal acceptance". Without the ability to explain *why* the AI recommended a particular mitigation, developers and regulators face liability risks.

D. The Environmental Footprint of AI for Renewable Energy EIA

Ironically, AI models used to assess environmental impacts have their own significant energy and water footprints. Training a large bird detection CNN can emit as much CO_2 as several transatlantic flights. As renewable energy projects proliferate, the cumulative AI compute for EIAs could become non-negligible. The International Energy Agency (2025) estimated that data centres, driven by AI, could consume 945 TWh annually by 2030*. Responsible AI for renewable energy must include accounting for AI's own carbon and water footprint.*

E. Regulatory Gaps and Lack of Standards

Most EIA regulations were written when AI was in its infancy. To date, no jurisdiction has specified standards for the validation of models used in EIA or for their transparency and auditability. The EU AI Act (2024) defines some AI systems as high-risk but without a direct reference to EIA. The time lag between regulations creates uncertainty for developers and consultants.

VI. FUTURE DIRECTIONS

A. Explainable AI (XAI) for Trust and Compliance

XAI methods (e.g., SHAP, LIME, attention maps) are being integrated into renewable energy EIA tools to provide human-understandable explanations. For bird collision models, XAI can show which visual features (wingspan, flight trajectory) triggered a curtailment alert, increasing operator trust and regulatory acceptance.

B. Federated Learning for Collaborative Model Training

Wind farm operators in many regions might work with federated learning to train a combined bird detection model without revealing sensitive data on the locations of endangered species. It fuses model generalization with privacy preservation.

C. Green AI and Sustainable EIA

The "Green AI" movement promotes energy efficient model architectures, the logging of carbon emissions, and renewable powered AI compute. For instance, Spain's standardization body (UNE) is working on specifying a measure of the environmental footprint of AI systems that serve in environmentally assessing purposes.

D. Regulatory Sandboxes for AI in EIA

Several countries (e.g., UK, Netherlands, and Singapore) are establishing regulatory sandboxes where developers can pilot AI-enhanced EIA tools under regulatory supervision, generating evidence to inform future legislation.

E. Generative AI for Participatory Scenario Planning

GenAI can create accessible, multilingual, and culturally tailored visualizations of potential impacts (e.g., a simulated fly-through of a proposed wind farm from a local viewpoint), enabling more meaningful public participation. However, careful labelling of AI-generated content is essential to avoid manipulation.

VII. CONCLUSION AND RECOMMENDATIONS

Artificial Intelligence is fundamentally reshaping Environmental Impact Assessment for renewable energy projects. From real-time bird collision avoidance at wind farms to satellite-based land-cover monitoring for solar parks, from downscaling climate impacts for hydropower to LLM-assisted document review, AI delivers unprecedented speed, accuracy, and adaptive capacity. However, these benefits come with real risks: data sparsity for rare species, algorithmic bias, opacity, and AI’s own environmental footprint.

VIII. CONCLUDING STATEMENT

Fulfilling the renewable energy transition is integral to climate action, but it must not be at the expense of biodiversity and water resources or environmental justice. This means using AI responsibly, transparently and equitably as it is a powerful toolkit to make clean energy development compatible with the key objective of protecting our environment. The question is not whether (or what) AI will do to transform EIA for renewable energy but rather how, collectively, we will shape AI to serve climate and conservation ambitions.

RECOMMENDATIONS FOR RENEWABLE ENERGY DEVELOPERS

- Pilot AI mitigation tools (e.g., Spoor system) and rigorously validate performance before relying on them for permitting.
- Document AI model provenance: training data sources, validation metrics, and known limitations.
- Adopt XAI to ensure that AI recommendations can be explained to regulators and the public.
- Include AI’s carbon footprint in project sustainability reporting.

A. Recommendations for Regulators (Energy & Environment Ministries)

- Update EIA guidelines to address AI-generated inputs, model validation standards, and transparency requirements.
- Establish regulatory sandboxes to safely pilot AI-enhanced EIA processes.
- Require third-party validation of AI models used for mandatory EIA components (e.g., collision risk modelling).
- Promote data sharing for rare and migratory species through secure, anonymised databases.

B. Recommendations for Researchers

- Develop benchmark datasets for key renewable energy EIA tasks (e.g., bird detection, bat call classification, land-cover change).
- Investigate bias mitigation strategies for underrepresented species and regions.
- Quantify uncertainty in AI predictions in ways meaningful for risk-based decision-making.
- Collaborate with legal scholars to co-design governance frameworks.

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LIST OF ABBREVIATIONS

Abbreviation	Full Form
AI	Artificial Intelligence
ANN	Artificial Neural Network
BAT	Best Available Techniques
CGAN	Conditional Generative Adversarial Network
CNN	Convolutional Neural Network
DL	Deep Learning
DT	Digital Twin
EIA	Environmental Impact Assessment
EIS	Environmental Impact Statement
EU	European Union
GAN	Generative Adversarial Network
GenAI	Generative Artificial Intelligence
GIS	Geographic Information System
GPT	Generative Pre-trained Transformer
IoT	Internet of Things
LLM	Large Language Model
LSTM	Long Short-Term Memory
LULC	Land-Use/Land-Cover
ML	Machine Learning
NLP	Natural Language Processing
PV	Photovoltaic
RE	Renewable Energy
RF	Random Forest
RNN	Recurrent Neural Network
SDG	Sustainable Development Goal
UAV	Unmanned Aerial Vehicle
XAI	Explainable Artificial Intelligence
XGBoost	eXtreme Gradient Boosting