Physical Education, Health and Social Sciences

https://journal-of-social-education.org
E-ISSN: 2958-5996
P-ISSN: 2958-5988

Satellite-Based Environmental Monitoring: AI-Assisted Analysis for Land, Water, and Air Systems

Ayesha Naz[1], Abdul Wasay[2], Samsor Sherani[3], Abdul Wahab Ul Murtaza[4], Iqra Aslam[5], Muhammad Haseeb Saleem[6], Saif ul Rehman[7], Muhammad Naveed Khalil[8]

[1] Department of Meteorology, COMSATS Islamabad, Email: ayesha.bilall87@gmail.com
[2] Institute of Soil and Environmental Sciences, University of Agriculture, Faisalabad, Pakistan, Email: wasay2060@gmail.com
[3,4] Department of Forestry and Range Management, University of Agricultural Faisalabad, Email: samsorsherani143@gmail.com, mianabdul555@gmail.com
[5] Department of Geography, Government College University, Lahore, Email: iqraaslam270@gmail.com
[6] Department of Forestry and Range Management, University of Agriculture Faisalabad, Email: haseebuaf@outlook.com
[7] Department of Geography. Government College University, Lahore, Email: saif.geography.lhr@gmail.com
[8] National Centre of Excellence in Geology, University of Peshawar, Pakistan, Email: geonaveed@uop.edu.pk

DOI: https://doi.org/10.63163/jpehss.v4i1.1003

Abstract

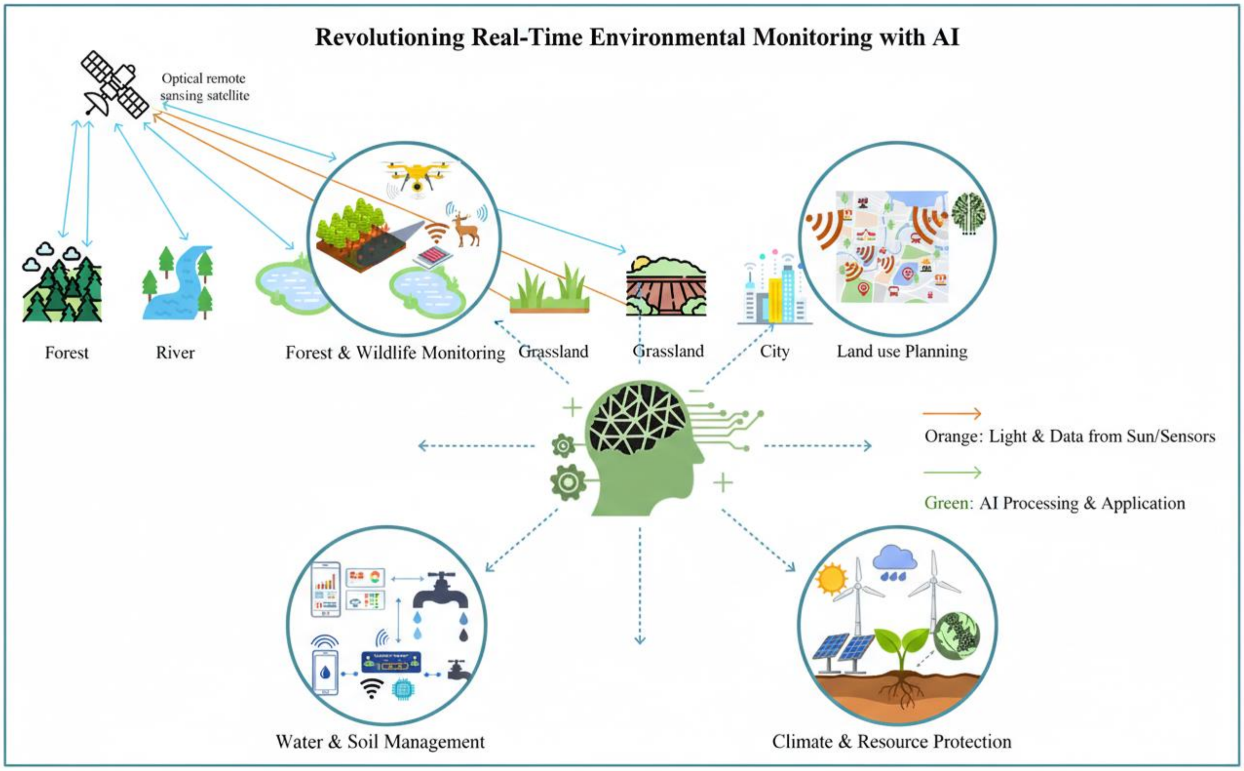
The convergence of satellite technology and artificial intelligence (AI) has revolutionized environmental monitoring, enabling real-time, high-resolution analysis of Earth's land, water, and air systems. This paper explores the evolution from traditional remote sensing to AI-driven paradigms, highlighting key orbital platforms such as Sentinel-5P, Landsat-8/9, and GHGSat for data acquisition. Foundational AI methodologies, including Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) networks, and Vision Transformers (ViTs), are examined for their roles in feature extraction, time-series analysis, and global context capture. Applications span terrestrial land cover change detection and precision agriculture; hydrospheric water quality assessment, groundwater tracking, and cryospheric dynamics; and atmospheric greenhouse gas detection and air quality modeling. Technological optimizations like edge computing and image restoration address data bottlenecks, while socio-economic implications, including Explainable AI (XAI), the AI digital divide, and environmental footprints, underscore ethical considerations. Through a synthesis of emerging trends, the paper posits that AI-assisted monitoring fosters proactive sustainability but risks rebound effects and inequities, urging balanced policy frameworks for equitable planetary stewardship.

Keywords: Satellite Monitoring, Artificial Intelligence, Remote Sensing, Environmental Systems, Deep Learning, Vision Transformers, Precision Agriculture, Greenhouse Gas Detection, Edge Computing, Explainable AI

Introduction

The global imperative for comprehensive Earth observation has entered a new epoch, defined by the convergence of high-frequency satellite constellations and advanced computational intelligence. Historically, environmental monitoring was constrained by the dual bottlenecks of sensor resolution and manual analytical capacity (Ustin et al., 2021). However, as the volume of Earth Science Data Systems (ESDS) is projected to escalate from 148 petabytes in 2023 to over 250 petabytes by 2025, the traditional methodologies of remote sensing have become increasingly untenable (Duggan et al., 2025). The current paradigm shift centers on the deployment of artificial intelligence (AI) to transform these massive datasets into actionable planetary intelligence. This evolution is not merely a quantitative increase in processing speed but a qualitative transition toward automated, real-time sensing of the Earth's respiration tracking the complex flux of carbon, the depletion of hidden aquifers, and the subtle shifts in land cover that signal broader ecological collapse (Hasan et al., 2025).

Figure 1: Conceptual Framework of AI-Assisted Multi-Domain Environmental Monitoring Across Terrestrial, Hydrosphere, and Atmospheric Systems.



The Evolution of Orbital Intelligence and Data Synthesis

The architecture of modern environmental monitoring is built upon a tiered observation strategy that integrates diverse orbital platforms with varying spatial and temporal resolutions. Early missions focused on broad Earth system processes, providing foundational but often coarse information on trace gases and climate parameters (Wei et al., 2024). In contrast, contemporary frameworks leverage a synergy between public geostationary spectrometers, like the Geostationary Environment Monitoring Spectrometer (GEMS), and private point-source imagers such as those operated by GHGSat and Carbon Mapper (Prism Sustainability Directory, 2025). This multi-platform approach allows for both the qualitative monitoring of transboundary pollutant transport and the quantitative detection of individual emission hotspots, such as methane leaks at specific industrial facilities (Fox et al., 2019). The integration of these disparate data streams is facilitated by AI tools that manage observations, model complex non-linear relationships, and provide high fidelity environmental forecasting (Chauhan et al., 2025). These tools have proven effective in critical tasks ranging from noise reduction and sensor calibration to the fusion of multi-source data including LiDAR, multispectral, hyperspectral, and Synthetic Aperture Radar (SAR). The ability of AI to handle high-dimensional data and adapt to diverse problem domains with minimal human intervention makes it an ideal candidate for feature extraction and time-series analysis in Earth observation (Vu-Duc et al., 2025).

Table 1: Key Orbital Platforms and Sensors for AI-Driven Environmental Observation

Satellite Instrument/Platform	Primary Function	Spectral/Spatial Capability	Role in AI-Assisted Monitoring
Sentinel-5P (TROPOMI)	Atmospheric Composition	7 x 3.5 km resolution	Daily global tracking of NO2, CH4, and O3 (Hasan et al., 2025)
Sentinel-2 (MSI)	Land and Coastal Water	Multispectral (10-60 m)	Land cover change, crop health, water quality (Al-Khafaji et al., 2025)
Landsat-8/9 (OLI/TIRS)	Terrestrial Monitoring	30 m (optical) / 100 m (thermal)	Long-term land-use trends and biomass estimation (Hasan et al., 2025)
GHGSat / WorldView-3	Point-Source Imaging	Very High Resolution (<5 m)	Detection of methane "super-emitters" (Prism Sustainability Directory, 2025)
GRACE-FO	Gravitational Field	Coarse Spatial Resolution	Tracking changes in global groundwater storage
Sentinel-1 (SAR)	Radar Imaging	C-band (all-weather)	Flood mapping and glacial movement (Duggan et al., 2025)

Foundational AI Methodologies and Architectural Transitions

The efficacy of AI in remote sensing is contingent upon the underlying neural network architectures, which have evolved from simple pixel-based classifiers to complex systems capable of capturing both local textures and global contextual relationships (Paheding et al., 2024). While traditional machine learning techniques like Random Forest (RF) and Support Vector Machines (SVM) remain relevant for their lower computational demands and interpretability, the research community has pivoted toward deep learning (DL) for superior accuracy and scalability (Ahmad et al., 2018).

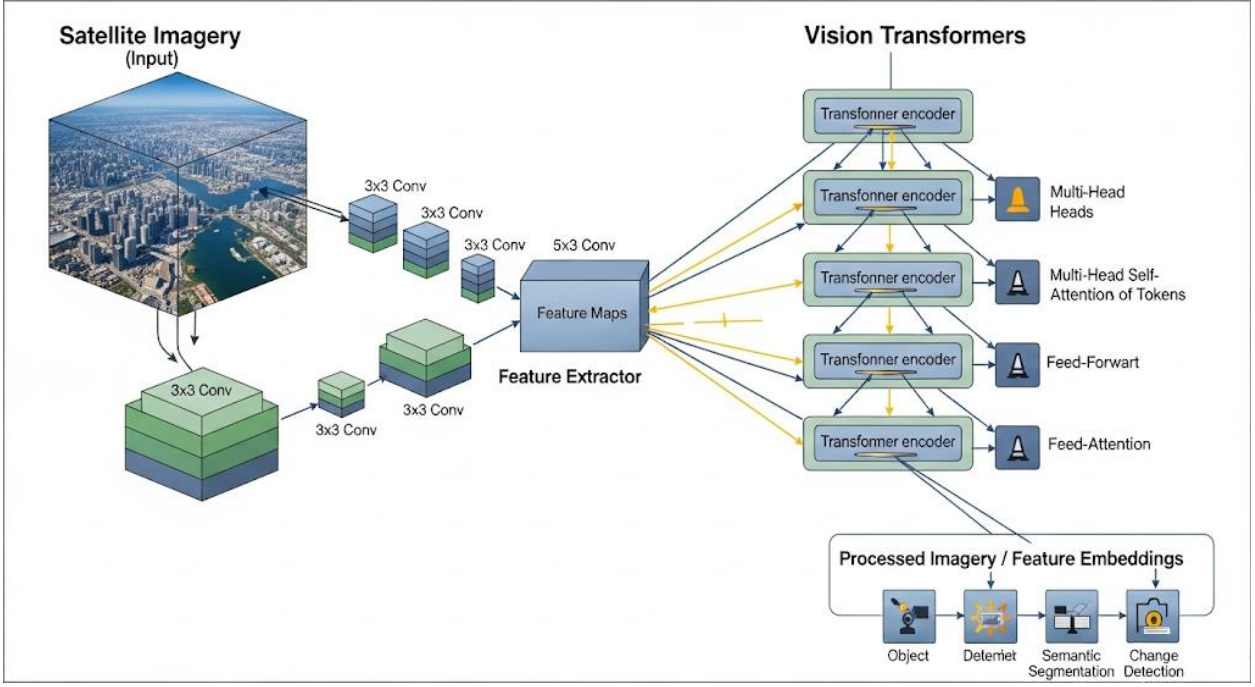
Convolutional and Recurrent Neural Networks

Convolutional Neural Networks (CNNs) revolutionized the field by eliminating the need for manual feature engineering. (Khan et al., 2020). By automatically extracting hierarchical features through a series of filters, CNNs have achieved remarkable success in object detection, semantic segmentation, and land cover classification For instance, the application of CNNs to satellite image analysis has improved methane hotspot identification accuracy from 80% to 95%. However, standard CNNs often struggle with long-range dependencies due to their inherent inductive biases of locality and spatial hierarchy (Wang et al., 2023). To address temporal dynamics, researchers employ Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks. These architectures are designed to process sequential data, making them indispensable for modeling time-series patterns such as seasonal vegetation growth, runoff forecasting, and greenhouse gas emission trends (Al-Khafaji et al., 2025). Hybrid architectures, specifically CNN+LSTM models, offer a potent solution for tasks requiring both spatial and temporal awareness. In these systems, CNNs extract spatial features from individual satellite frames, which are then passed to LSTMs to model temporal evolution, enabling the system to identify localized hotspots while simultaneously tracking long-term trends (Pelletier et al., 2019).

The Paradigm Shift to Vision Transformers (ViTs)

A major recent advancement is the transition from CNN-based architectures to Vision Transformers (ViTs). Unlike CNNs, which rely on local connectivity, Transformers utilize a self-attention mechanism that allows the model to weigh the importance of every pixel or patch in an image relative to all others (Vu-Duc et al., 2025).

Figure 1: Hybrid Architectural Workflow for Satellite Imagery Analysis: From Convolutional Feature Extraction to Vision Transformer (ViT) Encoders.



This global perspective is particularly advantageous in remote sensing, where the context of a pixel such as its proximity to a river or an urban boundary is crucial for accurate classification (Yu et al., 2023). In precision agriculture, ViTs have demonstrated superior performance in identifying heterogeneous crop types and detecting early signs of plant disease, capturing intricate spatial relationships that CNNs might overlook. Experimental results comparing these architectures on Sentinel-2 and Landsat-8 datasets show that ViTs can attain a high classification accuracy of 94.6% and a Cohen's kappa coefficient of 0.91 (Lata et al., 2025).

Table 2: Comparative Analysis of Neural Network Architectures in Remote Sensing Applications

AI Architecture	Primary Mechanism	Strengths	Limitations
CNN	Hierarchical Filters	Local feature extraction, spatial hierarchy	Struggles with long-range global dependencies (Vu-Duc et al., 2025)
LSTM	Gated Memory Cells	Modeling temporal dependencies and time-series	High computational cost for long sequences (Hasan et al., 2025)
ViT	Self-Attention	Capturing global context, scalability	High data and computational requirements
Hybrid CNN+ViT	Integrated Features	Combines local precision with global context	Complex architecture design and training
GAN	Adversarial Training	Image synthesis, super-resolution, data augmentation	Training instability and mode collapse risks (Liu, 2025; Vu-Duc et al., 2025)

Monitoring Terrestrial Systems and Precision Agriculture

The terrestrial environment is under continuous stress from anthropogenic activities, including urban sprawl and deforestation. AI-assisted remote sensing provides the tools to monitor these changes at scale, enabling a shift from reactive to proactive land management (Sabir et al., 2024).

Land Cover Change Detection (LCCD)

Land Cover Change Detection (LCCD) is critical for maintaining ecological balance and informing urban development. Modern LCCD methods are increasingly categorized by their learning approach supervised, semi-supervised, or unsupervised and their analysis unit, which can be pixel-based or object-based (Hmamou et al., 2025). Post classification comparison is a widely utilized methodology because it independently classifies images from different phases, thereby overcoming discrepancies caused by atmospheric conditions or sensor differences between acquisitions (Wan et al., 2019). Advanced models like U-Net for semantic segmentation and Swin Transformers for hierarchical modeling have set new benchmarks in detecting subtle land-use shifts. One significant challenge in LCCD is the requirement for massive labeled datasets, which is often labor-intensive and geographically biased (Peng et al., 2025). To mitigate this, research is trending toward foundation models large-scale, pre-trained models capable of performing multiple downstream tasks with minimal fine-tuning. These models use self-supervised learning on vast amounts of unlabeled satellite data to learn robust feature representations that generalize across different geographic regions (Zhang et al., 2023).

Innovations in Precision Agriculture

In the agricultural sector, AI-powered monitoring has become the backbone of sustainable practice by 2025. By integrating satellite imagery, IoT sensors, and drones, AI systems enable real-time tracking of soil health, water usage, and crop growth (Farmonaut, 2025). Precision agriculture relies on advanced models to optimize resource utilization, reducing water and fertilizer waste by up to 20-40% (Al-Khafaji et al., 2025).

Key research findings in this domain include:

- **Pest and Disease Identification:** Hybrid models like HyPest-Net, which combine CNNs for local feature extraction and ViTs for global dependencies, have achieved 95% accuracy in identifying rice crop pests. (Wei et al., 2024).
- **Vegetation Indices:** AI algorithms analyze multispectral bands to calculate indices such as NDVI and EVI, allowing farmers to monitor crop health and intervene before visible damage occurs, leading to yield increases of up to 15-20% (Chauhan et al., 2025).
- **Variable Rate Application:** AI-driven maps provide precise irrigation and fertilization schedules, minimizing environmental runoff and curbing greenhouse gas emissions from agricultural operations (Duggan et al., 2025)

Hydrospheric Monitoring and Cryospheric Dynamics

Water systems, from urban reservoirs to massive polar ice sheets, are among the most dynamic and sensitive components of the Earth system. AI provides the necessary fidelity to monitor these systems, bridging the gap between sporadic ground measurements and global satellite observations (Spiridonov et al., 2025).

Water Quality and Resource Management

Traditional water quality monitoring is often hindered by high costs and inadequate spatial resolution. AI transforms this field by enabling the estimation of physical, chemical, and biological indicators from satellite reflectance data. Indicators such as chlorophyll-a, turbidity, and total suspended solids are modeled using non-linear algorithms that account for complex atmospheric and surface interactions (Assaf et al., 2025). A systematic review of over 1,000 studies reveals that AI-driven systems now achieve 94% accuracy in water quality prediction and can reduce field sampling costs by 60% through the integration of Landsat-8 data. (Paheding et al., 2024). Furthermore, AI-integrated IoT systems are increasingly used in "smart cities" to provide real-time anomaly detection and contamination forecasting, allowing for rapid regulatory responses to pollution events (El Ghati et al., 2024).

Groundwater and Glacial Analysis

One of the most profound applications of AI is in monitoring invisible water resources, such as groundwater. (Ustin et al., 2021). By fusing gravity data from missions like GRACE-FO with earth system models and AI, researchers can project future evolutions in groundwater storage (GWS). In High Mountain Asia (HMA), integrated assessments have revealed that approximately 69% of regions experienced GWS declines between 2003 and 2020, with annual losses totaling 24.2 gigatonnes (Lata et al., 2025). In the cryosphere, AI-based approaches are increasingly adopted to inventory and map glaciers worldwide. Techniques like U-Net and Random Forest are utilized to differentiate snow from ice and model ice dynamics with high efficiency. (Yu et al., 2023) Research on the Greenland Ice Sheet has used AI to quantify the impact of microscopic algae on melt rates; by training algorithms on drone imagery and validating with satellite data, scientists determined that algal blooms caused 12.2 billion tonnes of ice melt in a single summer (Cook et al., 2020).

Table 3: Summary of AI Models and Performance Metrics for Water and Ice Dynamics

Hydrological/Cryospheric Task	Primary AI Model	Performance Metric	Scientific Insight
Groundwater Storage Projection	Explainable AI (XAI)	Historical Trend Analysis	Sustained climate-induced threat in HMA
Hydrological Forecasting	LSTM / Hybrid PINN	Nash-Sutcliffe Efficiency > 0.90	Reliable drought and flood predictions (Al-Khafaji et al., 2025)
Glacial Lake Mapping	Per-pixel compositing	0.58% annual expansion rate	Temperature and thinning are lead drivers
Effluent Quality Prediction	DNN / DBN	Real-time Anomaly Detection	Optimization of wastewater treatment

Atmospheric Monitoring and Air Quality Assessment

The atmosphere acts as a conduit for pollutants and greenhouse gases, necessitating a monitoring system that can track transboundary movements and identify specific emission sources. AI-assisted satellite analysis has evolved from coarse global averages to high-resolution, source-specific attribution (Wei et al., 2024).

Greenhouse Gas (GHG) Detection

AI has revolutionized GHG monitoring by reducing data reporting latency from 24 hours to 1 hour and increasing spatial resolution from 30 meters to 10 meters. Using CNNs and spectral analysis, systems can now identify methane and CO2 plumes and attribute them to specific sources such as power plants or oil and gas facilities (Yavari et al., 2023). The use of hybrid CNN+LSTM models allows for the tracking of localized hotspots alongside long-term temporal patterns, achieving a correlation of R2 = 0.89 for future emission trends (Kaveh et al., 2025). A critical advancement is the tiered observation paradigm. In this system, broad area mappers like TROPOMI provide initial alerts of high methane concentrations, which then trigger targeted acquisitions by high-resolution point-source imagers like GHGSat to pinpoint the exact leak location (Prism Sustainability Directory, 2025). This dynamic approach is essential for identifying "super-emitters" and managing corporate emission inventories (Hmamou et al., 2025).

Air Pollution and Aerosol Optical Depth (AOD)

Monitoring air quality, particularly particulate matter (PM2.5 and PM10), is a major public health priority. Satellite sensors measure Aerosol Optical Depth (AOD), which must be converted to surface-level concentrations using complex AI models that integrate meteorological data and ground-station readings. Techniques such as random-forest-based data-driven models have been used to create "gap-free" AOD datasets, effectively filling in missing values caused by cloud cover (Wei et al., 2024). The development of the LGHAP v2 dataset demonstrates the power of big Earth data analytics, weaving together multimodal AODs and air quality measurements to provide high-resolution global coverage (Bai et al., 2024). Furthermore, the introduction of AirFusionNet, a multimodal deep learning model, allows individuals to use built-in smartphone sensors alongside satellite data to predict local air quality in a cost-effective and accessible manner (Omidvarborna et al., 2021).

Technological Optimization: Edge AI and Image Restoration

As satellite constellations grow, the "downlink bottleneck" the limited bandwidth available to transmit data back to Earth has become a primary constraint. AI-enabled edge computing and advanced image restoration are the key technologies addressing this challenge (Huynh, 2025).

Edge Computing in Space

Edge computing refers to processing data directly onboard the satellite. By acting as the "edge" of the network, satellites equipped with high-performance AI accelerators (e.g., NVIDIA Jetson, space-grade FPGAs) can analyze data in orbit and transmit only mission-relevant information This approach significantly enhances transmission efficiency by discarding low-quality or cloud-covered imagery before it ever reaches the downlink (Ubotica, 2025).

Operational workflows for onboard AI include:

- **Autonomous Filtering:** Cloud removal and compression (CRC) techniques detect and remove cloudy image regions, increasing useful data transmission (Fox et al., 2019).
- **Event Prioritization:** AI assigns urgency scores to detected events, such as wildfires or flood zones, ensuring critical insights reach decision-makers within minutes rather than hours (Ustin et al., 2021).
- **Autonomous Navigation:** Onboard AI managing rendezvous and proximity operations (RPOs) allows for more responsive payload tasking and improved satellite survivability in congested orbits (Alizadeh et al., 2024).

Image Restoration and Super-Resolution

Environmental factors, particularly atmospheric disturbances, often degrade satellite image quality. AI-driven restoration techniques are now essential for maintaining data fidelity. Remote sensing image super-resolution (RSISR) aims to reconstruct high-resolution images from low-resolution counterparts, enhancing fine details critical for land-cover mapping and disaster assessment (Vu-Duc et al., 2025). For cloud removal a task where traditional methods often fail due to the complexity of cloud patterns the Elucidated Mean-Reverting Diffusion Model (EMRDM) has emerged as a state-of-the-art solution (Wei et al., 2024). Unlike standard diffusion models that start from pure noise, EMRDM uses the original cloudy image as the distribution mean, preserving structural consistency and allowing for the restoration of fine-grained details that are otherwise lost (Liu, 2025).

Table 4: Technical Optimizations for Data Transmission and Image Fidelity in Satellite Systems

Optimization Technique	Mechanism	Primary Benefit	Reference
Edge AI CRC	Onboard cloud removal and compression	Up to 50% increase in downlink efficiency	(Ubotica, 2025)
EMRDM Diffusion	Mean-reverting diffusion process	High-fidelity restoration of cloud-obscured data	(Liu, 2025)
RSISR (Super-Res)	Multi-frame deep learning reconstruction	Enhances spatial detail without hardware upgrades	(Vu-Duc et al., 2025)
Transfer Learning	Pre-trained feature extraction	Reduces computational load for downstream tasks	

Socio-Economic Implications, Policy, and Ethics

The integration of AI into environmental monitoring is not occurring in a vacuum; it is reshaping governance, policy-making, and the global economic landscape. The ability to monitor natural resources with unprecedented granularity introduces new risks and opportunities (Prism Sustainability Directory, 2025).

Explainable AI (XAI) and Trustworthy Decision-Making

As AI systems increasingly influence high-stakes environmental decisions, the "black box" nature of deep learning has become a barrier to adoption. Scientists in hydrology and atmospheric research often prioritize models with clear physical meanings over opaque statistical predictions (Lata et al., 2025). Explainable AI (XAI) addresses this by providing insights into model behavior, such as identifying which spectral bands or meteorological features were most influential in a flood prediction (Khan et al., 2020). XAI techniques like SHAP, LIME, and Grad-CAM are now being integrated into hydrological and land-use models to facilitate "human-centered" decision-making. This transparency is foundational for regulatory acceptance, risk mitigation, and stakeholder alignment in mission-critical domains (Al-Khafaji et al., 2025). Furthermore, the EU AI Act highlights the need for transparency, explicability, and environmental wellbeing as fundamental rights, a regulatory trend likely to be mirrored globally (European Parliament, 2024).

The AI Digital Divide and Environmental Impact

While AI provides powerful solutions for sustainability, its own ecological footprint is a critical concern. AI models are becoming larger and more energy-intensive; the computational effort required for training doubles approximately every five months (Sabir et al., 2024). By 2030, the power demand of AI data centers is expected to be 11 times higher than in 2023, consuming vast quantities of energy and water for cooling. This is particularly problematic in water-scarce regions where data centers may compete with local communities for resources (Öko-Institut, 2025). Moreover, the "AI divide" represents a growing disparity in access to these technologies. Vulnerable communities and developing nations often lack the financial and technical resources to leverage advanced AI-driven monitoring, potentially exacerbating existing global inequalities. (Jha et al., 2025). There is a risk that AI-assisted monitoring could be weaponized for geopolitical coercion or that "algorithmic water brokers" could emerge private entities that control the proprietary models governing shared watersheds, prioritizing industrial profit over social equity (Simmons et al., 2024).

Synthesis of Second and Third Order Insights

The data suggests several emerging trends and causal relationships that will define the next decade of satellite monitoring: (Zhao et al., 2022).

- **The Rebound Effect (Jevons Paradox):** While AI improves the efficiency of resource monitoring, these gains may lower the costs of extraction for instance, in the oil and gas sector potentially increasing overall fossil fuel consumption and offsetting carbon reduction goals (Luccioni et al., 2025).
- **Dynamic Carbon and Nature-Based Markets:** The transition from self-reported to dynamic, observational inventories enables the creation of verifiable nature-based solutions. Projects claiming to sequester carbon through reforestation can now be continuously monitored and verified, potentially unlocking trillions of dollars in ecological restoration capital (Prism Sustainability Directory, 2025).
- **Intelligent Supply Chains:** AI can analyze the entire ecological footprint of products, from raw material extraction to final transport, providing a "carbon receipt" that empowers informed consumer and corporate choices (Huang et al.,m 2024).
- **Hydro-Solidarity:** XAI can move from a tool of individual farm optimization to a platform for collective governance. By modeling the consequences of individual actions on a shared aquifer, these systems can demonstrate the community-wide benefits of cooperative water conservation (Loopmans et al., 2024).

Conclusion

In conclusion, the integration of AI with satellite-based environmental monitoring represents a transformative leap toward intelligent Earth observation, converting vast datasets into actionable insights for land, water, and air systems. By leveraging advanced architectures like ViTs and hybrid models, alongside optimizations such as edge AI and super-resolution techniques, this paradigm enhances accuracy, efficiency, and real-time responsiveness in addressing ecological challenges—from methane super-emitters to groundwater depletion and glacial melt. However, the socio-economic ramifications, including the AI divide, energy-intensive computations, and potential rebound effects, necessitate robust ethical frameworks, XAI for transparency, and inclusive policies to mitigate disparities. Ultimately, this synergy not only empowers verifiable nature-based solutions and intelligent supply chains but also promotes hydro-solidarity and global equity, paving the way for a sustainable future where technology serves as a guardian of planetary health rather than a source of division. Future research should focus on scalable foundation models and regulatory harmonization to fully realize this potential.

References

Aderemi, I. A., Kehinde, T. O., Okwor, U. D., Ahmad, K. H., Adjei, K. Y., & Ekechi, C. C. (2025). Explainable AI for water quality monitoring: A systematic review of transparency, interpretability, and trust. *IEEE Sensors Reviews*, *2*, 419–443.

Ahmad, I., Basheri, M., Iqbal, M. J., & Rahim, A. (2018). Performance comparison of support vector machine, random forest, and extreme learning machine for intrusion detection. *IEEE access*, *6*, 33789-33795.

Alizadeh, M., & Zhu, Z. H. (2024). A comprehensive survey of space robotic manipulators for on-orbit servicing. *Frontiers in Robotics and AI*, *11*, 1470950.

Al-Khafaji, M. S., Abdulameer, L., AL-Shammari, M. M. A., Al Maimuri, N. M. L., Dulaimi, A., & Al-Jumeily, D. (2025). Revolutionizing water quality monitoring with artificial intelligence: A systematic review. *Journal of Studies in Science and Engineering*, *5*(1), 358–385.

Assaf, M. N., Abdelal, Q., Hussein, N. M., Halaweh, G., & Alzubaidi, A. J. (2025). Water quality monitoring and management: integration of machine learning algorithms and Sentinel-2 images for the estimation of Chlorophyll-a. *Modeling Earth Systems and Environment*, *11*(5), 348.

Bai, K., Li, K., Shao, L., Li, X., Liu, C., Li, Z., ... & Guo, J. (2024). LGHAP v2: a global gap-free aerosol optical depth and PM 2.5 concentration dataset since 2000 derived via big Earth data analytics. *Earth System Science Data Discussions*, *2024*, 1-29.

Chauhan, B. V., Vedrtnam, A., Wyche, K. P., & Verma, S. (2025). Review on Artificial Intelligence in the Environmental Monitoring. *Prospects of Artificial Intelligence in the Environment*, 29-60.

Duggan, A., Andrade, B., & Afli, H. (2025). Advancing Earth observation: A survey on AI-powered image processing in satellites. *European Journal of Remote Sensing*, *58*(1). https://doi.org/10.1080/22797254.2025.2567921

El Ghati, O., Alaoui-Fdili, O., Chahbouni, O., Alioua, N., & Bouarifi, W. (2024). Artificial intelligence-powered visual internet of things in smart cities: A comprehensive review. *Sustainable computing: informatics and systems*, *43*, 101004.

European Parliament. (2024). *Artificial Intelligence Act*.

Fox, T. A., Barchyn, T. E., Risk, D., Ravikumar, A. P., & Hugenholtz, C. H. (2019). A review of close-range and screening technologies for mitigating fugitive methane emissions in upstream oil and gas. *Environmental Research Letters*, *14*(5), 053002.

Hasan, R., Khatoon, R., Akter, J., Mohammad, N., Kamruzzaman, M., Shahana, A., & Saha, S. (2025). AI-driven greenhouse gas monitoring: Enhancing accuracy, efficiency, and real-time emissions tracking. *AIMS Environmental Science*, *12*(3), 495–525. https://doi.org/10.3934/environsci.2025023

Hmamou, M., Chafiq, T., Ouhammou, I., Lmoudden, O. A., Raji, M., & Ouaskit, S. (2025). Assessing land cover change detection in a developing country with machine and deep learning algorithms: a case study. *Environment, Development and Sustainability*, 1-21.

Huang, R., & Mao, S. (2024). Carbon footprint management in global supply chains: A data-driven approach utilizing artificial intelligence algorithms. *IEEE Access*, *12*, 89957-89967.

Huynh, C. (2025). *AI on the edge of space: Securing space superiority and avoiding surprise in orbit*. Center for Security and Emerging Technology.

Jha, A., & Singh, S. R. (2025). Bridging the divide: capacity building for AI adoption in developing countries. In *AI strategies for social entrepreneurship and sustainable economic development* (pp. 133-150). IGI Global Scientific Publishing.

Kaveh, M., Mesgari, M. S., & Kaveh, M. (2025). A Novel Evolutionary Deep Learning Approach for PM2. 5 Prediction Using Remote Sensing and Spatial–Temporal Data: A Case Study of Tehran. *ISPRS International Journal of Geo-Information*, *14*(2), 42.

Khan, A., Sohail, A., Zahoora, U., & Qureshi, A. S. (2020). A survey of the recent architectures of deep convolutional neural networks. *Artificial intelligence review*, *53*(8), 5455-5516.

Lata, K., Kaur, N., & Singh, S. (2025). Satellite-Based Crop Recognition Using Virtual Transformer Models for Smart Agriculture. In *Presented at the 12th International Electronic Conference on Sensors and Applications (ECSA-12)* (Vol. 12, p. 14).

Liu, Y. (2025). *Effective cloud removal for remote sensing images by an improved EMRDM*. Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR).

Loopmans, M., & Hoogesteger, J. (2024). Hydrosolidarity: A Socio-Political Reading of a Moral Concept. *Water Alternatives-An Interdisciplinary Journal On Water Politics And Development*, *17*(3), 688-711.

Luccioni, A. S., Strubell, E., & Crawford, K. (2025, June). From efficiency gains to rebound effects: The problem of jevons' paradox in AI's polarized environmental debate. In *Proceedings of the 2025 ACM Conference on Fairness, Accountability, and Transparency* (pp. 76-88).

Öko-Institut. (2025). *Environmental impacts of AI*. Greenpeace Germany.

Omidvarborna, H., Kumar, P., Hayward, J., Gupta, M., & Nascimento, E. G. S. (2021). Low-cost air quality sensing towards smart homes. *Atmosphere*, *12*(4), 453.

Paheding, S., Saleem, A., Siddiqui, M. F. H., Rawashdeh, N., Essa, A., & Reyes, A. A. (2024). Advancing horizons in remote sensing: a comprehensive survey of deep learning models and applications in image classification and beyond. *Neural Computing and Applications*, *36*(27), 16727-16767.

Pelletier, C., Webb, G. I., & Petitjean, F. (2019). Temporal convolutional neural network for the classification of satellite image time series. *Remote Sensing*, *11*(5), 523.

Peng, D., Liu, M., Zhang, Y., & Guan, H. (2025). Toward Label-Efficient Deep Learning Change Detection for Remote Sensing Imagery: A Comprehensive Review. *The Photogrammetric Record*, *40*(191), e70021.

Prism Sustainability Directory. (2025). *Explainable AI for sustainable water resource management*. https://prism.sustainability-directory.com/scenario/explainable-ai-for-sustainable-water-resource-management/

Sabir, R. M., Mehmood, K., Sarwar, A., Safdar, M., Muhammad, N. E., Gul, N., ... & Akram, H. M. B. (2024). Remote sensing and precision agriculture: a sustainable future. In *Transforming agricultural management for a sustainable future: climate change and machine learning perspectives* (pp. 75-103). Cham: Springer Nature Switzerland.

Simmons-Edler, R., Badman, R., Longpre, S., & Rajan, K. (2024). Ai-powered autonomous weapons risk geopolitical instability and threaten ai research. *arXiv preprint arXiv:2405.01859*.

Spiridonov, V., Ćurić, M., & Novkovski, N. (2025). Hydrosphere and Cryosphere: Key Challenges. In *Atmospheric Perspectives: Unveiling Earth's Environmental Challenges* (pp. 83-105). Cham: Springer Nature Switzerland.

Ustin, S. L., & Middleton, E. M. (2021). Current and near-term advances in Earth observation for ecological applications. *Ecological Processes*, *10*(1), 1.

Vu-Duc, A., Nguyen-Vi, K., Bui-Quoc, B., & Kamel, N. (2025). A comprehensive survey of super-resolution remote sensing image datasets: Evolution, challenges, and future directions. *IEEE Access*. https://doi.org/10.1109/ACCESS.2025.3599535

Wan, L., Xiang, Y., & You, H. (2019). A post-classification comparison method for SAR and optical images change detection. *IEEE Geoscience and Remote Sensing Letters*, *16*(7), 1026-1030.

Wang, Z., & Wu, L. (2023). Theoretical analysis of the inductive biases in deep convolutional networks. *Advances in Neural Information Processing Systems*, *36*, 74289-74338.

Wei, J., Li, Z., Sun, L., Peng, Y., & Zhang, L. (2024). Quality-enhanced LGHAP v2 dataset generated through big Earth data analytics. *Earth System Science Data*, *16*, 2425–2440.

Yavari, A., Mirza, I. B., Bagha, H., Korala, H., Dia, H., Scifleet, P., ... & Shafiei, M. (2023). Artemon: Artificial intelligence and internet of things powered greenhouse gas sensing for real-time emissions monitoring. *Sensors*, *23*(18), 7971.

Yu, D., & Fang, C. (2023). Urban remote sensing with spatial big data: A review and renewed perspective of urban studies in recent decades. *Remote Sensing*, *15*(5), 1307.

Zhang, X., & Han, L. (2023). A generic self-supervised learning (SSL) framework for representation learning from spectral–spatial features of unlabeled remote sensing imagery. *Remote Sensing*, *15*(21), 5238.

Zhao, Q., Yu, L., Du, Z., Peng, D., Hao, P., Zhang, Y., & Gong, P. (2022). An overview of the applications of earth observation satellite data: impacts and future trends. *Remote Sensing*, *14*(8), 1863.