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Atlas AI: Watching the planet evolve through AI-Powered Satellite Intelligence

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Abstract: Environmental changes such as deforestation, urban expansion, and reduction in water bodies have increased in recent years. Monitoring these changes using traditional field surgeys is often time-consuming and difficult for large areas. Because of this, satellite remote sensing combined with artificial intelligence has become an effective approach for environmental monitoring. This paper reviews recent studies that use satellite pfatforms such as Sentinel-1, Sentinef-2, and Landsat along with models including CAT, U-Net, Vision Transformers (ViT), and LSTM for change detectton The reviewed studies suggest that combining multispectral and SAR data improves monitoring accuracy in different land-cover conditions. it is also obsewed that transformer and hybrid deed learning models oflen Perform better than traditional approaches. Oreraff, the combination of AI and satellite imagery provides a useful way to monitor environmental changes and support better planning and consewation decisions.

Keywords: Environmental Monitoring, Remote Sensing, Satellite Imagery, Artificial Intelligence, Deep Learning, Deforestation Detection, Urban Expansion, Water Body Shrinkage, Sentinel-1, Sentinel-2, Landsat, Convolutional Neural Network (CNN), U-Net 3D, Vision Transformer (ViT), Long Short-Term Memory (LSTM), Transformer-Based Models, Change Detection, Sustainable Development, Urban Planning, Land Use Land Cover (LULC).

I. INTRODUCTION

In recent years, environmental changes such as deforestation and urban growth have become increasingly noticeable. Forests that once stretched for hundreds of kilometres are being cleared for agriculture and settlement. Cities are spreading outward at rates that make decade-old maps look obsolete. Lakes and rivers that communities have depended on for generations are shrinking, some to the point of disappearing entirely. These transformations are driven by the intersecting pressures of rapid population growth, accelerating industrialisation, and constant demand for new infrastructure. These changes have created several environmental problems: biodiversity loss, altered rainfall patterns, more frequent extreme weather events, and declining freshwater availability. Given that deforestation and urban expansion are the two largest direct drivers of these changes, there is a clear and pressing need for monitoring systems capable of tracking them with precision and at scale.

Historically, environmental monitoring depended on periodic field surveys, ground-based observation networks, and early satellite imagery with limited spatial and temporal resolution. While these methods produced useful data, they were fundamentally constrained in what they could deliver. Covering large geographic areas through ground surveys is logistically expensive and slow, and early optical satellites were frequently obstructed by cloud cover. The data gaps between observation cycles meant that fast-moving changes such as a burst of illegal logging or a construction surge at the city fringe could go undetected for months. What is needed instead is a monitoring approach that provides continuous, high-resolution, cloud-penetrating coverage across diverse landscapes.

The convergence of satellite remote sensing and artificial intelligence addresses these limitations directly. Modern satellite constellations, including the Sentinel series managed by the European Space Agency and the long-running Landsat program operated jointly by NASA and the USGS, now provide frequent, high-resolution, multispectral coverage of the Earth's surface. When paired with deep learning models such as Convolutional Neural Networks (CNNs), U-Net architectures, Transformer-based networks, and Long Short-Term Memory (LSTM) models, these data streams can be analysed at a speed and accuracy that no human-led process could replicate. The result is a monitoring capability that is both scalable and sensitive enough to detect subtle environmental changes across enormous spatial extents.

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This paper surveys methods and findings across five distinct studies, each addressing a specific dimension of environmental change: deforestation, urban expansion, general land cover shifts, and water body reduction. By examining what each research group did and what their results showed, the review aims to establish how multispectral-SAR data fusion elevates the performance of contemporary change detection systems. The broader objective of this survey is to demonstrate that remote sensing, when combined with deep learning, can serve as a living, automated infrastructure for environmental monitoring. Such a system generates the kind of verifiable, up-to-date data that policymakers, urban planners, and conservation practitioners need to make informed decisions decisions that can slow ecological degradation, guide resource management, and support long-term sustainable development.

II. LITERATURE SURVEY

Solorzano et al. (2023) addressed tropical deforestation by developing a spatio-temporal deep learning framework grounded in a 3D U-Net architecture [1]. Their approach combined Sentinel-1 SAR data with Sentinel-2 multispectral imagery, enabling the model to distinguish between outright canopy loss and more subtle forms of forest degradation. The model gave good results in identifying forest-related changes, demonstrating that processing time-series satellite imagery through volumetric deep networks substantially reduces label confusion and refines long-term forest monitoring.

Focusing on urban dynamics, Mohiuddin et al. (2023) investigated the spatial patterns of city growth using Landsat 8 imagery processed through Google Earth Engine [2]. By applying the Indices-Based Built-Up Index (IBI), the study traced how impervious surface area expanded over time and examined the relationship between urban growth and rising land surface temperatures. The study mainly focused on qualitatively different from what older methods could offer how cloud-based remote sensing platforms can make large-scale urban monitoring both computationally feasible and practically useful for sustainable urban planning.

Isaienkov et al. (2021) directed their work toward forest change detection at the regional scale, building a deep learning pipeline to identify regular and irregular canopy changes across Ukrainian forests using Sentinel-2 imagery [3]. U-Net models were trained on multitemporal image stacks, allowing the system to isolate illegal logging activity and broader canopy thinning from the background of normal seasonal variation. The study's findings support the practical value of multitemporal deep learning inputs for forest governance and ecological monitoring at the national scale.

Song et al. (2022) introduced DMATNet, a Dual-Feature Mixed Attention Transformer Network designed to push the boundaries of remote sensing change detection [4]. The architecture combines conventional CNN feature extraction with transformer-based attention mechanisms, enabling the model to capture both fine-grained spatial detail and broad contextual relationships within a single forward pass. When compared with traditional CNN models, better results were observed, DMATNet produced superior results on all key metrics, with better contextual understanding, cleaner feature representations, and notably fewer false-positive detections.

Chen et al. (2021) took a parallel transformer-based direction with the Bitemporal Image Transformer **(BIT),** a model specifically designed to handle the temporal comparison central to change detection [5]. By applying self-attention across bi-temporal image pairs, the model was able to simultaneously process spatial structure and temporal transitions across different acquisition dates, resulting in improved land-cover change classification. The authors highlighted that **BIT** achieves this while maintaining computational efficiency, a significant practical advantage over more complex convolutional architectures.

John and Zhang (2022) approached deforestation detection through an attention-augmented segmentation model, constructing an Attention-Based U-Net tailored to identify forest loss across multiple biome types [6]. The incorporation of attention modules allowed the network to selectively emphasise ecologically relevant spatial features, leading to higher accuracy scores than those produced by conventional pixel-based classifiers. The results demonstrated that attention mechanisms usefully guide the model toward discriminative landscape features rather than noise.

Adarme et al. (2020) conducted a comparative evaluation of several deep learning configurations for deforestation monitoring across two contrasting South American biomes: the Amazon rainforest and the Cerrado savanna [7]. Testing frameworks including early fusion networks, Siamese architectures, and convolutional SVM hybrids, they consistently found that deep learning approaches outperformed traditional machine learning classifiers. The improvement extended beyond raw accuracy deep learning also reduced the manual effort associated with feature engineering and data preprocessing.

Chen et al. (2021) addressed the subtler problem of forest degradation rather than outright deforestation [8]. Using the CCDC-SMA algorithm applied to long-term Landsat time series data within Google Earth Engine, they combined spectral mixture analysis with temporal trend modelling. This dual-method framework successfully identified both abrupt disturbances from logging events and gradual, low-intensity canopy deterioration that conventional classifiers often miss.

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The study reinforced the suitability of cloud-based Earth observation platforms for sustained, long-horizon environmental monitoring.

Yin et al. (2021) contributed a comprehensive review examining how the integration of remote sensing with geospatial big data is reshaping urban land use mapping [9]. Synthesising evidence from across the literature, they found that multi-source data integration consistently reduces classification errors compared to single-source approaches, and that the combination enables more nuanced spatial characterisation of urban environments. The review positioned this kind of data fusion as a key enabler of evidence-based urban management and smart city planning.

Geethashree et al. (2025) took a forward-looking approach, developing a hybrid ViT-LSTM model for predicting the reduction in water body extent driven by urban encroachment [10]. The model was trained on quarterly Sentinel-2 image sequences, allowing it to learn both the spatial patterns of water body boundaries and the temporal dynamics of their shrinkage over time. When evaluated against standalone CNN and LSTM baselines, the combined architecture produced superior predictive performance, offering a practical tool for anticipating water resource pressures in rapidly urbanising regions.

III. FINDINGS

The reviewed studies show that artificial intelligence and satellite imagery together have improved environmental monitoring. Earlier methods often had limitations such as low update frequency, reduced accuracy, and limited geographical coverage. Recent developments in remote sensing and deep learning have helped solve many of these problems. As a result, environmental changes such as forest loss, urban growth, and water body reduction can now be identified more effectively.

A clear pattern emerges across the architectures surveyed: deep learning models, whether CNNs, U-Net variants, attention-augmented encoders, or transformer networks, consistently outperform conventional image processing pipelines. Spatio-temporal architectures are particularly effective in this context. By processing sequences of satellite observations collected over months or years, these models gain sensitivity to gradual change processes that single-image classifiers are likely to miss. This makes them especially suited to detecting early-stage forest loss, incremental logging activity, and slow land-use transitions [1], [3], [6], [7].

One of the more consistent findings across the reviewed literature is the performance benefit of combining multispectral optical imagery with Synthetic Aperture Radar (SAR) data. Platforms such as Sentinel-1 and Sentinel-2, together with the long-running Landsat archive, provide complementary data streams that cover different parts of the electromagnetic spectrum and respond differently to surface conditions. SAR, in particular, is not obstructed by cloud cover or atmospheric haze, which is a significant advantage in tropical and temperate environments where optical sensors are frequently compromised by weather. Studies that made use of both data types reported more reliable deforestation detection and finer-grained land cover classification than those relying on optical data alone [1], [7], [8].

Research focused on urban dynamics shows that cloud-based Earth observation platforms, particularly Google Earth Engine, dramatically simplify the process of generating built-up area indices such as IBI and NDBI at large scale. These indices, derived from Landsat or Sentinel imagery, provide quantitative and reproducible measures of urban expansion over time. The resulting data goes well beyond an academic exercise: it supplies city planners and policymakers with concrete evidence of where urban growth is most intense, how it is changing the thermal environment, and what interventions might be needed to pursue more sustainable development trajectories [2], [9].

The evidence from the transformer-focused studies is particularly noteworthy. Architectures like BIT and DMATNet demonstrate a measurable advantage over standard CNNs specifically in change detection tasks, where the ability to model spatial context across the full image extent matters as much as the ability to identify individual features. By attending to global relationships rather than local patches, transformer models are better at distinguishing genuine land-cover changes from look-alike phenomena such as seasonal vegetation shifts or shadow patterns caused by different illumination angles. This reduces false-positive rates in a setting where spurious detections are costly [4], [5].

The water body study by Geethashree et al. adds an important dimension to these findings by demonstrating the value of hybrid architectures for predictive modelling. Coupling ViT-based spatial feature extraction with LSTM-based temporal sequence learning allows the model to do something that neither component could achieve alone: it can learn both what a shrinking water body looks like and how the shrinkage process unfolds over time. This dual capacity helps the network to project future water body conditions based on current urban growth trends, providing environmental managers with a forward-looking analytical tool rather than just a retrospective one [10].

Across all the reviewed studies, the convergence of high-resolution satellite data, multisource data fusion, and advanced deep learning architectures produces an environmental monitoring capability that is more effective compared to older

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monitoring methods. This integrated approach generates the kind of accurate, timely, and spatially comprehensive data that conservation organisations, urban planning authorities, and environmental policymakers need to act decisively- whether to protect remaining forest cover, redirect urban development away from ecologically sensitive areas, or safeguard shrinking water reserves [2], [4], [5], [9], [10].

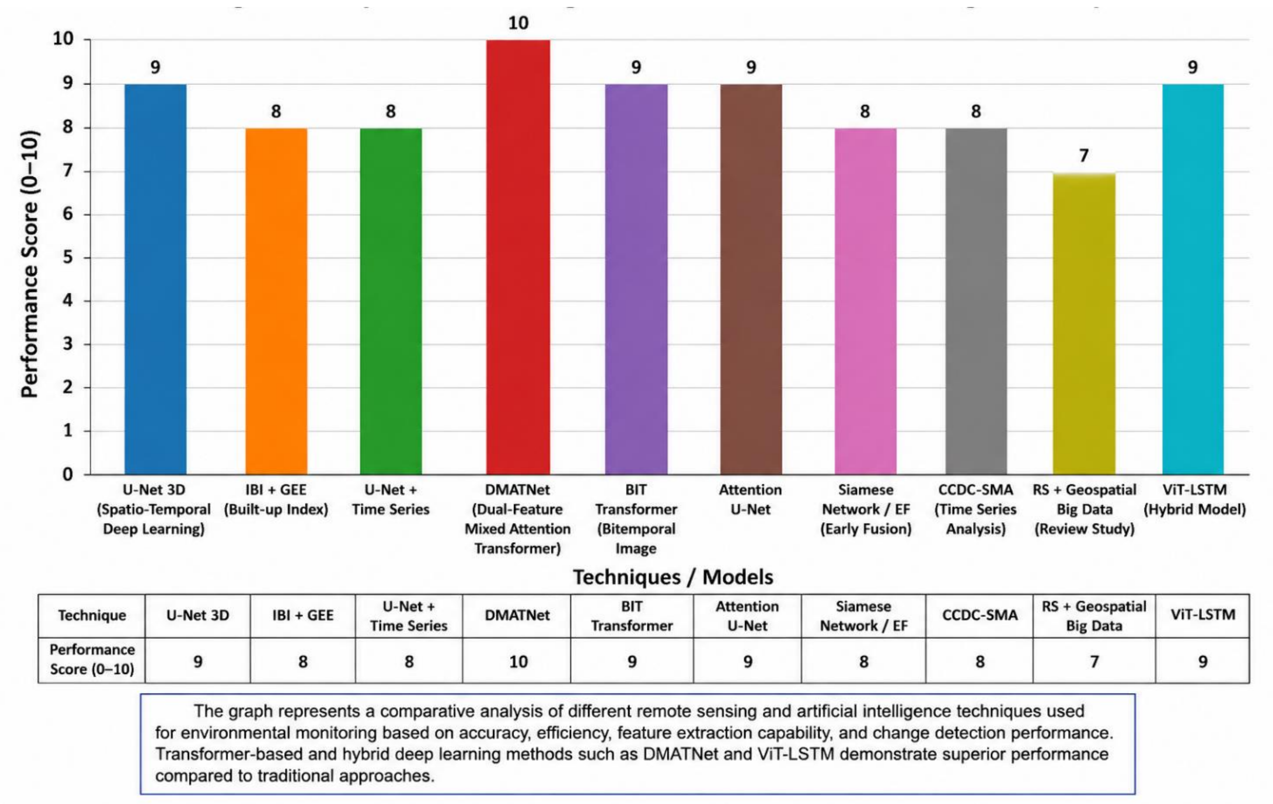

Fig 1: Analysis of Existing Environmental Monitoring Techniques

Table 1 Comparative analysis of reviewed CPM and PERT research papers

S.No	Research Paper	Technique / Methodology	Satellite Data Used	Main Objective	Accuracy / Performance	Key Contribution	Overall Score
1	Solorzano et al. (2023)	U-Net 3D + Spatio-Temporal Deep Learning	Sentinel-1 & Sentinel-2	Deforestation Detection	97% Accuracy, F1-score 0.94	Improved forest loss detection using SAR + multispectral imagery	9
2	Mohiuddin et al. (2023)	IBI + Google Earth Engine	Landsat 8	Urban Expansion Detection	Consistent built-up growth detection	Effective urban monitoring using built-up indices	8
3	Isaienkov et al. (2021)	U-Net + Time-Dependent Deep Learning	Sentinel-2	Forest Change Detection	High efficiency in illegal logging detection	Multitemporal forest monitoring	8
4	Song et al. (2022)	DMATNet (Transformer + CNN)	High-Resolution RS Images	Remote Sensing Change Detection	F1-score 90.75%, IoU 84.13%	Better feature extraction with mixed attention transformer	10
5	Chen et al. (2021)	Bitemporal Image	High-Resolution	Change Detection	Higher efficiency than CNN methods	Efficient spatio-temporal contextual learning	9

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S.No	Research Paper	Technique / Methodology	Satellite Data Used	Main Objective	Accuracy / Performance	Key Contribution	Overall Score
		Transformer (BIT)	Satellite Images				
6	John & Zhang (2022)	Attention U-Net	Sentinel-2	Deforestation Detection	F1-score up to 0.9769	Improved forest segmentation accuracy	9
7	Adarme et al. (2020)	Early Fusion, Siamese Network, CSVM	Landsat 8	Deforestation Detection	Better than traditional SVM	Reduced manual effort in forest monitoring	8
8	Chen et al. (2021)	CCDC-SMA + Time Series Analysis	Landsat + GEE	Forest Degradation Monitoring	91% Overall Accuracy	Effective long-term forest monitoring	8
9	Yin et al. (2021)	Remote Sensing + Geospatial Big Data	Multi-source Satellite Data	Urban Land Use Mapping	Review-based Study	Improved urban planning through RS + GBD integration	7
10	Geethashree et al. (2025)	ViT-LSTM Hybrid Model	Sentinel-2	Water Body Shrinkage Prediction	$R^2 = 0.8748$, IoU = 0.4359	Accurate prediction of water body reduction due to urbanisation	9

IV. CONCLUSION

Deforestation, urban expansion, and reduction in water bodies are among the major environmental challenges faced today. Monitoring these changes over large areas requires accurate and continuous observation systems. From the studies reviewed in this paper, it can be understood that combining satellite remote sensing with artificial intelligence improves the process of environmental monitoring.

Satellite platforms such as Sentinel-1, Sentinel-2, and Landsat, when used together with deep learning models like CNN, U-Net, **BIT,** DMATNet, and ViT-LSTM, help in detecting environmental changes more accurately than traditional methods. These approaches are useful for monitoring forests, urban development, and water resources.

Although some challenges still remain, the use of AI with satellite imagery offers a practical and reliable method for environmental monitoring. It can support policymakers, urban planners, and researchers in making better decisions related to sustainability and resource management.

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