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A Comparative Analysis of Manual and AI-Based Approaches for Green Cover Loss Detection

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Abstract—Rapid urbanisation, deforestation, and environmental deterioration have made it more crucial than ever to monitor the loss of green cover. In the past, vegetation assessment has depended on environmental agencies' manual field surveys and physical inspection techniques. These methods offer in-depth local insights, but they are limited by frequent monitoring cycles, high operating costs, and limited spatial coverage. Artificial intelligence (AI) and satellite remote sensing have recently brought automated frameworks that can identify and analyse changes in vegetation over wide geographic areas. An organised comparison of manual and AI-based techniques for detecting green cover degradation is presented in this research. Scalability, temporal efficiency, operational cost, spatial resolution, and consistency of monitoring are the criteria used for the evaluation. The investigation shows that while lowering reliance on labour-intensive procedures, AI-driven methods greatly improve large-scale environmental monitoring capabilities. The study underscores the significance of automated systems for sustainable environmental management and the technical advancements in vegetation monitoring.

Index Terms—Artificial Intelligence, Remote Sensing, Environmental Monitoring, Green Cover Monitoring, Vegetation Loss Detection, and Change Detection.

I. INTRODUCTION

Over the past few decades, natural landscapes have undergone tremendous change due to the ongoing growth of urban infrastructure, transportation networks, and industrial zones. The progressive loss of green space in urban and periurban areas is one of the most obvious effects of this change. Because it controls microclimates, absorbs carbon dioxide, lowers air pollution, and promotes biodiversity, vegetation is essential to preserving ecological equilibrium. As a result, planning for sustainable development and environmental governance now heavily relies on the regular monitoring of green cover degradation [2],[7],[16]. Administrative land-use data and manual field-based surveys have historically been the main methods used to assess vegetation cover. To estimate canopy density, tree dispersion, and vegetation health, forestry departments and environmental authorities do routine inspections. Usually, these techniques rely on human observation, sample plot analysis, and physical measurements. While these methods are precise and provide localised data and direct ground validation, their geographical and temporal scalability is intrinsically constrained by conducting repeated surveys across large metropolitan areas, which require substantial manpower, financial investment, and time, making it difficult to generate frequent updates. The drawbacks of manual monitoring become increasingly obvious as urbanisation picks up speed. Cities are dynamic systems where changes in land use can happen quickly as a result of commercial development, road expansion, or construction projects. These quick changes are frequently not captured by manual approaches in a timely way. Additionally, subjectivity and variability are introduced by human-based evaluation, which could have an impact on the consistency of documented observations. A fresh viewpoint on environmental monitoring has been made possible by developments in satellite remote sensing. Large geographic areas can be periodically monitored using high-resolution satellite photography, negating the necessity for in-person site visits. However, without proper processing and analysis, raw satellite data by itself cannot provide useful insights [3],[4]. Because of this need, environmental analysis workflows now incorporate machine learning and artificial intelligence (AI) approaches. Artificial intelligence (AI)-based systems are able to process multi-temporal satellite images, extract pertinent information, and spot trends related to the presence or absence of vegetation. AI-driven methods allow for automated large-scale analysis with greater consistency and efficiency than manual surveys, which rely on small sample areas. It is possible to routinely detect vegetation across wide areas by using computational models to analyse spectral and spatial data from satellite platforms. An important technical change in environmental monitoring techniques is the switch from manual observation to AI-assisted analysis. Nevertheless, a systematic comparison of conventional manual procedures and AI-based approaches is still required, despite the frequent discussion about intelligent monitoring systems [5],[17].

Designing efficient frameworks for monitoring green cover requires an understanding of the advantages, disadvantages, and real-world applications of both approaches. This research offers a thorough comparison of AI-based and manual techniques for identifying the loss of green cover. The analysis assesses both strategies based on operational effectiveness, spatial coverage, monitoring frequency, cost implications, and scalability rather than just algorithmic performance.

The goal of the study is to identify the technical limits of traditional field-based monitoring while simultaneously elucidating how AI-driven systems overcome these constraints. The following is a summary of this work's principal contributions:

- 1) Methodical analysis of conventional manual green cover detection methods and their functional attributes.
- 2) A critical review of AI-based vegetation monitoring techniques that make use of computational models and satellite data.
- 3) An organized framework for comparison that highlights variations in performance across important evaluation criteria.
- 4) A conversation about the realistic shift to automated environmental intelligence systems for sustainable urban design.

Through this study, the paper highlights the need for effective, scalable, and data-driven solutions to combat continued green cover degradation and highlights the emerging role of artificial intelligence in aiding large-scale environmental monitoring.

II. TRADITIONAL MANUAL METHODS FOR GREEN COVER LOSS DETECTION

Prior to the widespread availability of computational intelligence and satellite-based analysis, vegetation monitoring was mostly carried out using manual assessment methods. These methods depend on field measurements, human interpretation of spatial data, and physical observation. These techniques have historically served as the cornerstone of environmental monitoring systems, but in the context of rapidly urbanising areas, they have serious practical limits.

A. Field Survey-Based Assessment

In field-based vegetation surveys, trained individuals physically inspect specific geographic areas. Typically, survey teams take measurements of species variety, tree density, canopy coverage, and trunk diameter. Usually, pre-made sample plots that depict a wider area are used to record these measurements. In general, the procedure consists of:

- Selection of sampling locations
- On-site tree counting and canopy estimation
- Documentation of vegetation health
- Compilation of regional vegetation reports

Since information is gathered directly from the site, this method yields precise ground-level data. It enables in-depth ecological studies that are sometimes impossible to obtain from remote photography, such as species composition and the physical state of trees. However, the effectiveness of field-based surveys is limited by a number of structural limitations:

- 1) Limited Spatial Coverage: Within a specified time frame, survey teams are only able to cover a limited area. It takes a lengthy time and intensive logistical planning to monitor a whole city or sizable forest area.
- 2) High Labor and Operational Costs: Personnel with the necessary training, equipment, transportation, and administrative assistance are needed for fieldwork. Financial expenditures are often increased by repeated surveys.
- 3) Low Monitoring Frequency: Because of financial and temporal limitations, surveys are usually carried out once a year or occasionally. This makes it challenging to identify transient alterations brought on by abrupt building or changes in land use.
- 4) Human Error and Subjectivity: Depending on the experience and interpretation of the observer, measurements like canopy density estimation may differ, resulting in disparities between datasets.

While field surveys are still crucial for ecological validation and study, they are not the best option for large-scale, ongoing monitoring in urban environments that are changing quickly.

B. Manual Interpretation of Aerial and Land Records

The manual examination of aerial photos, old maps, and official land-use records is another traditional method for identifying green cover. To evaluate vegetation changes, environmental officials compare records from various time periods. This method frequently comprises:

- Visual inspection of aerial imagery
- Comparison of historical and current maps
- Identification of land conversion patterns
- Manual digitization of vegetation boundaries

Eventhoughthismethodcoversmoregroundthanlocalised field plots, human interpretation is still required. Visual in- spection might be difficult for identifying small vegetation changes, especially in densely populated areas with dispersed green spaces.

Someofthismethod'smaindrawbacksare:

- Delayed Data Processing: Manual comparison of recordsrequiresignificanttime, reducingresponsiveness to ongoing changes.
- Inconsistent Classification Standards: Different ana- lysts may interpret the same image differently, affecting reliability.
- Difficulty in Monitoring Rapid Urban Expansion: Urban areas experience frequent modifications due to infrastructure projects. Manual documentation often lags behind actual land transformation.
- Scalability Constraints: Processing large volumes of aerial imagery manually becomes increasingly imprac- tical as city sizes grow.

C. StructuralLimitationsofManualMonitoringSystems

Thecollectiveanalysisofclassicmanualproceduresreveals basic limitations that restrict their long-term viability as pri- mary monitoring systems.

First, they are reactive rather than proactive, which means that data is usually gathered after major changes in land use have already taken place. Second, they need constant human interventionsincetheyarereresource-dependent.Third,theyare notautomated,whichlowersproductivityinmetropolitanareas with rapid expansion.

Furthermore,real-timeoralmostreal-timedataisbecoming more and more necessary for modern environmental gover- nance in order to support policy decisions. By their very nature, manual techniques are unable to produce analytical results quickly over wide areas.

Even with these limitations, traditional approaches are nev- ertheless useful in some situations. They support ecological study, test computerised predictions, and offer useful ground- truthdata.However,dependingjustonmanualmethods is no longer adequate as environmental monitoring requirements grow in scope and complexity.

III. AI-BASED APPROACHES FOR GREEN COVER LOSS DETECTION (WITH MATHEMATICAL FORMULATION)

AI-based green cover monitoring systems use computer analysis and satellite photos to automatically identify vege- tation and detect changes. These methods rely on statistical classification, temporal comparison models, and spectral fea- ture extraction, in contrast to manual field surveys [8]–[11].

A. SpectralFeature Representation

Satellite images consist of multiple spectral bands. For a givenpixel p ,itsspectralfeaturevectorcanberepresentedas:

$$X_p=[B_1, B_2, B_3, \dots, B_n]$$

where:

- B_i representsreflectancevalueinband i
- n is the total number of spectral bands For example:

$$B_{red}, B_{green}, B_{blue}, B_{NIR}$$

Vegetation exhibits high reflectance in the near-infrared band and lower reflectance in the red band, forming the basis for index- based detection [4],[5].

B. VegetationIndexComputation

A widely used vegetation indicator is the Normalized Dif- ference Vegetation Index (NDVI) [3].Other indices such as SAVI have been proposed to improve accuracy in areas with soil influence [5], defined as:

$$NDVI = \frac{B_{NIR} - B_{Red}}{B_{NIR} + B_{Red}}$$

where:

- B_{NIR} =NearInfraredreflectance
- B_{Red} =Redbandreflectance

NDVI values range between -1 and $+1$. Interpretation:

- $NDVI > 0.3 \rightarrow$ Healthyvegetation

- $NDVI \approx 0 \rightarrow$ Sparse vegetation or soil
- $NDVI < 0 \rightarrow$ Water or built-up areas

Vegetation classification using thresholding can be expressed as:

$$C(p) = \begin{cases} 1, & \text{if } NDVI(p) \geq T \\ 0, & \text{if } NDVI(p) < T \end{cases}$$

where:

- $C(p)$ = vegetation class label
- T = selected threshold value

This converts spectral measurements into binary vegetation maps.

C. Machine Learning-Based Classification

Instead of fixed thresholding, classical machine learning models learn decision boundaries from training samples.

Given a dataset:

$$D = \{(X, y)\}_{i=1}^m$$

where:

- X_i = feature vector of pixel i
- $y_i \in \{0, 1\}$ = class label (vegetation/non-vegetation)
- m = number of training samples

A classifier function $f(X)$ is trained such that:

$$\hat{y} = f(X)$$

1) *Support Vector Machine (SVM)*: Classical machine learning models such as Support Vector Machines (SVM) [9],[10] and Random Forests [8],[11] have been widely applied in remote sensing for vegetation classification. The decision function can be written as:

$$f(X) = w^T X + b$$

where:

- w = weight vector
- b = bias term

Classification is determined by:

$$\hat{y} = \begin{cases} 1, & \text{if } f(X) \geq 0 \\ 0, & \text{otherwise} \end{cases}$$

2) *Random Forest*: Random Forest constructs multiple decision trees:

$$\hat{y} = \text{mode}\{T_1(X), T_2(X), \dots, T_k(X)\}$$

where:

- T_j = individual decision tree
- k = number of trees

The final classification is obtained through majority voting. Compared to manual interpretation, these models reduce subjectivity and improve classification consistency.

D. Multi-Temporal Change Detection Model

Green cover loss detection requires comparison between two time periods. Change detection techniques using NDVI time-series and multi-temporal imagery are well established in remote sensing literature [12]–[14],[18].

Let:

- $NDVI_{t_1}(p)$ = NDVI at time t_1
- $NDVI_{t_2}(p)$ = NDVI at time t_2

Change magnitude is computed as:

$$\Delta NDVI(p) = NDVI_{t_2}(p) - NDVI_{t_1}(p)$$

Greencoverlossisdetectedwhen:

$$\Delta NDVI(p) < -\theta$$

where:

- θ =changethreshold

Ifvegetationclassificationmaps $C_{i1}(p)$ and $C_{i2}(p)$ are available, change detection can also be expressed as:

$$Loss(p) = \begin{cases} 1, & \text{if } C_{i1} \\ 0, & \text{otherwise} \end{cases}$$

$$C_{i1}(p) = 1 \text{ and } C_{i2}(p) = 0$$

$$C_{i1}(p) = 0 \text{ and } C_{i2}(p) = 1$$

Incontrast,AI-basedsystemsusesatellitephotos,which maycapturevastregionsinasingleframe.Oncethecom-
0,otherwise

This allows pixel-level identification of vegetation-to-non- vegetation transitions.

E. AccuracyAssessment

To evaluate AI-based classification performance, standard metrics are used. Accuracy assessment methods for remote sensing classification are discussed extensively in Congalton and Green [1] and Foody [19].

Let:

- TP =TruePositives
- TN =TrueNegatives
- FP =FalsePositives
- FN =FalseNegatives Overall Accuracy:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Precision:

$$Precision = \frac{TP}{TP + FP}$$

Recall:

$$Recall = \frac{TP}{TP + FN}$$

KappaCoefficient:

$$K = \frac{P_o - P_e}{1 - P_e}$$

where

- P_o =observedagreement
- P_e =expectedagreement

Thesemetricsprovidequantitativecomparisonagainstman- ual assessments.

IV. COMPARATIVE ANALYSIS OF MANUAL AND AI-BASED APPROACHES

To understand the practical impacts of transitioning from manual monitoring systems to AI-driven frameworks, a num-
berofoperationalandtechnologicalfeaturesarecompared. In addition to computational ability, real-world deployment features such as
scalability, efficiency, cost, reliability, and adaptability to urban dynamics are considered.

A. SpatialCoverageandScalability

Manual field surveys are inherently limited by physical constraints. Survey teams are limited to inspecting specific geographic areas
within the given time period. The extension of coverage must be proportional with increases in personnel andlogisticalcoordination.

As a result, using manual methods to monitor entire states or large urban areas becomes operationally challenging.

In contrast, AI-based systems use satellite photos, which may capture vast regions in a single frame. Once the computational pipeline is established, the same algorithm may process several sites without further physical deployment. As a result, AI-powered solutions are much more scalable than manual querying. AI technologies provide consistent monitoring at regional, national, or even global levels from a spatial perspective, whilst manual procedures are typically restricted to localized sampling.

B. Temporal Monitoring Capability

The ability to monitor time must be done often in order to detect sudden changes in land usage. Manual surveys are frequently conducted once a year or on a seasonal basis due to resource constraints. Because of this, the loss of green cover goes unnoticed, especially in rapidly growing urban areas.

AI-based methods, on the other hand, employ repeated satellite visits. Many satellite platforms produce images at a few-day to week-long intervals. Automated change detection algorithms can interpret these records quickly, allowing for nearly real-time vegetation change tracking.

This enhanced temporal resolution provides decision-makers with timely insights, enabling them to react more effectively to illegal construction or deforestation activities.

C. Operational Efficiency and Processing Time

Manual techniques involve a number of phases, including data input, field data gathering, report compilation, and administrative review. Every step increases the processing time. Months may pass before comprehensive reviews' final results are finished.

AI-based solutions simplify this procedure by automating image analysis and classification. When satellite data is acquired, algorithms can process and create vegetation maps considerably more quickly. Processing time is primarily determined by computer infrastructure rather than field logistics. Thus, in terms of operational efficiency, AI-based monitoring systems offer substantial advantages.

D. Human Dependency and Consistency

Manual surveys mostly depend on human judgment and experience. Inconsistencies in the data gathered can be introduced by variations in training, interpretation, and measurement methods. Decisions about land classification or canopy estimation may be affected by subjective assessments.

After being trained and validated, AI-based systems apply uniform classification rules to all datasets. This minimizes the variation brought on by human subjectivity. The operational phase of AI systems guarantees consistent outputs across time periods and regions, despite the need for meticulous validation during model training. Long-term monitoring programs are more reliable and replicable when there is less reliance on humans.

E. Cost Implications

Recurring costs associated with manual monitoring include administrative expenses, equipment, transportation, and employee pay. Operational expenses increase in direct proportion to the degree of monitoring.

Initial investments in computer power and technological expertise may be necessary for AI-based solutions. After deployment, though, there aren't many marginal expenses to analyze more areas. Recurring costs are further decreased by using satellite data from freely accessible sources.

When compared to repeated manual surveys, AI-driven systems show improved cost-effectiveness over longer monitoring periods.

F. Adaptability to Complex Urban Environments

Diverse surface materials, varied land-use patterns, and broken green patches are characteristics of urban landscapes. Due to sample constraints, manual surveys may miss small or isolated vegetation clusters.

Both vast forest patches and smaller urban green spaces can be detected thanks to AI-based classification techniques that examine pixel-level information across full photos.

Computational models enhance the ability to distinguish between vegetation and built-up structures by integrating several spectral information. In crowded places, this flexibility improves accuracy of detection.

G. Summary of Comparative Evaluation

The overall comparison is summarized in Table I.

TABLE I
COMPARISON OF MANUAL AND AI-BASED METHODS

Parameter	Manual	AI-Based
Spatial Coverage	Localized	Large-scale
Monitoring Frequency	Low	High
Processing Speed	Slow	Fast
Automation	None	Fully automated
Human Dependency	High	Low
Cost Efficiency	Moderate–High	Scalable
Urban Adaptability	Limited	Improved

The comparative assessment indicates that while manual methods remain valuable for ground validation and ecological research, AI-based approaches offer superior scalability, efficiency, and operational sustainability.

H. Interpretation of Findings

In areas that are quickly urbanizing, a change to AI-assisted green cover monitoring is not just a technology trend but also a practical requirement. Reliance on manual processes alone is no longer adequate when environmental change develops in scale.

Key drawbacks of conventional methods are addressed by AI-based monitoring frameworks, which offer:

- Broader spatial observation
- Faster analytical turnaround
- Higher monitoring frequency
- Standardized classification processes

However, manual methods continue to serve as essential ground-truth validation mechanisms. A hybrid framework combining automated detection with selective field verification may represent the most practical long-term solution.

V. CHALLENGES AND LIMITATIONS

AI-based methods greatly increase vegetation monitoring’s automation and scalability, but they have drawbacks. To give a true assessment of their actual deployment, these constraints must be critically examined. Designing more resilient environmental monitoring frameworks is also aided by an understanding of these difficulties.

A. Dependence on Data Quality and Availability

The quality and accessibility of satellite imagery are critical components of AI-driven systems. Image clarity and spectral consistency can be impacted by a number of factors like cloud cover, atmospheric disturbances, seasonal fluctuations, and sensor noise. It could be challenging to get acceptable imagery at regular intervals in areas with a lot of cloud cover. Inconsistencies in spectral readings may also be introduced by differences in sensor properties among satellite platforms. The analytical pipeline becomes more complex as a result of these fluctuations, which call for preprocessing processes like radiometric normalization and atmospheric correction. The reliability of vegetation detection results may also decrease if the quality of the input data is compromised.

B. Requirement of Training Data for Machine Learning

Labeled training data is crucial when using traditional machine learning methods. Vegetation and non-vegetation regions must be manually annotated in order for creating high-quality labeled datasets. This procedure may need professional supervision and can take a long period.

Biased or inadequate training data might limit a model's capacity to generalize to new geographic areas and lower classification accuracy. Therefore, early model training still requires rigorous planning and validation, even though AI lowers manual effort during large-scale implementation.

C. Computational Infrastructure Requirements

Sufficient computer resources are needed to process high-resolution satellite pictures over wide regions. Operations involving machine learning categorization, multi-temporal comparison, and change detection may require a large amount of memory and computing power.

Even while infrastructural challenges have been reduced by developments in cloud computing and geospatial computing platforms, smaller organizations or local governments may still encounter technological difficulties when implementing large-scale automated systems. However, with the right infrastructure planning, computational limitations—which are mainly technological rather than methodological—can be lessened.

D. Sensitivity to Parameter Selection

Parameter adjustment is necessary for both machine learning classification and vegetation index thresholding. Misclassification may result from incorrect threshold values or poorly chosen model parameters, especially in diverse urban settings where sparse vegetation and built-up surfaces coexist. Systematic validation, accuracy evaluation, and recurring recalibration are necessary to guarantee dependable performance of models.

E. Interpretation and Decision-Making Challenges

Even though AI systems produce quantitative results, domain knowledge is still needed to interpret those results for policy decisions. For instance, contextual knowledge is necessary to differentiate between seasonal vegetation change and permanent loss of green cover. Therefore, rather than taking the role of expert evaluation entirely, AI should be viewed as a decision-support tool.

F. Ethical and Governance Considerations

Large amounts of spatial data are produced by automated monitoring systems, and this data may have an impact on environmental policies, urban planning choices, and regulatory actions. Maintaining accountability in decision-making and guaranteeing transparency in algorithmic processes are crucial factors. For automated environmental monitoring frameworks to continue to evoke confidence in the public, methods and validation procedures must be properly documented.

G. Overall Assessment of AI Limitations

Despite these difficulties, AI-based monitoring's limits are mostly technical and controllable. Rather than underlying methodological flaws, the majority of restrictions are related to parameter optimization, computational capability, and data quality. Many of these issues are gradually being resolved thanks to ongoing advancements in computing infrastructure, open-access geospatial data platforms, and satellite resolution. Therefore, when compared to manual monitoring methods, the operational benefits of AI systems surpass the associated technical complexities, even though they require careful design and validation.

VI. DISCUSSION AND FUTURE DIRECTIONS

This study's comparative analysis demonstrates a distinct technological advancement in green cover monitoring techniques. The fundamental framework for vegetation evaluation was created by manual field-based techniques, which still offer important ecological insights at the ground level. However, depending just on conventional methods becomes impracticable as urbanization picks up speed and the need for environmental monitoring grows in scale and frequency.

The investigation shows that major operational gaps related to manual monitoring are filled by AI-based technologies. AI-driven frameworks are particularly well-suited for modern environmental governance due to advancements in automation, long-term cost efficiency, monitoring frequency, and spatial coverage [20]. Processing multi-temporal satellite images makes it possible to identify vegetation loss early, which is essential for sustainable urban design and regulatory compliance.

However, the discussion also makes clear that AI-based monitoring shouldn't be seen as a whole substitute for conventional techniques. For environmental studies, automated output verification, and ground-truth validation, field surveys are still crucial [1], [19]. The best approach might be to combine selective manual verification with automated large-scale detection in many real-world applications. The ecological accuracy of field observations and the scalability of AI are combined in this hybrid technique.

Looking forward, several directions can enhance the effectiveness of AI-assisted green cover monitoring systems:

- 1) **Integration of Multi-Source Data:** Combining satellite imagery with geographic information systems (GIS), demographic data, and land-use records can provide a more comprehensive understanding of environmental changes.
- 2) **Improved Spatial Resolution:** Advancements in satellite technology are increasing image resolution, enabling detection of smaller and fragmented urban green spaces that were previously difficult to identify.
- 3) **Automated Alert Systems:** Developing threshold-based alert mechanisms can support municipal authorities by automatically flagging potential vegetation loss events.
- 4) **Standardized Accuracy Assessment Protocols:** Establishing consistent validation metrics such as overall accuracy, precision, recall, and kappa coefficient can improve reliability and comparability of monitoring results.
- 5) **Cloud-Based Processing Platforms:** Utilizing cloud computing infrastructure can reduce computational barriers and enable scalable environmental analytics even for resource-constrained institutions.
- 6) **Policy Integration:** Incorporating AI-generated vegetation maps into urban planning and regulatory frameworks can improve transparency and evidence-based decision-making.

Future studies should concentrate on increasing the interpretability of AI-generated outputs, strengthening classification robustness in diverse urban environments, and optimizing computing efficiency. To create sustainable monitoring ecosystems, environmental scientists, urban planners, and computational researchers must continue to work together.

All things considered, the move toward intelligent environmental monitoring represents a strategic change in how cities manage ecological resources as well as a technological breakthrough. Effective and scalable monitoring systems will be essential to environmental sustainability initiatives as green cover becomes more and more important for resilience to climate change.

VII. CONCLUSION

An organized comparison of AI-based techniques and traditional human methods for detecting green cover decline was offered in this research. The practical efficiency of both monitoring systems was evaluated by looking at operational, spatial, temporal, and economic parameters.

Field surveys and record-based inspection are two manual vegetation evaluation methods that yield thorough ecological information and are still useful for ground validation. However, these methods are limited by delayed reporting, infrequent monitoring cycles, high labor dependency, and limited spatial coverage. These restrictions lessen the efficiency of manual monitoring systems in assisting prompt environmental decision-making as urban landscapes continue to grow at an accelerated rate.

On the other hand, scalable, automated, and repeatable solutions for large-scale green cover monitoring are provided by AI-based methods that make use of satellite imagery and computational analysis. Methods for multi-temporal change detection, vegetation index calculation, and machine learning classification allow for the systematic identification of vegetation loss over large areas. According to the comparison analysis, AI-driven frameworks greatly increase the frequency of monitoring, operational effectiveness, spatial uniformity, and long-term cost sustainability.

AI-based monitoring systems show significant advantages over conventional manual techniques in quickly evolving urban environments, despite technical difficulties with data quality, processing demands, and parameter optimization. The results indicate that a hybrid architecture that combines automated detection with selected ground validation may offer the most dependable and sustainable monitoring approach, rather than entirely replacing manual surveys.

Intelligent green cover monitoring technologies will be crucial in strengthening evidence-based planning and ecological governance as environmental sustainability becomes more and more important for urban resilience and climate adaptation. An important development in contemporary vegetation management techniques is the shift from manual observation to AI-assisted environmental analytics.

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