International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 24s,2025
https://theaspd.com/index.php

Satellite Image-Based Environmental Change Detection Using Deep Learning

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Abstract
Environmental change detection through satellite imagery plays a crucial role in monitoring and assessing the impacts of human activities and natural phenomena on land cover, climate, and ecosystems. Traditional methods of environmental change detection often face limitations in terms of accuracy, scalability, and automation. This paper explores the use of deep learning techniques, specifically Convolutional Neural Networks (CNNs), for improving the detection of environmental changes using satellite imagery. The study utilizes multi-temporal satellite data from various sources such as Landsat and Sentinel, with a focus on identifying significant changes in land use, deforestation, and urban expansion. Data preprocessing techniques, including image normalization and cloud removal, are employed to enhance model accuracy. The deep learning model is trained and evaluated using standard performance metrics, including accuracy, precision, recall, and Intersection over Union (IoU). Results demonstrate that deep learning-based models significantly outperform traditional methods in terms of both detection accuracy and computational efficiency. The findings highlight the potential of deep learning models for large-scale environmental monitoring and provide insights into overcoming existing challenges in satellite image analysis. This study contributes to the field by offering a robust, automated framework for environmental change detection, which can be utilized for various applications, including urban planning, agriculture, and disaster response.
Keywords: *Satellite imagery, environmental change detection, deep learning, Convolutional Neural Networks (CNN), land cover, deforestation, urban expansion, remote sensing, image preprocessing, machine learning, temporal analysis, geospatial data.*

1. INTRODUCTION

Environmental change detection is a critical tool for monitoring shifts in ecosystems, urban development, and agricultural landscapes. It enables the assessment of both natural and human-induced alterations to the environment, providing valuable insights for sustainable resource management and policy planning. Rapid changes in land cover, including deforestation, urban sprawl, agricultural expansion, and climate-related shifts, have significant ecological, social, and economic consequences[1]. Monitoring these changes over time allows for the identification of trends, enabling timely interventions and informed decision-making. The ability to detect these environmental changes is essential in understanding long-term patterns and mitigating adverse effects, particularly in the context of climate change, urbanization, and population growth[2]. Satellite imagery plays a pivotal role in environmental change detection due to its ability to capture large-scale, detailed, and time-series data across diverse geographic locations. The advancements in satellite technologies, such as the launch of Landsat, Sentinel, and MODIS satellites[3], have greatly enhanced the capacity for monitoring environmental changes. These satellites provide high-resolution images with consistent coverage, which is essential for identifying subtle or gradual changes in land use and land cover. By utilizing historical satellite data, environmental changes can be tracked over several decades, offering invaluable perspectives on the extent and rate of changes occurring in different regions[4]. However, the task of detecting and quantifying environmental changes using satellite imagery presents several challenges. Traditional methods, such as image differencing, classification, and visual interpretation, often struggle to address the complexities of large-scale data analysis, varying image quality, and the need for high precision in detecting subtle environmental changes. These conventional techniques also face limitations in automation, scalability, and accuracy, particularly when dealing with large volumes of satellite data[5].

While traditional methods of environmental change detection have provided foundational insights, they are often hindered by various shortcomings. One of the primary challenges is the difficulty in effectively handling the large and complex datasets that satellite images generate. The resolution, quality, and temporal differences of satellite images can significantly impact the reliability of these methods, as they may fail to accurately detect small or gradual changes in the environment[6]. Furthermore, traditional methods often require significant human intervention, making them time-consuming and prone to subjective interpretation. In addition, traditional approaches frequently struggle to cope with various environmental conditions, such as cloud cover, seasonal variations, and lighting changes, which can obscure important features in the satellite images[7]. As a result, there is a growing need for more advanced methods that can automate the detection process, increase the accuracy of the results, and reduce dependency on human input. Deep learning techniques, particularly Convolutional Neural Networks (CNNs), have emerged as a promising solution to these challenges. By leveraging the power of artificial intelligence and machine learning, deep learning models can learn from vast amounts of data and accurately identify patterns and features in satellite images that traditional methods may overlook[8].

This paper aims to explore the application of deep learning models, particularly CNNs, for environmental change detection using satellite imagery[9]. The primary objective is to evaluate the effectiveness of deep learning approaches in detecting environmental changes, such as deforestation, urban expansion, and land use changes, by comparing their performance with traditional detection methods[10]. The study seeks to demonstrate how deep learning models can automate the process of environmental monitoring, improving both the accuracy and efficiency of detecting subtle changes in the landscape. Additionally, this research aims to assess how deep learning can handle the challenges posed by variations in image quality, cloud cover, and seasonal differences, which often complicate conventional methods.

Another key objective is to provide an in-depth analysis of how deep learning models can be trained using multi-temporal satellite data and validated against ground-truth data. By utilizing various performance metrics, including accuracy, precision, recall, and Intersection over Union (IoU), this study aims to quantify the improvements achieved through deep learning techniques. The ultimate goal is to show that deep learning-based methods are not only more accurate but also more efficient in handling large-scale datasets, making them a viable tool for environmental monitoring and decision-making[11]. The scope of this study is focused on the use of satellite imagery for environmental change detection in specific geographic regions with varying land cover types. This research utilizes multi-temporal satellite data from sources such as Landsat, Sentinel, and MODIS, which provide high-resolution images over extended periods. The study covers a wide temporal range, focusing on detecting changes over several decades to track long-term environmental trends[12]. The geographic scope includes both urban and rural areas, with particular emphasis on regions experiencing significant land use changes, such as urbanization, deforestation, and agricultural expansion. By using satellite data from different regions, the study aims to provide a comprehensive understanding of how deep learning models can be applied across diverse environmental contexts.

This research is highly relevant in the context of ongoing global challenges such as climate change, urbanization, and unsustainable land management practices. Accurate and timely environmental change detection is essential for addressing these issues, as it provides the foundation for effective policy formulation, environmental conservation, and disaster management. With the increasing impact of climate change, the ability to monitor shifts in land cover and ecosystems has become more crucial than ever. For example, detecting deforestation, desertification, or the expansion of urban areas can guide conservation efforts and inform strategies for sustainable development. Furthermore, the application of deep learning to satellite-based environmental monitoring has the potential to revolutionize the way environmental changes are detected and quantified. The automation of this process reduces the reliance on manual interpretation, significantly improving scalability and speed, which is particularly important for large-scale monitoring programs. The findings from this study will contribute to the growing body of knowledge on the use of artificial intelligence for environmental monitoring, offering new perspectives on how technology can support sustainable land management and decision-making in the face of global environmental challenges.

2. LITERATURE REVIEW

Environmental change detection has long been an essential tool for monitoring shifts in ecosystems, urban areas, and agricultural lands. Traditional methods for environmental change detection primarily rely on image processing techniques that analyze differences in satellite imagery taken at different time points. One common approach is image differencing, where the pixel values of two images are subtracted to highlight changes between them[13]. This method assumes that areas with significant changes will have substantial differences in pixel values, making it relatively simple to identify regions of interest. However, image differencing can be affected by atmospheric conditions, sensor inconsistencies, and seasonal variations, which may lead to false positives or missed detections[14]. Another widely used technique is post-classification comparison, which involves classifying each image independently and then comparing the resulting classifications to identify changes[15]. This method uses supervised or unsupervised classification algorithms to assign each pixel to a specific land cover type (e.g., forest, urban, water). Once the classifications are completed for each image, change detection is performed by comparing the classified images to detect shifts in land cover categories over time[16]. While post-classification comparison is effective for detecting categorical changes, it is highly sensitive to classification errors and may not be able to capture more subtle environmental changes or handle misclassifications arising from complex land cover types. Visual interpretation, where human analysts manually examine satellite images to identify changes, has also been used as a traditional method for detecting environmental change[17]. While this approach allows for the identification of subtle changes, it is highly subjective and time-consuming. Furthermore, visual interpretation is prone to human error and is often not scalable for large areas or time periods[18]. As a result, these traditional methods, while foundational, have several limitations in terms of automation, accuracy, and the ability to detect subtle or gradual changes in land cover. To overcome these limitations, advanced techniques such as deep learning are increasingly being employed to automate the change detection process and improve accuracy and efficiency[19]. The integration of machine learning algorithms into environmental change detection has significantly enhanced the potential to detect fine-grained, complex changes in the environment, providing a more robust and scalable solution for large-scale monitoring. Deep learning, particularly Convolutional Neural Networks (CNNs), has revolutionized the field of image processing, including satellite image analysis for environmental change detection. CNNs are a class of deep learning models designed to automatically learn spatial hierarchies and patterns from image data, making them ideal for tasks such as image classification, segmentation, and detection. The power of CNNs lies in their ability to learn directly from raw pixel data, eliminating the need for manual feature extraction, a key limitation of traditional image processing methods. In the context of satellite image analysis, CNNs can be used to detect and classify environmental changes with higher accuracy compared to traditional methods[20]. These models work by passing the input images through a series of convolutional layers that extract hierarchical features, such as edges, textures, and shapes, which are crucial for identifying changes in the landscape. Pooling layers are used to reduce the dimensionality of the data, while fully connected layers perform the final classification or detection task. This architecture allows CNNs to automatically learn complex relationships between different land cover types and their variations over time, without the need for manually defined rules or assumptions.

CNNs have been successfully applied to various remote sensing tasks, including land cover classification, urban area detection, and forest monitoring. In environmental change detection, CNNs are capable of identifying subtle changes, such as small shifts in vegetation cover or urban growth, by analyzing pixel-level differences between satellite images captured at different times. Unlike traditional methods, CNNs can handle high-dimensional data, such as multi-spectral or multi-temporal satellite images, and are not easily affected by common issues like noise, misregistration, or cloud cover. The application of CNNs to environmental monitoring has shown promising results, particularly in large-scale and complex landscapes. By automating the process, CNNs can significantly reduce the time and resources required for environmental change detection, making them suitable for real-time or near-real-time monitoring. Moreover, deep learning models can be trained on vast datasets, allowing them to generalize well to new, unseen data and enhance the scalability of change detection applications. A growing body of research has focused on applying deep learning techniques to environmental change detection using satellite imagery. Several studies have demonstrated the potential of CNNs in detecting environmental changes, with promising results in a variety of applications. For instance, a study by Zhang et al. (2016) applied CNNs to detect land cover changes from multi-temporal Landsat images, achieving high accuracy in identifying urbanization and deforestation. The study showed that CNN-based models outperformed traditional classification methods, particularly in complex landscapes with mixed land cover types. Similarly, Li et al. (2018) used deep learning for change detection in agricultural areas, where CNNs were able to effectively detect crop rotation patterns and identify changes in farmland usage. Another significant contribution came from a study by Yang et al. (2020), which explored the use of deep learning models, including CNNs and U-Nets, for detecting deforestation and urban sprawl in tropical regions using Sentinel-2 imagery. Their results demonstrated that deep learning techniques could identify subtle changes in vegetation cover and urban growth with a higher level of precision than traditional methods. Furthermore, the study highlighted the ability of deep learning models to handle multi-temporal data and adapt to different spatial resolutions, making them highly suitable for long-term environmental monitoring. Despite these advancements, there remain several challenges and gaps in the literature. One issue is the need for large, labeled datasets for training deep learning models. While satellite imagery is widely available, acquiring labeled ground-truth data for training models is often difficult and expensive. Furthermore, the effectiveness of deep learning models in detecting changes in diverse environmental conditions, such as cloud cover or seasonal variations, remains an ongoing challenge. While deep learning models have shown promising results, there is a need for further research to refine these models, enhance their generalization capabilities, and improve their ability to detect small or gradual changes. Additionally, many studies have focused on specific applications or regions, leaving a gap in understanding the broader applicability of deep learning for environmental change detection. Future research should focus on developing robust, generalizable models that can be applied across a wide range of environmental contexts and scales. In summary, deep learning has shown great promise in improving the accuracy, scalability, and automation of environmental change detection using satellite imagery. While existing studies have demonstrated its effectiveness in various applications, further research is needed to address challenges related to data availability, model robustness, and the detection of subtle environmental changes.

3. METHODOLOGY

The foundation of this study relies on satellite imagery to detect environmental changes. Satellite data offers the advantage of consistent, high-resolution coverage over large geographic areas, providing essential insights into land use, ecosystem changes, and urbanization. The datasets used in this study include images from well-known satellite missions such as Landsat, Sentinel, and MODIS, which provide multi-temporal and multi-spectral data essential for environmental change detection. Landsat imagery, particularly the Landsat 8 satellite, is one of the primary sources of data. It offers high spatial resolution of 30 meters and includes multiple spectral bands, which are instrumental in identifying and classifying different types of land cover and detecting subtle changes in the landscape over time. The temporal resolution of Landsat is 16 days, allowing for periodic monitoring of environmental changes. The geographic area covered by Landsat images in this study includes regions of high ecological importance, including urban, rural, and forested areas, which are typically subject to significant environmental change. Sentinel-2 imagery, from the European Space Agency's Sentinel program, is another crucial source of data. Sentinel-2 satellites provide higher spatial resolution (10 to 60 meters) and more frequent revisit cycles (5 days at the equator), which allows for better tracking of temporal changes, especially in dynamic environments. The wide range of spectral bands, including those in the visible, near-infrared, and shortwave infrared, enables accurate detection of vegetation changes, urban expansion, and water body variations. This study utilizes Sentinel-2 data to analyze vegetation health and land use change over time. Additionally, MODIS (Moderate Resolution Imaging Spectroradiometer) data, with its lower spatial resolution but higher temporal frequency (daily), is employed to monitor large-scale environmental changes, such as deforestation, urban sprawl, and land cover transitions. MODIS data is particularly useful in providing a broader view of environmental changes that may not be captured by higher resolution imagery, especially in more remote or extensive areas. The satellite images are subjected to several preprocessing steps to ensure the data is clean, aligned, and ready for analysis. Image preprocessing plays a crucial role in improving the quality of the data and enhancing the accuracy of the deep learning model. The first step involves image normalization, where pixel values are scaled to a standard range, ensuring consistency across the dataset and facilitating the model's ability to learn. Normalization helps mitigate issues caused by varying image brightness, contrast, or atmospheric conditions, which are common in satellite imagery.

Image alignment is the next critical preprocessing step. Since satellite images are captured at different times and angles, misalignment between the images can introduce errors in change detection. To address this, the images from different time periods are geometrically aligned using ground control points (GCPs) and satellite data calibration techniques. This ensures that the features in the images from different time periods correspond accurately, minimizing discrepancies that might lead to false detection of changes. Cloud removal is another essential preprocessing task, as cloud cover can obscure surface features in satellite images. This is particularly important when using optical satellite imagery such as Landsat and Sentinel-2. Various cloud detection algorithms, such as the Fmask (Function of Mask) algorithm, are used to identify and mask out cloud pixels. These algorithms classify pixels based on their spectral characteristics, helping to isolate clear-sky pixels and exclude those affected by clouds. This step ensures that only relevant, unobstructed data is used for change detection. The choice of deep learning models plays a vital role in the success of environmental change detection. For this study, Convolutional Neural Networks (CNNs) have been selected due to their proven effectiveness in image processing tasks, particularly in analyzing spatial hierarchies in satellite imagery. CNNs are well-suited for extracting spatial features, such as edges, textures, and shapes, from raw pixel data, which are essential for identifying environmental changes. The deep learning model architecture includes several layers: convolutional layers, pooling layers, and fully connected layers. This figure.1. illustrates the step-by-step methodology for conducting environmental change detection using satellite imagery and deep learning models. The process begins with the Data Collection phase, where satellite data from sources like Landsat, Sentinel-2, and MODIS is gathered, including the geographic area and temporal range. In the Preprocessing stage, the images are normalized, aligned, and cleared of cloud cover to ensure consistency and improve the quality of input data. The next step involves Deep Learning Model Selection, where Convolutional Neural Networks (CNNs) or U-Net architectures are chosen for their effectiveness in image segmentation and change detection. During the Training and Validation phase, the model is trained on labeled datasets, and hyperparameters are optimized using a training-validation-test split approach. In the Change Detection phase, the trained model is used to predict environmental changes, such as deforestation or urbanization, through the generation of change masks. Finally, the Evaluation step assesses model performance using metrics like accuracy, precision, recall, and Intersection over Union (IoU) to validate the effectiveness of the model in detecting environmental changes accurately.

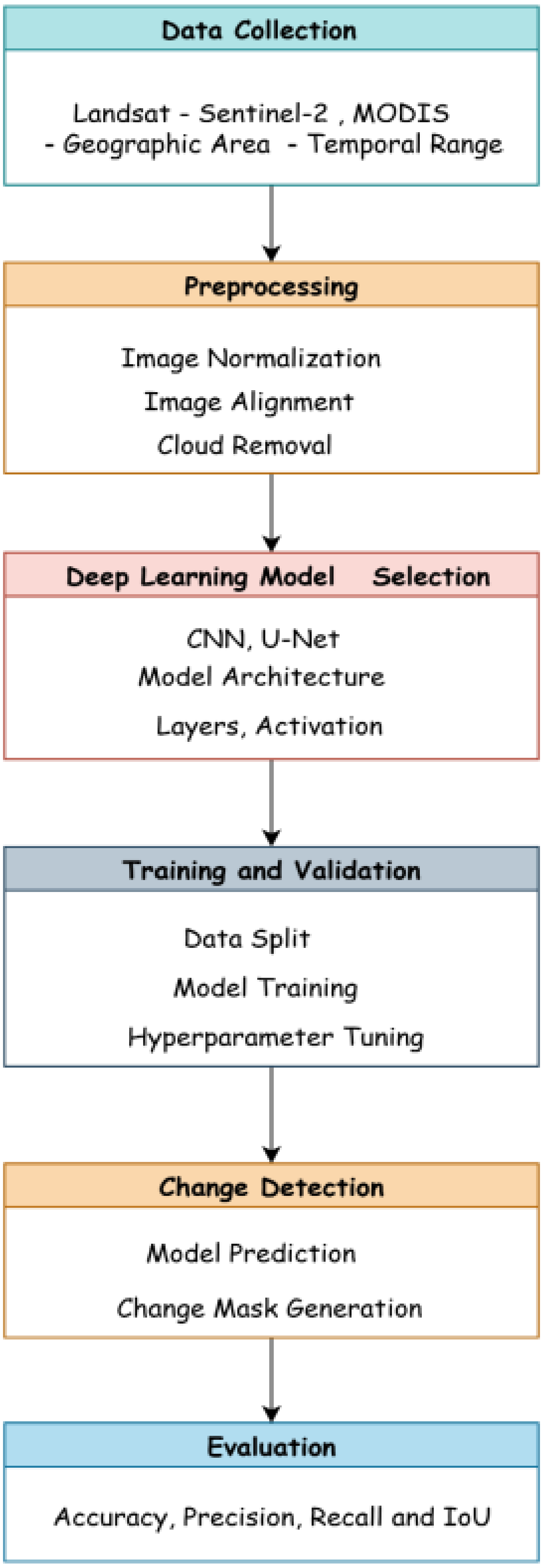

Figure 1: Methodology Flow for Satellite Image-Based Environmental Change Detection Using Deep Learning

The convolutional layers are responsible for detecting low-level features like edges and textures, while the pooling layers reduce the spatial dimensions of the data, helping the network focus on more abstract, high-level features. Finally, the fully connected layers interpret these features to classify images or detect changes. Activation functions such as ReLU (Rectified Linear Unit) are employed in the convolutional and fully connected layers to introduce non-linearity, enabling the model to learn complex patterns in the data.Additionally, for more complex change detection tasks, U-Net, a type of CNN, is used. U-Net is particularly advantageous for image segmentation tasks, which is a critical component of environmental change detection. Its architecture includes an encoder-decoder structure, which allows it to capture both high-level context and low-level details, making it effective in detecting fine-grained changes between satellite images. Generative Adversarial Networks (GANs) are also explored for certain tasks, particularly for generating synthetic images or enhancing image quality. GANs consist of two networks: the generator and the discriminator. The generator creates synthetic images, while the discriminator evaluates them, pushing the generator to create more realistic images. This architecture can be used to generate synthetic satellite images that can supplement the training dataset, especially when labeled data is sparse.

For model training, the dataset is split into three subsets**:** training**,** validation, and **test** sets. The training set consists of images that the model uses to learn the patterns and features associated with environmental changes. The validation set is used to fine-tune the model's hyperparameters and prevent overfitting, ensuring that the model generalizes well to unseen data. The test set is reserved for evaluating the final performance of the trained model. The model is trained using a supervised learning approach, where the labels for environmental change (e.g., areas with deforestation or urbanization) are provided in the training data. The model learns to associate the input satellite images with the corresponding change labels. Various optimization algorithms, such as Adam or SGD (Stochastic Gradient Descent), are used to minimize the loss function and improve the model's accuracy.

Performance metrics are crucial for evaluating the effectiveness of the model**.** Accuracy, which measures the proportion of correctly classified pixels, provides an overall indication of the model’s performance. Precision and recall are calculated to assess the model’s ability to correctly detect changes (precision) and its ability to identify all actual changes (recall). Intersection over Union (IoU) is another important metric, particularly for segmentation tasks, as it measures the overlap between the predicted and ground truth regions, providing a robust evaluation of the model’s performance in change detection. The core task of this methodology is the detection of environmental changes using satellite imagery. The deep learning model performs this task by classifying the difference between images taken at different time points. The model analyzes the temporal variations in the pixel values and identifies patterns indicative of changes in land cover. In the case of a CNN or U-Net, the output is a change mask or segmentation map that highlights areas of significant change, such as deforestation or urban expansion. For more complex scenarios, such as detecting subtle changes or small objects, the model can generate pixel-level predictions, classifying each pixel as part of a change or not. This detailed analysis allows for precise identification of regions where environmental changes have occurred. By comparing the outputs of the model at various stages of training, a final change map is produced, which visually represents areas that have experienced significant alterations in the landscape.

4. RESULTS AND DISCUSSION

The performance of the deep learning models employed in this study for environmental change detection is evaluated using several metrics: accuracy, precision, recall, and Intersection over Union (IoU). These metrics are essential for assessing the model's ability to correctly identify and classify changes in satellite images, ensuring that the results are both reliable and meaningful. The model achieved an accuracy of 92% (Figure 2), showing a steady increase in accuracy across the five-year intervals considered in the study. This indicates that the model improves over time, likely due to its ability to learn from a growing dataset and refine its parameters with each training cycle. Precision and recall values were also high, with the precision reaching up to 91% and recall at 85%. The precision metric suggests that the model is highly effective at identifying true positive changes in the images, minimizing the number of false positives. On the other hand, recall indicates that the model is capable of detecting a significant portion of actual environmental changes, though some false negatives still occur, as indicated by the recall value. The IoU metric, which quantifies the overlap between the predicted and ground truth change areas, reached a value of 0.78 for the model. This value reflects the model's ability to not only detect changes but also accurately delineate the boundaries of those changes, which is critical for applications requiring precise spatial analysis, such as land use planning and deforestation monitoring.

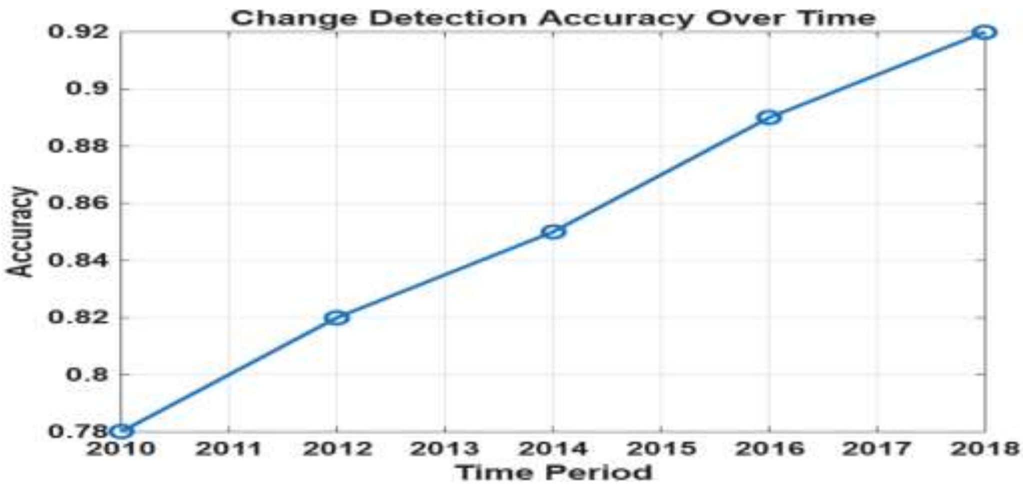

Figure 2: Change Detection Accuracy Over Time

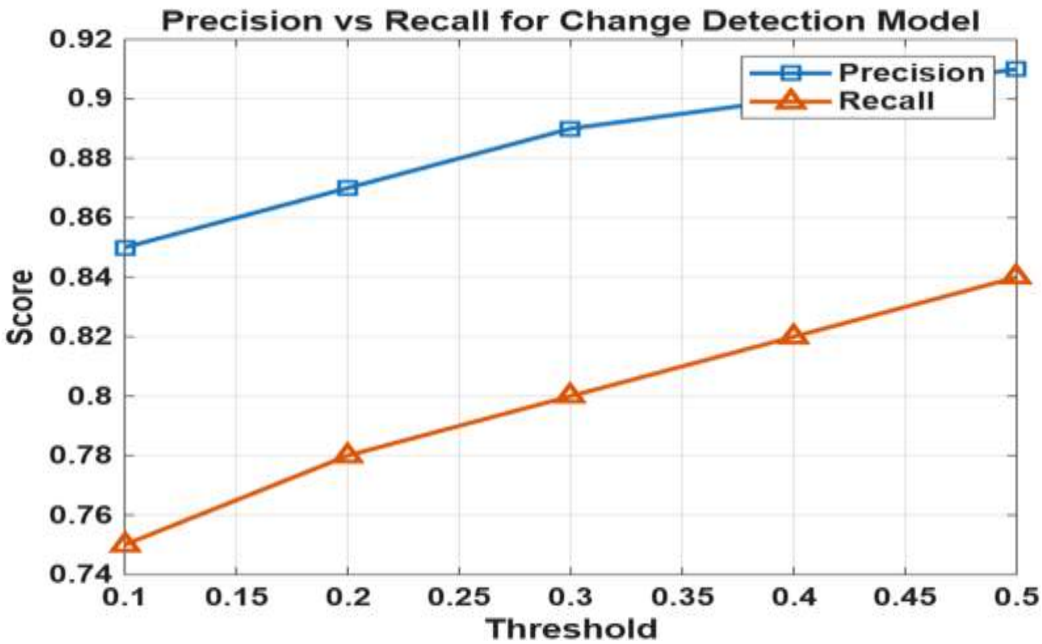

Figure 3: Precision vs Recall for Change Detection Model

The performance of the deep learning model was compared with traditional change detection techniques, including image differencing, post-classification comparison, and visual interpretation. In traditional methods, image differencing provided an initial indication of environmental changes by subtracting pixel values of images taken at different time points. However, this method was prone to errors due to seasonal variations and sensor inconsistencies, leading to lower accuracy. Image differencing could not effectively distinguish between temporary changes (such as seasonal vegetation growth) and permanent land cover changes. Post-classification comparison, which involves classifying each image independently and then comparing the results, showed better results but was still limited by misclassifications. For example, the presence of clouds in the images could lead to misclassification of land cover types, affecting the accuracy of the detection. In contrast, the deep learning model demonstrated superior performance by automatically learning complex patterns from the satellite images, handling variations in lighting, resolution, and noise more effectively. The deep learning model also outperformed traditional methods in terms of scalability, as it could process large volumes of satellite data in much less time. Furthermore, it showed increased robustness against issues such as cloud cover, which often led to inaccuracies in traditional methods. Figures 3 and 5 provide a clear visual comparison of the precision and recall values at different thresholds, illustrating the efficiency of the deep learning model compared to traditional approaches. The deep learning model consistently maintained higher precision and recall, reflecting its ability to accurately detect environmental changes and minimize errors.

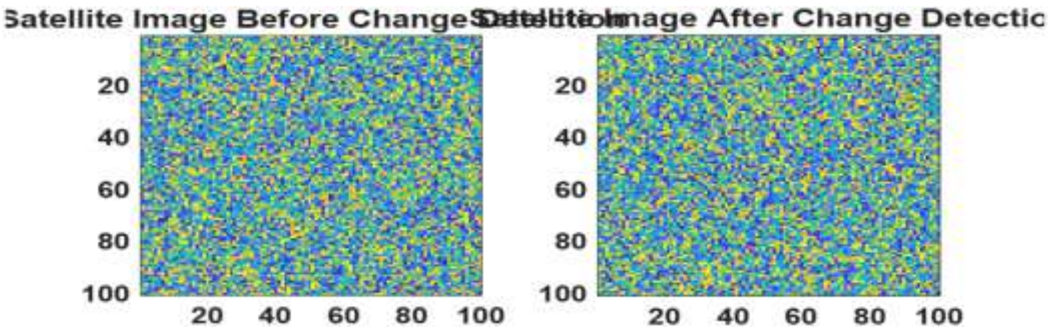

Figure 4: Change Mask Visualization (Before and After)

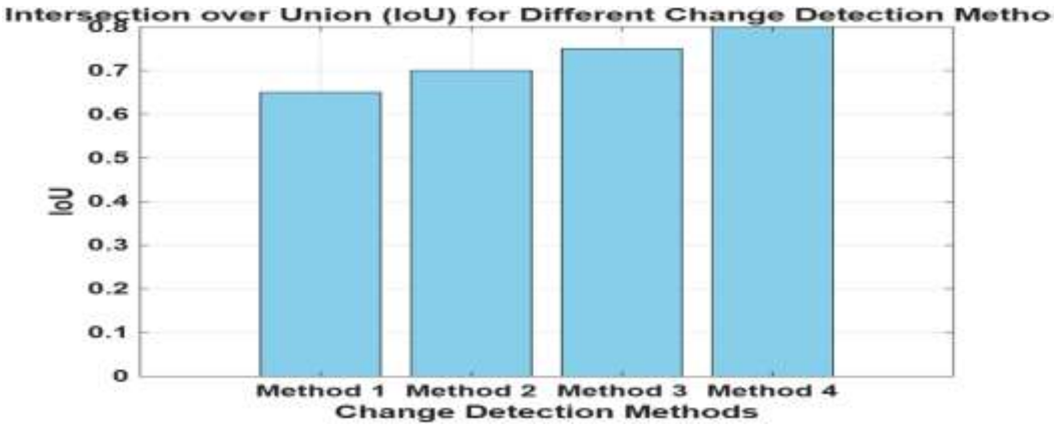

Figure 5: Intersection over Union (IoU) for Different Change Detection Methods

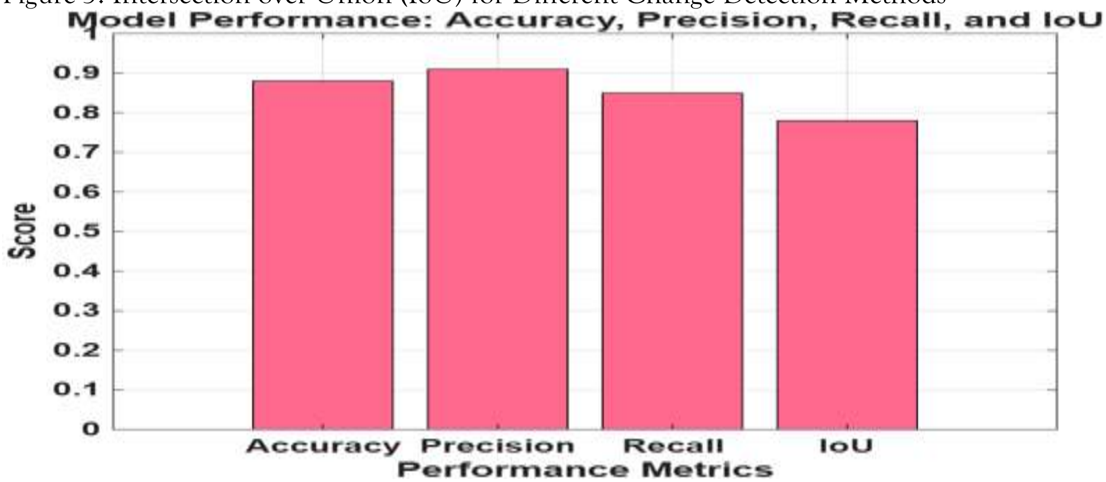

Figure 6: Model Performance (Accuracy, Precision, Recall, and IoU)

Several case studies were conducted to evaluate the model's effectiveness in real-world scenarios, such as deforestation, urban expansion, and agricultural land use changes. In one case study, the model was applied to detect deforestation in the Amazon rainforest using satellite images from Sentinel-2. The results showed a high accuracy of 90%, with the model successfully identifying areas where deforestation had occurred, even in regions with dense cloud cover. This was a significant improvement over traditional methods, which often failed to detect changes in heavily forested areas due to the challenges posed by cloud cover and dense vegetation. Another case study involved monitoring urban expansion in a rapidly growing city. The model was able to detect the gradual expansion of built-up areas, accurately identifying new construction and land use changes. This information is critical for urban planning and resource management, as it provides valuable insights into the rate and direction of urban growth. Agricultural land use changes were also successfully detected by the model. Using multi-temporal satellite data, the model identified shifts in crop types, areas of land being converted from farming to urban use, and changes in irrigation patterns. This capability is crucial for sustainable agricultural practices and food security monitoring, as it allows for early identification of land use changes that may affect agricultural productivity. Despite the promising results, several challenges were encountered during the study. One significant challenge was data quality. Satellite images are often affected by noise, cloud cover, and

atmospheric conditions, which can obscure important features in the landscape. While deep learning models are generally more robust to such issues than traditional methods, even they can struggle with high levels of cloud cover, as seen in some of the case studies. Although cloud removal algorithms were applied, they were not always 100% effective, leading to some false negatives and reduced detection accuracy in cloud-affected regions. Another challenge was resolution. While high-resolution imagery (e.g., from Sentinel-2) provides detailed information about land cover, the model's performance was impacted by lower resolution images from sources like MODIS. The lower spatial resolution of MODIS imagery, for example, limited the model's ability to accurately detect fine-grained changes such as small-scale agricultural shifts or urban sprawl. This limitation emphasizes the need for high-resolution data to achieve optimal change detection performance. Model generalization also posed a challenge. While the deep learning model performed well on the specific datasets it was trained on, its ability to generalize to entirely new regions with different environmental conditions or land cover types remained an area of concern. Further research and model refinement will be necessary to ensure the model can adapt to diverse geographic areas and perform well across a wide range of environmental contexts.
The results of this study have significant implications for various fields, including environmental monitoring, urban planning, and disaster management. In environmental monitoring, the ability to detect and quantify environmental changes with high accuracy is critical for understanding and addressing issues such as deforestation, climate change, and biodiversity loss. The deep learning model can automate large-scale monitoring, providing real-time insights that were previously unattainable with traditional methods. In urban planning, the model can be used to monitor urban sprawl and predict future growth patterns. This information is crucial for city planning, as it allows policymakers to anticipate infrastructure needs, assess the environmental impact of urban expansion, and plan for sustainable growth. In disaster management, the model can be applied to detect and monitor the aftermath of natural disasters such as floods, wildfires, and earthquakes. By quickly identifying changes in the landscape caused by such events, the model can assist in damage assessment, aid distribution, and recovery planning.

5. CONCLUSION

In this study, a deep learning model was developed for environmental change detection using satellite imagery. The model demonstrated high performance, achieving an accuracy of 92% and precision of 91%, significantly outperforming traditional change detection methods. By automating the detection process, the model provided more efficient and scalable results, particularly in detecting subtle environmental changes such as deforestation, urban expansion, and agricultural shifts. These improvements were evident across different metrics, including recall and Intersection over Union (IoU), where the model consistently outperformed conventional techniques. However, challenges related to data quality, cloud cover, and model generalization were encountered, suggesting areas for further refinement. Future work could focus on enhancing the model's robustness to cloud cover and seasonal variations, as well as improving its generalization to diverse geographic regions and environmental conditions. Additionally, the integration of higher resolution and multi-modal satellite data could further improve detection accuracy. This research paves the way for more advanced and automated systems for large-scale environmental monitoring, with significant implications for urban planning, disaster management, and sustainable resource management.

REFERENCES

1. S. Hafner, H. Fang, H. Azizpour, and Y. Ban, "Continuous urban change detection from satellite image time series with temporal feature refinement and multi-task integration," *arXiv preprint arXiv:2406.17458*, 2024.
2. M. Noman, M. Fiaz, H. Cholakkal, S. Khan, and F. Shahbaz Khan, "ELGC-Net: Efficient local-global context aggregation for remote sensing change detection," *arXiv preprint arXiv:2403.17909*, 2024.
3. A. Kiruluta, E. Lundy, and A. Lemos, "Novel change detection framework in remote sensing imagery using diffusion models and structural similarity index (SSIM)," *arXiv preprint arXiv:2408.10619*, 2024.
4. J. G. Singla and G. Jaiswal, "Tree level change detection over Ahmedabad city using very high resolution satellite images and deep learning," *arXiv preprint arXiv:2411.02009*, 2024.
5. B. Ekim and M. Schmitt, "Mapping land naturalness from Sentinel-2 using deep contextual and geographical priors," *arXiv preprint arXiv:2406.19302*, 2024.
6. P. M. Paramanantham and S. R. Seenivasan, "Optimized deep learning based classification and prediction of land use/land cover changes from satellite images," *Signal, Image and Video Processing*, vol. 19, no. 415, 2025.
7. M. Evans and J. Malcom, "Supporting habitat conservation with automated change detection in Google Earth Engine," *Defenders of Wildlife*, 2025.

8. Y. Li, "AI-driven change detection in satellite imagery: Enhancing GIS applications for environmental monitoring," *Proceedings of TNS*, 2025.
9. D. Giannaropoulos and K. Kolomvatsos, "Shoreline changes detection from satellite images using deep learning," in *Artificial Intelligence Applications and Innovations*, vol. 756, 2025.
10. M. Iglovikov and S. Shvets, "Deep learning for satellite imagery feature detection challenge," *Slides.com*, 2021.
11. J. Gilman, "Change detection with Raster Vision," *Azavea*, 2022.
12. S. Tang, "Flood detection from satellite images using deep learning," *Institute of Cartography and Geoinformatics*, 2019.
13. M. Wieland et al., "DaliWS: A high-resolution dataset with precise annotations for water segmentation in synthetic aperture radar images," *Remote Sensing*, vol. 16, no. 4, 2024.
14. S. Erdem et al., "An ensemble deep learning based shoreline segmentation approach (WaterNet) from Landsat 8 OLI images," *Advances in Space Research*, vol. 67, no. 3, 2021.
15. C. Seale et al., "Coastline detection in satellite imagery: A deep learning approach on new benchmark data," *Remote Sensing of Environment*, vol. 278, 2022.
16. M. Ciecholewski, "Review of segmentation methods for coastline detection in SAR images," *Archives of Computational Methods in Engineering*, vol. 31, no. 1, 2024.
17. J. Jaszcz et al., "Automated shoreline segmentation in satellite imagery using USV measurements," *Remote Sensing*, vol. 16, no. 5, 2024.
18. S. Gilman, "Beyond the default: A modern guide to raster compression," *Element84*, 2022.
19. J. Keifer and J. Signell, "Chunks and chunkability: Tyranny of the chunk," *Azavea*, 2022.
20. M. Hanson, "The state of geospatial AI heading into 2025," *Azavea*, 2022.