

Integrating Unsupervised Change Detection and Deep Learning Segmentation for Automated Landslide Mapping

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Abstract

Rapid and accurate detection of landslides after extreme climate events, such as heavy rainfalls or hurricanes, is essential for hazard response and mitigation. Traditional mapping methods rely on manual interpretation or labelled datasets, limiting scalability. This paper presents an integrated workflow combining unsupervised autoencoder-based + KMeans change detection and deep learning semantic segmentation to improve landslide identification in Western North Carolina following Hurricane Helene (September 2024). The approach leverages Planetscope RGB-NIR imagery at 3 m spatial resolution and North Carolina Department of Environmental Quality post-event landslide inventory points. The unsupervised autoencoder extracts latent features and highlights change zones, while segmentation models such as UNet learn spatial–contextual patterns from semi-automated labels. Results demonstrate high detection accuracy with segmentation models achieving strong overlap with ground-truth inventories and minimal false positives with an F1-score of 92%. This hybrid pipeline bridges rapid unsupervised detection and precise pixel-level segmentation, enabling scalable, near-real-time landslide mapping.

1. Introduction

Landslide detection using remote sensing data and deep learning models entails identifying landslide-affected areas by leveraging spectral and topographic information extracted from satellite imagery (Agboola & Hashemi-Beni, 2024; Zheng et al., 2023). Despite notable progress in this field, data scarcity continues to pose a critical challenge (Ghorbanzadeh et al., 2024; Liu et al., 2025). Existing datasets are predominantly concentrated on landslides triggered by large-scale events such as earthquakes and volcano (Meena et al., 2023; Xu et al., 2024). This imbalance hampers the reliable detection of shallow landslides, which often exhibit more subtle signatures and remain underrepresented in available datasets (Akosah et al., 2024). Furthermore, the application of transfer learning with pre-trained models trained on these limited datasets proves inadequate, as scalability issues arise—where non-landslide features such as roads and buildings are frequently misclassified as landslides, leading to an increased number of false positives (Dong et al., 2024; Zhang et al., 2021). These limitations collectively underscore an urgent need to expand and enrich landslide datasets, so they capture failures across different triggers, magnitudes, and landscapes. Enhancing data availability is therefore not simply an academic exercise; it is an essential step toward building models that generalize well and support real-world hazard monitoring and disaster-response workflows. Addressing this gap forms the central motivation for the present study. To bridge this critical divide, we set out the following objectives:

1. Develop annotated landslide label data by integrating ground-truth point data, visual interpretation of high-resolution Planetscope imagery before and after hurricane events, and unsupervised change detection using the auto-encoder with K-Means clustering method.
2. Evaluate the performance of deep learning segmentation models across different combinations of multi-channel datasets to assess their suitability for landslide detection.
3. Validate the most effective segmentation model by applying it to independent test areas in order to assess

generalizability and robustness in diverse geographic settings.

Achieving these objectives will contribute to a more scalable, reliable, and data-rich framework for landslide detection, one that reduces false positives, captures subtle shallow failures, and improves model transferability across diverse terrains.

2. Study Area and Data

2.1 Study area

The study area is situated in the western region of North Carolina, USA (Figure 1). It covers 9 counties that are historically prone to frequent and damaging landslides (Agboola et al., 2024; Wooten et al., 2022). Notable occurrences include major landslides in 2018 and, more recently, in 2024 following hurricane Helene. For this study, the landslide events triggered by Hurricane Helene were selected as the primary focus due to their scale and impact.

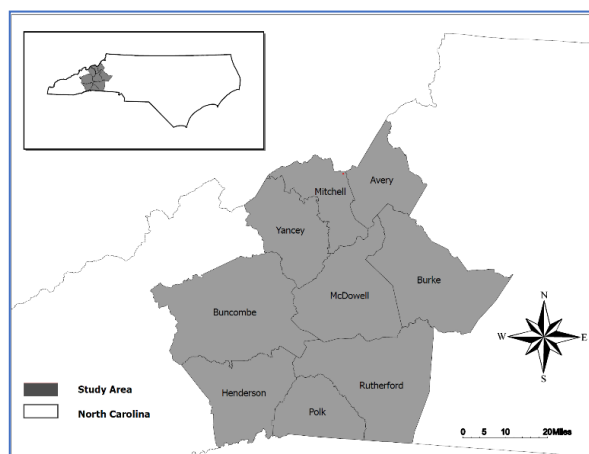


Figure 1. Study area located in western North Carolina, USA, covering nine landslide-prone counties affected by recent events, including the 2024 Hurricane Helene-triggered landslides.

2.2 Data

The datasets used in this work is listed in Table 1. The two major data were retrieved from the Planet labs and the landslide point inventory was retrieved from the [NCOneMap](#) website (NC Onemap, 2019), which was uploaded by North Carolina Department of Environmental Quality.

Data	Type	Source	Resolution
Pre-event imageries (September 24, 2024)	Optical Satellite Image	Planet Labs	3m
Post-event imageries (October 6, 2024)	Optical Satellite Image	Planet Labs	3m
Landslide Inventory Points	Vector (Point Features)	USGS & NCEM	(Ground-truth point locations)

Table 1. Description of the datasets used in this study, including satellite imagery acquired before and after the event, and landslide inventory point data used as ground-truth along with their sources and spatial resolution.

3. Methodology

The workflow (Figure 2) integrates unsupervised change detection for automatic data annotation, with supervised deep-learning segmentation for landslide mapping. Pre- and post-event images are first processed through an autoencoder and clustered to generate initial change masks (Figure 2). These weak labels (Figure 3) are then paired with image patches and used to train a supervised encoder–decoder network, producing refined landslide segmentation outputs.

3.1 Unsupervised Change Detection and Label Generation

The point-based inventory provided by USGS and NCEM was insufficient for training a semantic segmentation model because it only identified the approximate location of each landslide and did not describe its full spatial extent. To overcome this limitation, an unsupervised change detection approach was applied to automatically identify areas that experienced substantial surface disturbance between the pre-event and post-event PlanetScope images as shown in Figure 4.

The change detection process began by co-registering the two multi-spectral images so that corresponding pixels represented the same ground location. The aligned pre-event and post-event images were then separately passed through an autoencoder network. The autoencoder compresses the original RGB–NIR information into a lower-dimensional latent representation while preserving the dominant spectral and spatial patterns in the scene. Unlike traditional pixel differencing methods, this latent representation captures more complex changes in texture, vegetation cover, and surface composition.

The extracted features from the pre-event and post-event images were then compared, and the difference features were clustered using the KMeans clustering algorithm to identify regions with similar change characteristics. The clustering output produced a change detection map representing areas with different levels of spectral variation.

To isolate potential landslide regions, a threshold range between -3.5 and -4 was applied to the clustering results. Pixels within this range were found to correspond to areas with strong vegetation loss, exposed soil, and surface disturbance, which are typical spectral signatures of landslides in optical imagery. These threshold values were determined empirically by comparing clustering outputs with known landslide locations.

Although the unsupervised change detection approach successfully identified many affected areas, it also produced false positives, where non-landslide changes such as shadows, exposed soil, or riverbank variations were incorrectly classified as landslides (Agboola & Hashemi-Beni, 2025). To improve the accuracy of the annotations, the landslide inventory points were overlaid on the change detection map to guide the delineation process. In addition, PlanetScope imagery was visually inspected to refine the boundaries of the detected regions. The final landslide extents were digitized as polygon features using the editing tools in ArcGIS Pro v3.5, providing more accurate representations of landslide geometry than the original point data. For the entire dataset, landslides were manually traced to ensure high-quality labels suitable for supervised deep learning.

The PlanetScope imagery used in this study contains four spectral bands (Blue, Green, Red, and Near-Infrared) with a spatial resolution of approximately 3 m (Wasehun et al., 2025), which provides sufficient detail for detecting small to medium-scale landslides.

3.2 Semantic Segmentation Models

This study employs three widely used deep learning–based semantic segmentation models to detect disasters such as landslides and floods from aerial imagery (Blay & Hashemi-Beni, 2025, Anokye & Hashemi-Beni, 2025, Jamali et al., 2024). The selected models include U-Net, Attention U-Net (AttUNet), and LinkNet, which are encoder–decoder architectures commonly used for pixel-level classification in remote sensing applications.

UNet

- Classical encoder–decoder CNN designed for pixel-level segmentation (Ronneberger et al., 2015).
- Uses skip connections to preserve spatial detail from encoder to decoder and has been widely used in geospatial segmentation due to strong boundary localization (Dang et al., 2024).

Attention UNet (AttUNet)

- Extends UNet with attention gates that highlight relevant regions during decoding (Oktay et al., 2018).
- Suppresses irrelevant background noise (Gebre et al., 2025) and enhances landslide boundary detection. Particularly useful when lesions or landslide patches are small or low contrast.

LinkNet

- Lightweight encoder–decoder CNN with residual connections for efficient feature propagation (Chaurasia & Culurciello, 2017).
- Designed to be computationally fast, enabling large-area inference.
- Performs well in real-time or resource-constrained segmentation applications.

For model training, the annotated dataset was divided into 80% :20% for training and testing ratios. Image tiles of size 256×256 pixels were generated from the original PlanetScope scenes, and corresponding binary masks were created from the polygon

annotations. Table 2 summarizes the number of tiles used for training and testing.

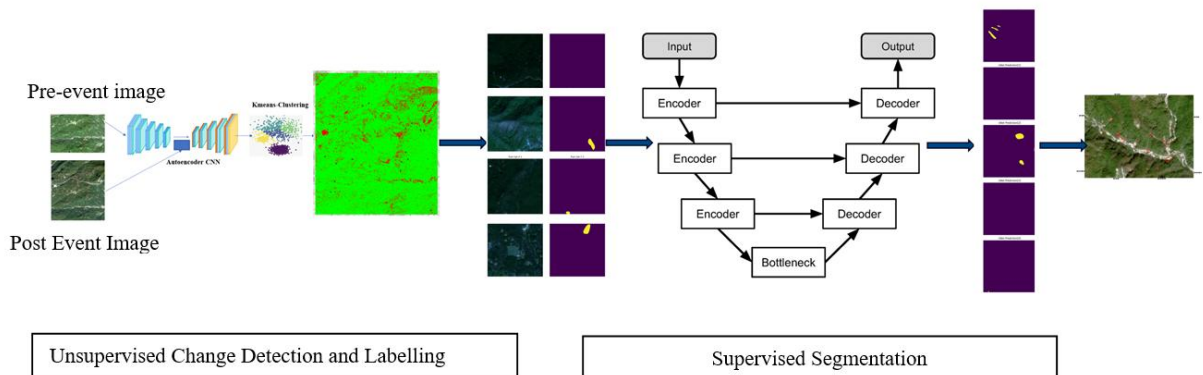


Figure 2. Overview of the proposed workflow showing unsupervised change detection for automatic landslide labelling from pre- and post-event satellite images, followed by supervised deep learning segmentation using an encoder–decoder architecture for landslide mapping.

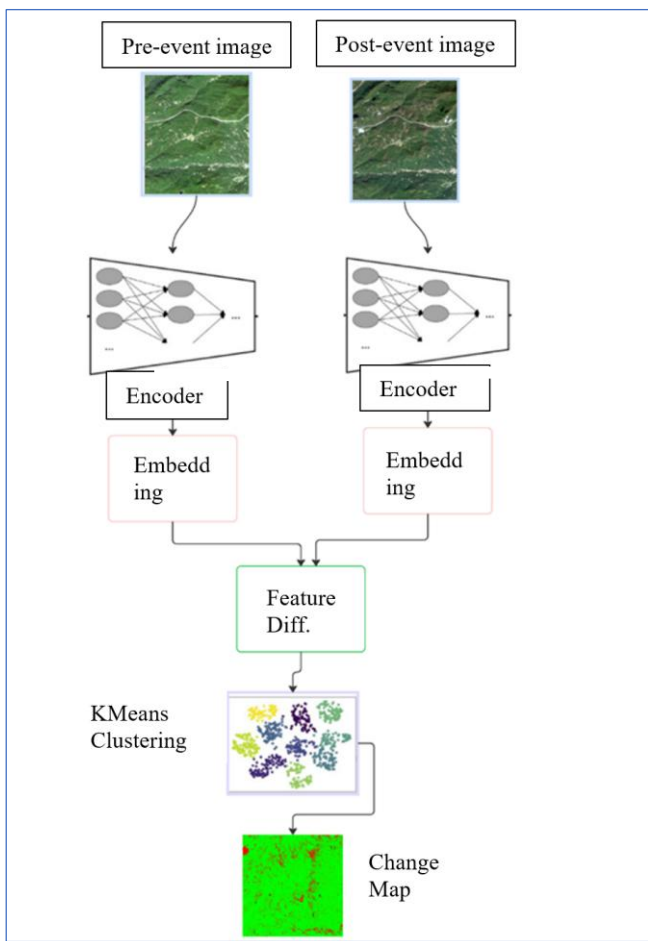


Figure 3. Automatic landslide labelling process showing clustering-based change detection from raw satellite imagery, followed by cropping into 256×256 optical image tiles and

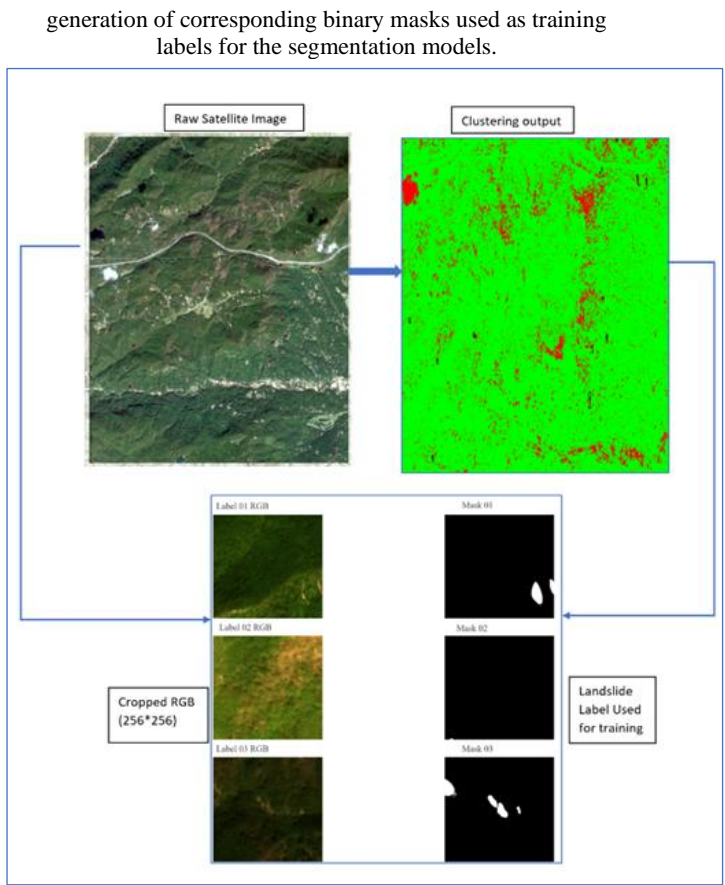


Figure 4. Unsupervised change detection using autoencoder feature embeddings and K-means clustering. Feature differences between pre- and post-event images are clustered to generate change masks, which are refined using landslide inventory data to final annotations.

Dataset	No of Tiles	No of channel
Train X	1843	4
Train Y	1843	1
Test X	527	4
Test Y	527	1

Table 2: Summary of the dataset showing the number of image tiles and channels for training and testing inputs (X) and corresponding labels (Y).

4. Result

4.1 Quantitative Performance

The quantitative performance of the models was evaluated on using the F1-score. The F1-score, which is harmonic mean of precision (the proportion of correctly identified landslides among all predicted landslides) and recall (the proportion of true landslides that were correctly detected), ranges from 0 to 1 and serves as the primary evaluation metric in this study. Sensitivity (or recall) reflects the model’s ability to correctly identify actual landslide areas. A highly sensitive segmentation model minimizes false negatives, ensuring that true landslides—especially small or fragmented ones—are not overlooked. This is important in disasters’ detection like landslide and flooding where missed detections could lead to severe consequences for infrastructure and public safety. Achieving strong sensitivity demonstrates the model’s effectiveness in recognizing the varied spectral and textural characteristics of landslide features across complex terrains. Table 3 present the result of the quantitative performance of the models.

Input Data	Model	Precision	Recall	F1-Score
RGB	U-Net	0.86	0.88	0.87
RGB	Att-U-Net	0.9	0.92	0.91
RGB	LinkNet	0.88	0.9	0.89
RGB+NIR	U-Net	0.86	0.88	0.87
RGB+NIR	Att-U-Net	0.91	0.93	0.92
RGB+NIR	LinkNet	0.88	0.9	0.89

Table 3. Precision, Recall, and F1-score comparison for the same experiments.

4.2 Visual Validation

The visual results (Figure 5) also demonstrate the model’s ability to preserve the spatial shape and continuity of landslide regions across different test datasets. Most predicted polygons closely align with the reference inventory locations, indicating reliable localization performance with limited false-positive detections as shown in Figure 6. In addition, the segmentation outputs successfully identify both isolated and clustered landslide occurrences along mountainous transportation corridors, highlighting the robustness of the proposed framework for rapid post-disaster mapping applications. The predicted boundaries generally follow the visible patterns observed in the imagery, demonstrating that the integration of unsupervised change detection and semantic segmentation improves both localization and boundary delineation. These qualitative observations are consistent with the quantitative performance metrics presented earlier and further validate the suitability of the framework for

scalable landslide inventory generation in complex mountainous environments.

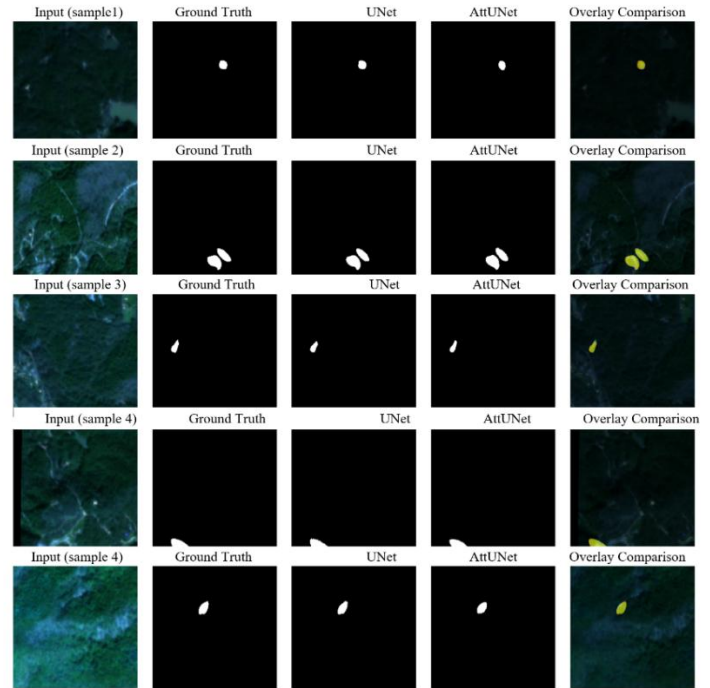


Figure 5. Visual comparison of landslide segmentation results showing test images, ground-truth masks, and predictions from U-Net, LinkNet, and Attention U-Net models for selected samples from the test dataset.



Figure 6. Example of detected landslides overlaid on high-resolution satellite imagery in the study area, showing the spatial distribution of predicted landslide polygons along a mountainous road corridor in western North Carolina.

5. Discussion

The results demonstrate that integrating unsupervised change detection with supervised semantic segmentation provides a more effective strategy for post-event landslide mapping than either approach alone. The autoencoder–KMeans stage served as

an efficient mechanism for rapidly identifying candidate disturbance zones from the pre- and post-event PlanetScope imagery. By learning compact latent representations of the multi-temporal imagery, the autoencoder was able to emphasize meaningful spectral and textural changes associated with vegetation removal, exposed soil, and terrain disturbance following Hurricane Helene. The resulting change map provided an important first approximation of potential landslide locations, significantly reducing the amount of manual interpretation required for label generation.

A major contribution of this study is that the unsupervised stage transformed sparse point-based inventory data into polygon-based landslide masks suitable for training deep-learning models. Existing post-disaster inventories frequently contain only landslide initiation points or approximate locations, which are insufficient for semantic segmentation. Through the integration of clustering outputs, inventory points, and manual refinement using PlanetScope imagery, this study produced a more detailed representation of landslide extent. Consequently, the workflow addresses one of the most persistent limitations in landslide deep learning research: the lack of high-quality, pixel-level labelled datasets.

The quantitative results further confirm the value of the proposed workflow. Among the tested models, Attention U-Net achieved the highest performance, with an F1-score of 0.92 using RGB+NIR imagery. The superior performance of Attention U-Net is likely due to the inclusion of attention gates, which selectively emphasize relevant landslide features while suppressing background noise. Landslides in the study area often occurred in highly heterogeneous environments containing forests, roads, exposed soil, stream corridors, and shadowed mountain slopes. In such environments, conventional convolutional architectures may incorrectly respond to irrelevant landscape features that share similar spectral characteristics with landslides. The attention mechanism appears to have improved the model's ability to focus on disturbed hillslopes and elongated scar features while ignoring surrounding vegetation and infrastructure.

The comparatively lower performance of U-Net and LinkNet, although still strong, suggests that lightweight architectures alone may not sufficiently distinguish between subtle landslide signatures and other post-event disturbances. UNet provided efficient inference and may still be advantageous in operational settings where computational speed is prioritized. However, its lower precision indicates a greater tendency to classify non-landslide changes as true failures. LinkNet produced balanced results but lacked the additional contextual filtering introduced by the attention mechanism. Therefore, for applications where accurate boundary delineation is critical, such as estimating landslide area or supporting infrastructure risk assessment, Attention U-Net appears to be the most appropriate model.

The inclusion of the near-infrared band also contributed modestly to model performance. Although the improvement between RGB and RGB+NIR inputs was relatively small, the RGB+NIR combination consistently produced slightly higher precision, recall, and F1-scores. The NIR band is particularly sensitive to vegetation condition and canopy disturbance. Since many shallow landslides triggered by Hurricane Helene were characterized by vegetation removal and exposure of bare soil, the additional spectral information likely improved the separation between disturbed and undisturbed terrain. This finding is consistent with previous remote sensing studies showing that

NIR information is valuable for detecting post-failure vegetation loss (Lu et al., 2019).

Visual assessment of the predictions further supports the quantitative findings. The predicted polygons showed strong agreement with the USGS and NCEM landslide inventory points and captured landslides across a wide range of sizes and morphologies. The models successfully detected both relatively large landslide scars along mountain slopes and smaller failures adjacent to roads and stream channels. In several cases, the segmentation output extended beyond the original point inventory, producing a more realistic delineation of the full landslide body. This demonstrates that the model is not merely reproducing the inventory locations but is learning the actual spatial characteristics of landslides.

Despite these encouraging results, several limitations remain. First, the threshold range used to isolate landslide-related change from the KMeans output was selected empirically. Although the threshold between -3.5 and -4 performed well in this study area, it may not transfer directly to other regions, seasons, or sensor types. Different environmental conditions may alter the spectral response of landslides and therefore require recalibration of the threshold values. Future studies could replace this manual thresholding step with adaptive thresholding or probabilistic clustering approaches.

Second, some false positives persisted in areas affected by non-landslide disturbance. Riverbank erosion flooded agricultural fields, exposed construction areas, vegetation clearing, and terrain shadows occasionally produced spectral patterns similar to landslides. These issues are particularly challenging in mountainous environments where topographic shadowing can substantially alter the appearance of optical imagery. Incorporating terrain-derived variables such as slope, curvature, aspect, topographic wetness index, and relative elevation may help reduce these errors by providing additional geomorphological context. Likewise, integrating DEM-derived slope units could constrain predictions to physically plausible hillslope regions.

Third, the analysis relied entirely on optical imagery, making the workflow sensitive to cloud cover and atmospheric conditions. Post-disaster optical acquisitions are often limited immediately after an event, particularly in hurricane-affected regions where cloud persistence is common. This limitation may delay rapid mapping efforts or introduce gaps in the training data. The addition of Synthetic Aperture Radar (SAR) imagery would improve the robustness of the framework because SAR can penetrate clouds and provide information on surface roughness and moisture conditions. A multi-sensor approach combining optical and SAR data may therefore produce more reliable landslide detection under a broader range of environmental conditions.

Another important consideration is the transferability of the model. The training and testing data were derived from the same general region of western North Carolina. Although the results indicate strong performance within this environment, the ability of the trained models to generalize to other regions, landslide types, or triggering mechanisms remains uncertain. Landslides caused by earthquakes, volcanic eruptions, or prolonged rainfall may exhibit different morphologies and spectral signatures than the shallow rainfall-induced failures examined in this study. Additional testing across diverse geographic settings will therefore be necessary to assess model robustness. Transfer learning, domain adaptation, and self-supervised learning

strategies may further improve the ability of the framework to generalize beyond the original training region.

The proposed workflow demonstrates that unsupervised change detection can serve as an effective bridge between sparse post-disaster inventories and supervised deep-learning models. Rather than treating unsupervised and supervised approaches as competing alternatives, this study shows that they are complementary. The unsupervised stage rapidly identifies potential landslides and generates initial labels, while the supervised stage refines these labels into more accurate and spatially consistent predictions. This combination is particularly valuable in disaster-response settings, where timely information is required but high-quality labelled data are rarely available.

6. Conclusion

This study developed and evaluated a hybrid framework that integrates autoencoder-based unsupervised change detection with supervised deep-learning semantic segmentation for rapid landslide mapping following Hurricane Helene in western North Carolina. The workflow successfully transformed sparse point-based landslide inventories into polygon-based training masks and substantially reduced the manual effort required to produce labelled datasets. By combining pre- and post-event PlanetScope imagery with KMeans clustering and deep-learning segmentation, the framework provided both rapid identification of disturbed areas and accurate delineation of landslide boundaries.

The results indicate that the proposed dual-stage approach is highly effective for post-disaster landslide assessment. Among the tested architectures, Attention U-Net with RGB+NIR imagery achieved the best performance, reaching an F1-score of 0.92. The attention mechanism improved the ability of the model to distinguish true landslide features from spectrally similar background disturbances, while the NIR band provided additional information related to vegetation loss and exposed soil. Visual comparison with the USGS and NCEM inventory data further confirmed that the model accurately captured the location, extent, and morphology of landslides across the study area.

Beyond the numerical performance, the principal contribution of this study lies in demonstrating a scalable strategy for overcoming the shortage of high-quality labelled landslide data. The unsupervised component offers a practical means of rapidly generating preliminary landslide masks immediately after an event, while the supervised segmentation stage refines these masks into operationally useful products. This capability is especially important in emergency response scenarios, where decision-makers require timely and accurate information to prioritize field investigations, road clearance, infrastructure protection, and hazard mitigation.

Although promising, the framework still has limitations related to optical-image dependence, threshold selection, and transferability to other environments. Future work should therefore focus on integrating additional data sources such as DEM-derived terrain variables, lithology, rainfall, and SAR imagery. Including these variables would likely reduce false positives and improve the detection of landslides obscured by shadow or cloud cover. Future research should also evaluate the model across different geographic regions and landslide-triggering mechanisms to assess its generalizability.

In conclusion, the findings demonstrate that combining unsupervised change detection with deep-learning segmentation provides an efficient, accurate, and scalable solution for automated landslide mapping. The proposed workflow offers strong potential for near-real-time hazard monitoring and can support future disaster-response systems in regions vulnerable to landslides.

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