

Article

ChangeFormer-Based Detection of Landslide-Damaged Areas Using Sentinel-2 Imagery in South Korea

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Abstract

Landslides triggered by heavy rainfall have become increasingly frequent and severe, creating a need for the rapid and accurate detection of damaged areas for post-disaster response and recovery planning. This study developed a ChangeFormer-based landslide damage detection model using single-channel differenced Normalized Difference Vegetation Index (dNDVI) imagery derived from pre- and post-event Sentinel-2 data. Landslide reference data were used to construct a patch-based training dataset, and model generalization was evaluated in Sancheong-gun and Hapcheon-gun, Gyeongsangnam-do, Republic of Korea, where landslide damage was reported following heavy rainfall in 2025. As available reference data differed between these regions, region-specific validation strategies were applied. In Sancheong-gun, polygon and point reference data were used for quantitative validation. All 12 reference-defined damaged sites were intersected by the model predictions, corresponding to a site-level detection rate of 100%. Point-based assessment showed an increasing distance-based detection rate with increasing positional tolerance, reaching 87.9% within the 80–100 m tolerance range. This result was interpreted as positional agreement between the reference points and predicted damaged areas rather than as overall accuracy. In Hapcheon-gun, where official polygon- and point-based reference data were unavailable, qualitative external validation using drone imagery indicated that the predicted areas were generally consistent with locations interpreted as landslide damage. These results suggest that the proposed framework is effective for the post-disaster spatial assessment of landslide-damaged areas.

Keywords: landslide damage detection; change detection; remote sensing; satellite imagery



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1. Introduction

Climate change-associated changes in rainfall patterns and increasing occurrences of localized extreme rainfall events have been closely associated with a growing frequency of landslides with increasing scales of damage worldwide [1,2]. In the Republic of Korea,

where mountainous areas account for more than 60% of the national territory, landslides tend to occur during periods of heavy summer rainfall and typhoons, and the extent of damage has recently increased [3]. After such events, the rapid and accurate identification of the location and extent of landslide-damaged areas provides essential baseline information for decision-making throughout the disaster response process, including the designation of restoration sites, prioritization of recovery, prevention of secondary damage, and estimation of restoration costs [4–6]. Accordingly, the demand for technologies capable of detecting landslide-damaged areas using satellite imagery and remote sensing data has steadily increased [1,7–14].

In early landslide damage detection research, landslide damaged-area boundaries were primarily extracted using spectral indices, such as the normalized difference vegetation index (NDVI) and dNDVI [15,16]. Although spectral index-based approaches are computationally efficient and applicable to large areas, they are sensitive to certain environmental factors in satellite imagery, including exposed soil, shadows, and seasonal vegetation variation, which may cause non-landslide areas to be misidentified as damaged areas [17–20]. Subsequently, conventional machine learning methods, such as the random forest and support vector machine algorithms, were introduced to improve detection performance by combining spectral information with topographic variables [21,22]. However, such approaches are sensitive to input feature composition and training data quality, and their generalizability across regions and time periods may be limited because of spatial and temporal biases in the training data [23,24]. In addition, pixel-based classification results may produce unrealistic spatially fragmented patterns, affecting the continuity of landslide-damaged-area boundary delineation [25]. To address these limitations, convolutional neural network (CNN)-based image segmentation techniques have been applied to the extraction of landslide damaged-area boundaries, with improved performances reported, particularly when using U-Net-based models [26–29]. Nevertheless, although CNN-based models are effective at learning local features among neighboring pixels, their ability to recognize structural patterns over broad spatial extents in satellite imagery, such as landslide damage continuously distributed across a slope, remains limited [30–34].

More recently, transformer architectures based on the self-attention mechanism have been introduced, allowing the relationships among all pixels within an image to be considered simultaneously [35,36]. Transformer-based models can learn long-range spatial dependencies and relationships in a structured manner, making them suitable for representing change patterns distributed over wide areas [37–41]. The ChangeFormer family of models is specifically designed to progressively extract and integrate differences between pre- and post-event imagery, enabling the joint learning of both the location of changed areas and their spatial continuity [42–44]. Sentinel-2-based dNDVI has also been used in previous landslide detection studies. Qin et al. [45] combined bitemporal Sentinel-2 imagery and NDVI-related change information with a Markov Random Field framework for landslide inventory mapping. Psomiadis et al. [46] analyzed pre- and post-event Sentinel-2 NDVI differences and showed that the detectability of landslide scars varied according to vegetation change and image conditions. Martinez et al. [47] used Sentinel-2 NDVI composite differences to identify landslides following the Anchorage earthquake. More recently, Lindsay et al. [48] incorporated dNDVI together with pre-event NDVI, post-event NDVI, and a persistence metric into a U-Net-based landslide detection model. These studies demonstrate that dNDVI can be used as a direct change indicator, an input feature in a classification or segmentation model, or a reference for validating other detection results. However, the use of single-channel dNDVI within a transformer-based spatial segmentation framework for rapid post-event landslide detection, together with evaluation across regions with different reference-data conditions, remains insufficiently addressed.

Therefore, this study developed a ChangeFormer-based landslide damage detection model using single-channel dNDVI to support the rapid detection of landslide-damaged areas following heavy rainfall.

The performance of a landslide damage detection model should be interpreted according to its intended application and the type of reference data available for evaluation. For restoration planning and damage assessment, the spatial distribution and extent of detected damaged areas are important, whereas for field investigation, emergency dispatch, and response prioritization, the correspondence between the predictions and actual landslide locations may be more relevant. Because the availability and structure of official reference data can differ across regions, a single validation criterion may not adequately represent the practical applicability of a detection model. Accordingly, the proposed model was evaluated in two geographically independent regions that were not included in model training. Quantitative validation using polygon- and point-based reference data was conducted in Sancheong-gun, while drone imagery was used for qualitative external validation in Hapcheon-gun, where official polygon- and point-based reference data were limited. By combining region-specific quantitative validation and qualitative external validation, this study evaluated both the spatial detection performance and the practical applicability of the proposed framework.

2. Materials and Methods

2.1. Study Area

Two study areas, one in Sancheong-gun and one in Hapcheon-gun in Gyeongsangnam-do, Republic of Korea, where landslide damage was reported following heavy rainfall in 2025, were selected to evaluate the applicability of the developed landslide damage detection model. Both areas were independent from the model training dataset and were used as validation sites to assess model performance for newly reported landslide damage cases. The geographic locations and spatial extents of the two study areas are presented in Figure 1.

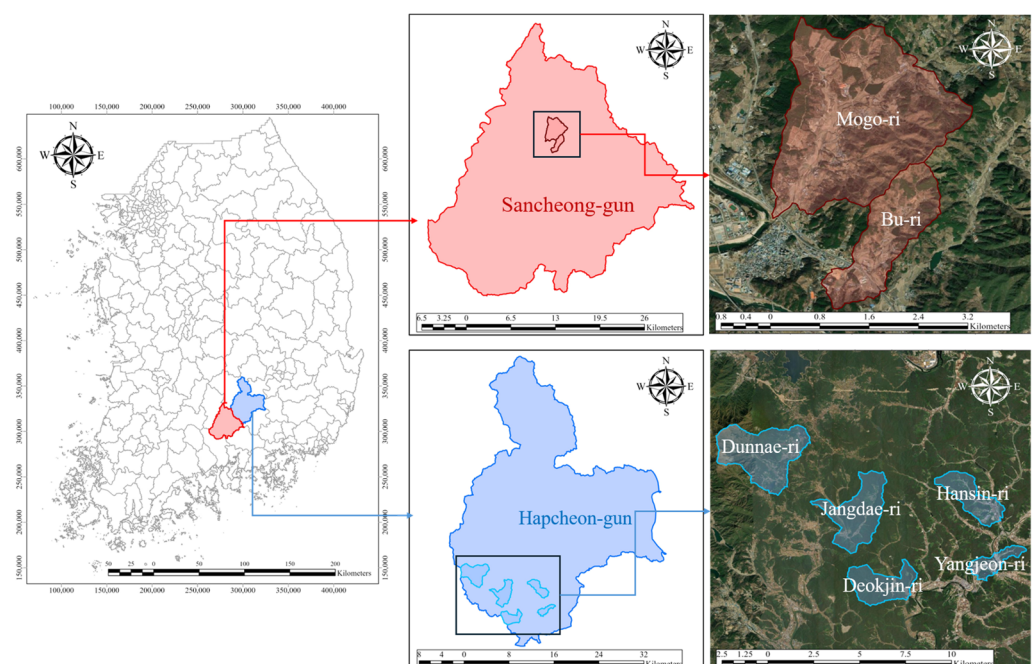


Figure 1. Geographic location of the Sancheong-gun and Hapcheon-gun study sites in Gyeongsangnam-do, Republic of Korea.

In Sancheong-gun, both polygon-type and point-type official reference data were available for the landslide damage reported in 2025. The National Institute of Forest Science (NIFoS) reference data provided landslide-damaged-area boundaries as polygons, whereas the Korea Forest Service (KFS) reference data provided landslide occurrence locations as points. Accordingly, quantitative validation was conducted in Sancheong-gun using polygon-based site detection and point-based distance assessment. Although landslide damage was reported in Hapcheon-gun in 2025, officially accessible reference data enabling quantitative validation, such as landslide-damaged-area boundary polygons or occurrence-location points, were limited. Therefore, Hapcheon-gun was evaluated through qualitative external validation using drone imagery.

2.2. Training Data Construction and Data Processing

2.2.1. Training Data for Landslide-Damaged Areas

To construct the training data for the landslide damage detection model, this study used landslide reference data provided by the Korea Association of Forest Environment Conservation Technology (KAFET). The inventory included boundary polygons for 8969 landslide-damaged sites recorded between 2016 and 2021. The reference data represented landslide-damaged areas as spatial polygons across multiple regions and years (Figure 2).

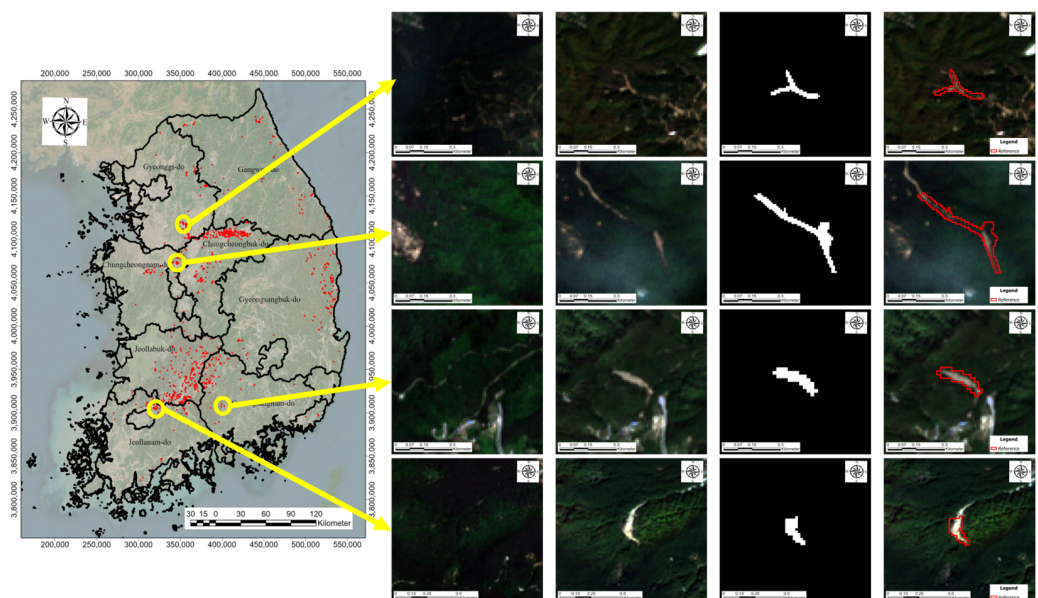


Figure 2. Spatial distribution of the reference polygons used for model development and an enlarged example of a representative training sample provided by the Korea Association of Forest Environment Conservation Technology (KAFET).

Prior to model training, a visual interpretation and quality review of the reference data were performed, and cases with relatively clear landslide damaged-area boundaries and sufficient comparability with satellite image-based detection results were selected for use in the analysis. Prior to model development, the reference data were visually interpreted and subjected to a quality review. Cases with relatively clear landslide-damaged-area boundaries and sufficient spatial comparability with satellite-based detection results were retained. Through this screening process, 1085 landslide-damaged-area polygons were selected for subsequent data processing. This screening procedure was applied to reduce the potential effects of positional errors and boundary uncertainty on model development. The selected polygons were subsequently used as the reference dataset for corresponding Sentinel-2 image selection and training-data construction.

2.2.2. Satellite Imagery and Vegetation Indices

To accommodate this spatial and temporal variability in the KAFET landslide reference dataset, Sentinel-2 Level-2A (L2A) imagery was used as the input in this study. Sentinel-2 provides multispectral bands at a 10 m spatial resolution, with a revisit cycle of approximately 5 days, making it suitable for analyzing vegetation changes before and after landslide events. For each landslide reference case in the KAFET inventory, a spatially corresponding pre-event and post-event Sentinel-2 image pair was selected according to the estimated occurrence period of the event. Scenes acquired within one month before the beginning of the event period were considered pre-event candidates, whereas scenes acquired within one month after the end of the event period were considered post-event candidates. Sentinel-2 scenes were obtained through the Copernicus Open Access Hub API, and scenes with less than 10% cloud cover were preferentially selected.

For the independent validation areas, the image-selection period was defined according to the heavy-rainfall event reported in 2025. Sentinel-2 scenes acquired during the one-month period preceding the event were used as pre-event data, whereas scenes acquired during the one-month period following the event were used as post-event data. The specific acquisition dates and cloud-cover information for Sancheong-gun and Hapcheon-gun are summarized in Table 1.

Table 1. Sentinel-2 imagery used for pre- and post-event dNDVI generation in the independent validation areas.

Study Sites	Pre-Landslide Imagery		Post-Landslide Imagery	
	Acquisition Date	Cloud Cover (%)	Acquisition Date	Cloud Cover (%)
Sancheong-gun	5 June 2025	7.1	29 July 2025	0.7
Hapcheon-gun	5 June 2025	7.1	1 August 2025	3.5

Landslide damage is generally associated with slope failure and soil runoff, which can cause an abrupt reduction in vegetation cover. To quantify this vegetation change, NDVI was calculated for the pre-event and post-event images, and dNDVI was derived as the difference between the two NDVI values. Unlike NDVI, which represents vegetation conditions at a single time point, dNDVI represents the change in vegetation condition between the pre-event and post-event observations. The resulting dNDVI image was used as the main input variable for the change-detection-based landslide damage detection model.

2.3. Development of the Landslide Damage Detection Model
2.3.1. Training and Validation Dataset Construction

The 1085 reference polygons selected through the quality-review process were allocated to the training and validation subsets at an approximately 80:20 ratio before image-patch extraction. This allocation retained a sufficiently large number of polygons for model training while reserving a separate group of polygons for internal validation.

The reference polygons and corresponding Sentinel-2 dNDVI data were aligned to the same coordinate system and processed separately within their assigned subsets. Input samples were prepared as spatially corresponding 128 × 128 pixels, approximately 1.28 km × 1.28 km, given the 10 m spatial resolution of Sentinel-2 imagery. This spatial extent was selected to include both landslide-damaged areas and adjacent slope environments within an individual sample. Up to three patches were extracted, with reference to the central part of each polygon, for each landslide-damaged-area boundary polygon. All patches were constructed so that the dNDVI imagery and damage mask shared the same spatial location, minimizing spatial mismatch between input and ground truth data.

As some images contained a low proportion of landslide-damaged pixels, the number of undamaged-area patches was limited to a maximum of twice that of damaged-area patches to control class balance in the training dataset. To reduce data imbalance, damaged-area patches were duplicated three times in the training data. The entire dataset was split into training and validation subsets at a ratio of 80% to 20% for use in change detection model training. The 80:20 allocation was established at the landslide-polygon level before image-patch extraction, and the patches generated from each polygon were retained within its assigned subset. Subsequent class-balancing procedures, including positive-sample duplication and augmentation, were applied within the training subset.

2.3.2. Model Configuration

In this study, landslide damage detection was approached as a matter of detecting changes between pre- and post-event conditions, and a transformer-based change detection model was applied to this problem. The model consisted of a ChangeFormer family encoder–decoder architecture and was designed to learn overall change patterns and long-range spatial dependencies through the self-attention mechanism.

Each input sample consisted of a spatially corresponding pair of pre-event and post-event Sentinel-2 image windows with a spatial size of 128×128 pixels. The two images were provided to the model as bi-temporal inputs, allowing the network to learn the differences between the pre-event and post-event conditions. The corresponding NDVI layers and dNDVI image were generated from the image pair to explicitly represent the vegetation change associated with the landslide event.

The pre-event and post-event inputs were processed by the ChangeFormer-family encoder–decoder architecture. The encoder extracted hierarchical spatial features from the two temporal observations, while the self-attention mechanism modeled spatial relationships beyond neighboring pixels. The temporal feature differences were subsequently integrated through the change-detection process, and the decoder combined multi-scale features to reconstruct a binary segmentation map of landslide-damaged areas. This configuration allowed the model to learn both the temporal change between the two observations and the spatial context of landslide-damaged areas.

Model training was conducted in a Python-based PyTorch 2.8 environment. Considering the sparsity of landslide-damaged pixels in the patches, a combination of loss functions emphasizing recall was applied during training, and both data augmentation and early stopping were applied to control overfitting. After training, the completed model was applied independently to the two validation study sites in Gyeongsangnam-do after generating dNDVI images from the corresponding pre-event and post-event Sentinel-2 image pairs.

2.4. Validation and Detection Assessment

Because the forms of reference data available for landslide damage differed between the Sancheong-gun and Hapcheon-gun study areas, using a single validation criterion for both areas would be difficult, and region-specific validation methods were applied.

For the Sancheong-gun study area, where both NIFoS polygon data (Figure 3) and KFS point data (Figure 4) were available, quantitative validation was conducted using polygon-based site detection and point-based distance assessment.

For the NIFoS polygon data, site-level detection was assessed by determining whether each reference-defined landslide site was intersected by a predicted damaged area. Site-level producer's accuracy (PA) was defined as the number of detected reference sites divided by the total number of reference sites. Site-level user's accuracy (UA) was defined

as the number of correct predicted sites divided by the total number of predicted sites. The site-level F1-score was calculated as the harmonic mean of PA and UA.

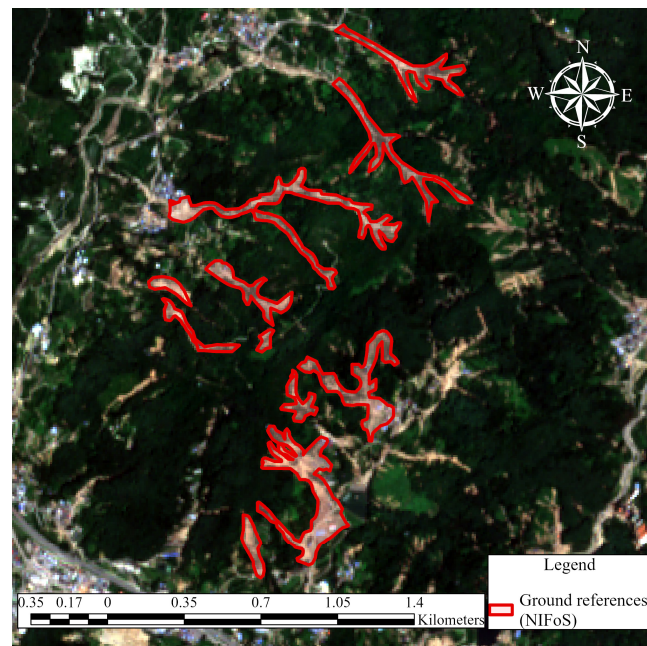


Figure 3. Landslide reference polygons provided by NIFoS (National Institute of Forest Science).

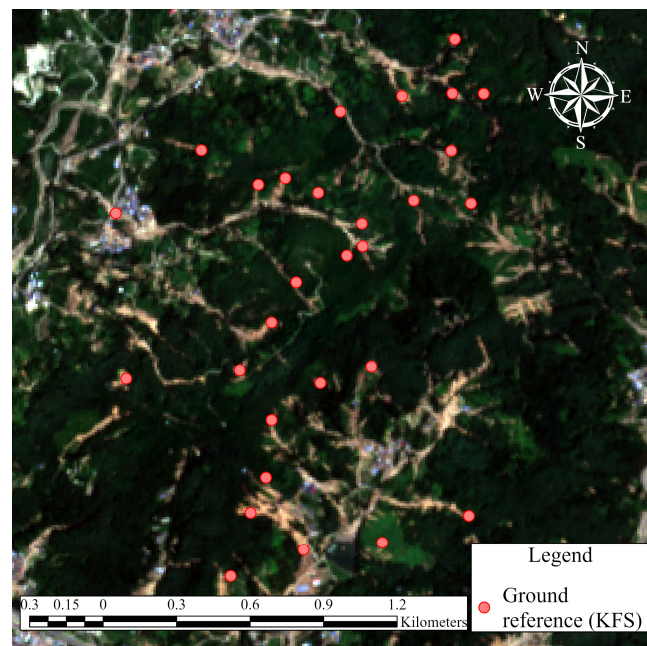


Figure 4. Landslide reference point data provided by the KFS (Korea Forest Service).

For the KFS point data, buffer zones ranging from 10 to 100 m were generated at 10 m intervals around each landslide occurrence point. The distance to the nearest predicted damaged area was assessed by determining whether a prediction was located within each buffer zone (Figure 5). This analysis was interpreted as a positional-proximity assessment rather than as an overall accuracy assessment. For each positional-tolerance level, the proportion of reference points associated with a predicted damaged area was calculated as the distance-based detection rate. Because larger buffers encompass wider search areas, the resulting detection rates were used to characterize the spatial proximity between the reference points and predictions, not as independent accuracy estimates.

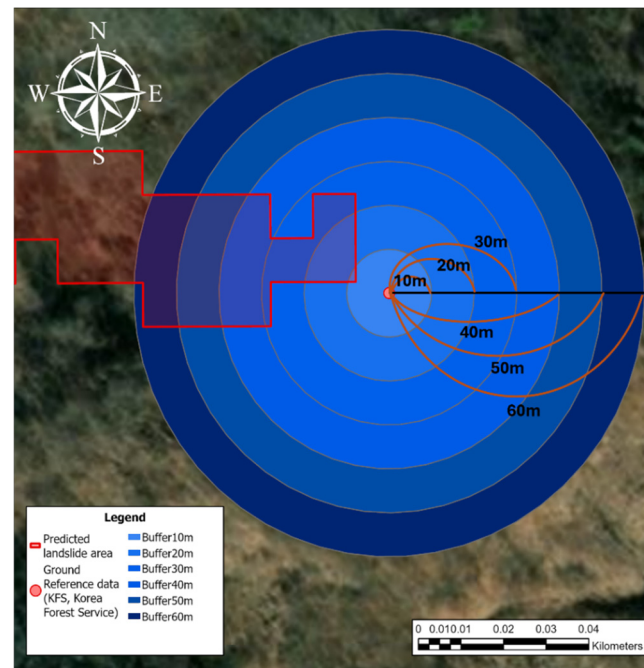


Figure 5. Example illustrating the distance-based validation method for accuracy assessment using the point-type landslide reference data provided by KFS.

As the availability of official reference data enabling quantitative validation, such as polygon or point datasets, was limited for the Hapcheon-gun sites, instead of calculating quantitative accuracy metrics, the detection results were evaluated through qualitative external validation using drone imagery. The drone imagery was acquired around locations where landslide damage had been reported, and the spatial overlap between the detection results and areas suspected to represent actual landslide damage in the imagery was assessed.

3. Results

3.1. Data Processing Results

Analysis of the dataset constructed from the KAFET landslide reference data and Sentinel-2 imagery showed that there were clear differences in the distributions of dNDVI values between landslide-damaged and undamaged areas. In undamaged areas, dNDVI values tended to be distributed around zero, indicating limited change between pre- and post-event conditions. By contrast, damaged areas showed relatively higher frequencies in ranges below zero. Thus, dNDVI values decreased more in damaged areas than in undamaged areas, suggesting that the disturbance to vegetation caused by landslides was reflected in the magnitude of change in the NDVI. This, in turn, indicates that a change-based approach is more suitable for landslide damage detection than an approach relying solely on vegetation status at a single time point. Accordingly, the dNDVI was used as the input variable for the change detection-based model in this study.

3.2. Results of Landslide Damage Detection Model Development

The ChangeFormer-based change detection model was trained for a total of 50 epochs. During training, the loss value was 0.5886 at epoch 1, decreased to 0.4953 at epoch 2 and to 0.4756 at epoch 3, and then remained at approximately 0.48 from epoch 4 until the end of training. Thus, after the initial rapid decrease, the loss value stabilized, indicating that dNDVI-based change patterns were consistently captured during the training process. No abrupt fluctuations in the loss value were observed, and convergence was maintained

throughout the process. Furthermore, analyzing the training logs for the internal validation data showed that recall-based performance metrics were maintained without sharp deterioration throughout training. This suggests that the training data design and loss function settings, which were configured considering the sparsity of landslide-damaged pixels, contributed to training stability.

3.3. Model Accuracy

3.3.1. Accuracy for the Sancheong-Gun Area

In Sancheong-gun, quantitative validation was conducted using NIFoS reference data, which provide landslide-damaged-area boundaries as polygons, and KFS reference data, which provide landslide occurrence locations as points. The NIFoS polygon data were used to evaluate site-level detection based on the spatial overlap between the predicted damaged areas and the reference polygons. The model detected 19 damaged areas in total, of which 12 overlapped with the NIFoS reference polygons. All 12 landslide-damaged sites included in the NIFoS reference data were detected, resulting in a site-level producer's accuracy (PA) of 100.0% (12/12). The remaining seven detections were additional predicted areas that were not included in the available reference polygons. The site-level user's accuracy (UA) was 63.2% (12/19), and the F1-score was 77.4%. The commission error and omission error were 36.8% and 0.0%, respectively (Table 2).

Table 2. Site-level prediction results based on reference data from the NIFoS.

Category		Reference		Sub-Total
		Damaged	Undamaged	
Predicted Class	Damaged	12	7	19
	Undamaged	-	-	-
Sub-total		12	7	19

Site-level producer's accuracy: 100%. Omission error: 0%. Site-level user's accuracy: 63.2%. Commission error: 36.8%. F1-Score: 0.77.

The distance from each KFS reference point to the nearest predicted damaged area was calculated. Among the 33 reference points, 17 were located within 10 m, 23 within 30 m, 25 within 40 m, 28 within 60 m, and 29 within 80 m of the nearest predicted damaged area. The corresponding cumulative distance-based detection rates were 51.5%, 69.7%, 75.8%, 84.8%, and 87.9%, respectively (Table 3). Four reference points were located more than 100 m from the nearest predicted damaged area. The mean distance was 38.8 m, the median distance was 9.5 m, and the interquartile range was 39.2 m. The distance distribution is presented in Figure 5.

Table 3. Distance-based detection rates according to positional tolerance based on KFS reference point data.

Positional Tolerance	Reference Points Within Interval (n)	Cumulative Associated Points (n)	Cumulative Distance-Based Detection Rate (%)
0~10 m	17	17	51.5
10~20 m	-	17	51.5
20~30 m	6	23	69.7
30~40 m	2	25	75.8
40~50 m	-	25	75.8
50~60 m	3	28	84.8
60~70 m	-	28	84.8
70~80 m	1	29	87.9
80~100 m	-	29	87.9
>100 m	4	33	100.0

3.3.2. Accuracy for the Hapcheon-Gun Area

In Hapcheon-gun, official polygon and point reference data were not available. The model detections were therefore compared with drone imagery for four sites: San 147, Hasin-ri; San 108, Deokjin-ri; San 33, Dunnae-ri; and San 563-6, Dunnae-ri. The detected areas were located around zones showing substantial vegetation changes after the rainfall event and followed patterns corresponding to the observed locations and development directions of the damaged areas in the drone imagery (Figure 6). At San 108, Deokjin-ri, the detected damaged area overlapped the bright soil-exposure area on the forested slope, while part of the detection boundary extended into the adjacent forest area (Figure 7a). At San 33, Dunnae-ri, several small detected damaged areas were distributed across the forested slope, with additional detections identified in adjacent forested terrain (Figure 7b). At San 563-6, Dunnae-ri, the detected damaged area was distributed along a linear soil-exposure feature in the central forested area, with additional isolated detections identified in the surrounding forested terrain (Figure 7c). At San 147, Hasin-ri, a small detected damaged area was located over the bright soil- and rock-exposure area on the lower part of the forested slope, with an additional detection identified in the adjacent terrain (Figure 7d). In some locations with relatively small-scale damage or complex terrain, the extent of the detected damaged area was smaller than the visible damage features in the drone imagery.

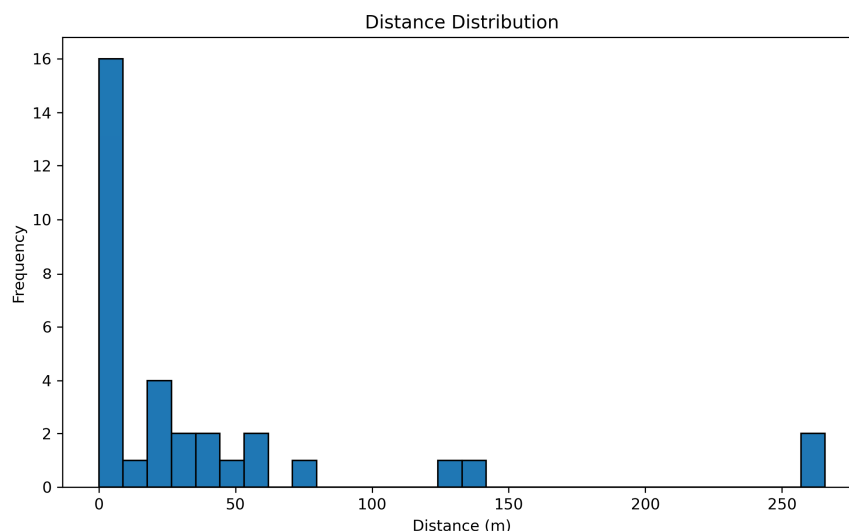


Figure 6. Distribution of distances from KFS reference points to the nearest detected damaged areas.

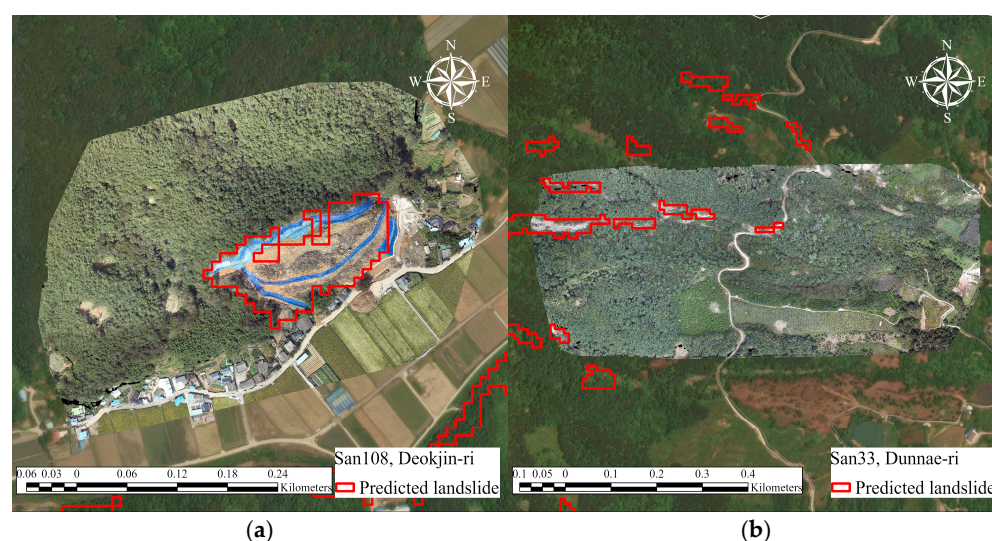


Figure 7. Cont.

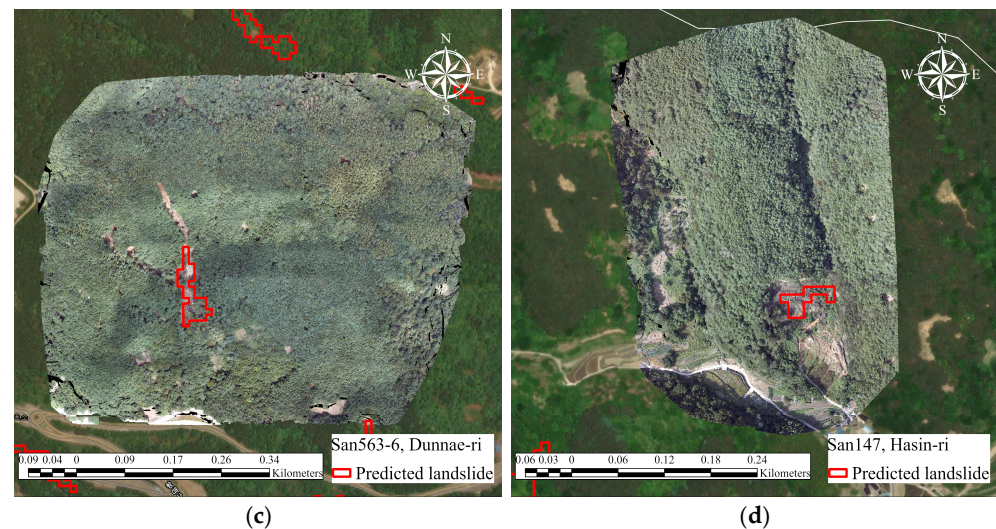


Figure 7. Results of the landslide detection model for Hapcheon-gun. Predicted landslide polygons are overlaid on drone imagery for (a) San108, Deokjin-ri; (b) San33, Dunnae-ri; (c) San563-6, Dunnae-ri; and (d) San147, Hasin-ri.

4. Discussion

During training of the dNDVI-based change detection model, loss values decreased in the early epochs and then remained relatively stable. This learning pattern indicates that the change features included in the training data were consistently captured during model learning and suggests that the patch-based dataset design and positive-patch duplication strategy, both developed to compensate for the sparsity of landslide-damaged pixels, contributed to training stability.

The Sancheong-gun results provide two implications for the interpretation of the proposed method. First, the model successfully identified all reference-defined damaged sites, indicating that the dNDVI representation was effective for detecting the occurrence locations included in the reference inventory. Second, the additional detections reduced the site-level UA relative to PA. These additional detections may reflect surfaces with vegetation-change patterns similar to landslide damage, including exposed soil, cleared areas, or other disturbance features. They may also include damaged areas that were not recorded in the available reference inventory. The point-based distance assessment provided information complementary to the polygon-overlap assessment. In total, 29 of the 33 reference points were located within 80 m of a predicted damaged area, whereas four points were located more than 100 m from the nearest prediction. These distance-based results describe the positional association between the reference points and the predicted damaged areas and provide information on spatial tolerance that cannot be obtained from the polygon-based site-level assessment alone. In Hapcheon-gun, since official quantitative reference data were unavailable, visual interpretation based on drone imagery was performed. Many cases showed relatively good agreement between the detection results and the actual damage areas and slope-failure directions, although improvement may still be needed in sites where the scale of damage is small or the terrain is complex.

The underestimation observed in some small or topographically complex damaged areas can be related to the characteristics of the dNDVI-based detection framework. Small damaged areas may produce weak or spatially mixed vegetation-change signals at the 10 m spatial resolution of Sentinel-2 imagery. In addition, slope-based filtering may exclude portions of damaged areas when their boundaries extend beyond the selected terrain conditions. These factors indicate that dNDVI alone may not represent all types of landslide damage, particularly when the damaged areas are small, spatially heterogeneous,

or partially obscured by surrounding vegetation. Overall, the change detection-based approach applied in this study appears capable of achieving a relatively high level of spatial accuracy in landslide damage detection. However, because detection results may vary with image acquisition timing, cloud effects, and topographic conditions, these factors should be considered when interpreting results.

5. Conclusions

This study approached landslide damage detection not as a single-date image segmentation problem, but as a change detection problem by estimating land-surface changes occurring during rainfall events and developing a transformer-based change detection model using the dNDVI as input. The training dataset was constructed using nationwide reference data on landslide-damaged areas, and independent validation datasets were conducted using newly reported landslide cases from 2025.

Previous Sentinel-2-based landslide studies reported different detection results depending on their data sources, reference-data structures, evaluation units, and methodological configurations. Martinez et al. [47] identified 21 of 43 documented landslides using an NDVI-difference approach, while Lindsay et al. [48] reported F1-scores of approximately 0.53 for the Jølster event and 0.39 for the Hans event using a U-Net-based workflow. In the present study, the Sancheong-gun assessment identified 19 damaged areas, including 12 detections overlapping the reference polygons and seven additional detections. The resulting site-level PA, UA, and F1-score were 100.0%, 63.2%, and 0.77, respectively. These values indicate the detection performance obtained under the present polygon-overlap evaluation protocol and may be used for indirect comparison with previously reported results. However, they do not establish quantitative superiority over the previous methods because the evaluation units and experimental conditions were not identical. The contribution of the present study is therefore not defined by a direct performance ranking against dNDVI thresholding or U-Net-based methods. Instead, the study applies bi-temporal Sentinel-2 information and dNDVI-based vegetation-change representation within a ChangeFormer-based spatial modeling framework and evaluates the resulting detections using site-level polygon overlap, point-based distance distribution, and region-specific validation. This framework provides a basis for comparing detection results across different reference-data conditions, while additional controlled experiments using identical datasets and evaluation protocols are required to isolate the effects of the model architecture, dNDVI representation, and training-data construction strategy.

In addition, the buffer analysis using reference points showed a stepwise increase in detection accuracy as the buffer radius increased, indicating that the predicted damage areas tended to be spatially distributed around actual damage occurrence locations. However, as observed in Hapcheon-gun, the damaged area was underpredicted in areas with relatively small-scale damage or complex terrain. This suggests that the sensitivity of change detection-based approaches may decrease when the magnitude of dNDVI is relatively small and that post-processing conditions, such as slope filtering, may directly affect detection results. These observations are consistent with model limitations repeatedly noted in previous studies.

To address the limitations of the single-index dNDVI approach, future research should first consider incorporating additional spectral indices sensitive to exposed soil or Synthetic Aperture Radar (SAR)-based change information. Second, to improve detection performance for small-scale landslides, comprehensive sensitivity analyses of patch extraction criteria and positive sample definition thresholds will be required. Third, strategies for applying adaptive, rather than fixed-threshold, post-processing rules for integrating slope and terrain should be examined. Finally, because differences in reference data construction

criteria can affect accuracy assessment, the systematic establishment of a multi-reference evaluation framework will be necessary in future studies.

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Abbreviations

The following abbreviations are used in this manuscript:

NDVI	Normalized Difference Vegetation Index
dNDVI	differenced NDVI
CNN	Convolutional Neural Network
U-Net	U-shaped Network
NIFoS	National Institute of Forest Science
KFS	Korea Forest Service
KAFET	Korea Association of Forest Enviro-Conservation Technology
API	Application Programming Interface
L2A	Level-2A
SAR	Synthetic Aperture Radar

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