Automated Urban Expansion and Land-Use Change Detection Using Deep Learning Ensembles on Sentinel-2 Imagery

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KEY WORDS: Change detection, deep learning, sentinel-2, urban expansion, and land-use transition.

ABSTRACT:
Satellite-based change detection plays a critical role in monitoring land-use dynamics, especially in rapidly developing urban areas. This study develops an advanced deep learning framework for analyzing land cover transitions in Mashhad and Maragheh, Iran, using multi-temporal Sentinel-2 Level-2A imagery (2019-2023) at 10m spatial resolution. We propose an ensemble approach combining multiple U-Net++ architectures to classify six key transition categories, focusing on urban expansion patterns such as the conversion of agricultural land and wastelands to built-up areas. The methodology incorporates a comprehensive processing chain including image tiling (112×112 pixel patches), multi-model inference, and post-classification refinement using seasonal NDVI analysis and cloud-shadow masking derived from Sentinel-2 probability layers. Ground truth data were meticulously prepared through visual interpretation in QGIS supplemented by Google Earth verification, ensuring accurate reference labels for model training and validation. Quantitative evaluation yielded precision (0.60), recall (0.72), and F1-score (0.65) metrics, demonstrating effective detection of major land-use changes while revealing challenges in distinguishing spectrally similar classes and precise boundary delineation. The framework's operational capability was further validated through successful application across different urban landscapes and temporal scenarios. This research contributes an automated, scalable solution for urban change monitoring that addresses practical challenges in heterogeneous environments. The integration of ensemble deep learning with multi-temporal spectral analysis advances current change detection methodologies, offering valuable tools for urban planners and environmental managers. Future work will focus on enhancing spectral discrimination capabilities and incorporating multi-sensor data fusion to improve detection accuracy for complex transition patterns.

1. INTRODUCTION

Change detection has rapidly become a cornerstone in satellite image analysis, enabling the identification and mapping of alterations on the Earth's surface (Gopal, S., & Pitts, J., 2025). This capability is vital for applications such as natural resource management, disaster monitoring, and urban planning (Cheng et al., 2024). The advent of deep learning has propelled this field forward, outperforming traditional techniques by extracting complex, multi-scale features and offering richer data representations (Bai et al., 2023).

Remote sensing, bolstered by an abundance of multi-temporal satellite data, has further streamlined the change detection process (Chi et al., 2025). Unlike conventional field-based approaches that require extensive on-site data collection, satellite imagery provides broad spatial coverage, frequent updates, and cost efficiency (Jiang et al., 2022). These datasets—spanning diverse spatial and spectral resolutions—enable accurate monitoring of geological changes, vegetation dynamics, and human infrastructure without the need for physical inspections (Wang et al., 2024).

The integration of artificial intelligence (AI) into remote sensing-based change detection has introduced automated frameworks capable of capturing intricate spatio-temporal patterns, allowing for rapid and precise analysis of multi-temporal imagery (Shi et al., 2020). Early machine learning methods such as Support Vector Machines (SVM) and Random Forests required manual feature engineering and struggled to scale effectively (Cheng et al., 2024). In contrast, recent advances in deep learning—particularly through Convolutional Neural Networks (CNNs) and Transformers—have enabled the hierarchical extraction of both low- and high-level features, significantly increasing the accuracy of change region identification (Saidi et al., 2024).

Recent literature underscores these advancements. Han et al. (2025) developed a deep learning method to improve change detection in remote sensing images, especially for subtle changes like small or low-contrast objects. Their approach combines multi-scale feature fusion with global context modeling using a VMamba Block, better preserving spatial details. Evaluated on the LEVIR-CD, S2Looking, and NALand datasets, their model achieved F1 score improvements of 1.06%, 1.41%, and 2.63%, respectively. Zhu et al. (2025) introduced a novel InSAR change detection method that identifies when and where changes occur and determines their underlying causes, distinguishing between definitive and temporary changes. Their approach combines four radar amplitude images with six interferometric coherences across different temporal baselines, processed through DANI-NET, a fully convolutional neural network designed with explainable AI principles. The model was trained on synthetic datasets for interpretability and tested against the permutational change detection (PCD) method, showing competitive performance. Applied to Sentinel-1 data from Iceland's 2023–2024 Sundhnúkur eruptions and TanDEM-X imagery of a mining site, DANI-NET accurately mapped lava flows and anthropogenic changes, validated against ground measurements. Wu et al. (2025) developed CD-Lamba, a novel Mamba-based

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change detection method that improves local feature perception in remote sensing images while maintaining global context. By introducing adaptive scanning strategies and cross-temporal fusion modules, their approach outperforms existing methods on four benchmark datasets, achieving better accuracy with efficient computation. Peng et al. (2025) demonstrated that convolutional architectures with attention mechanisms can boost change detection accuracy by over 5%. Yu et al. (2024) surveyed the use of foundation models, highlighting the promise of large pretrained models for robust feature extraction and data fusion, especially under low-data or multi-modal conditions. Zheng et al. (2024) introduced a unified Deep Probabilistic Change Model, offering interpretable and uncertainty-aware analysis of land surface transformations. Parelius (2023) reviewed deep learning strategies for multispectral remote sensing, addressing open-access datasets and the need for data-efficient methods amid issues like label imbalance. Debella-Gilo (2022) employed 1D-CNNs on Sentinel-2 time series to successfully detect urban expansion, while Singh et al. (2022) used deep neural networks and Sentinel-2 imagery to map land use transitions in Punjab, India, demonstrating that multi-scale spatial information significantly enhances detection accuracy.

This research presents a custom change detection framework based on our original semantic dataset covering two different years. The developed method specifically exploits these semantic labels to precisely detect and interpret temporal changes.

This study presents an innovative change detection framework based on a specialized semantic dataset spanning two years. The method uniquely exploits semantic labeling to precisely identify and analyze temporal changes through Sentinel-2 imagery. Combining ensemble learning with deep neural networks, the architecture achieves robust performance, with notable effectiveness in zero-shot cross-scene generalization.

2. MATERIAL AND METHOD

2.1 Case study

The cities of Mashhad (36.29°N, 59.61°E) and Maragheh (37.23°N, 46.15°E), as two major metropolitan centres in Iran, have undergone extensive land use changes in recent years (Figure 1a, b). Mashhad, located in northeastern Iran, is the country's second most populous city and a significant religious and economic hub. Maragheh, the capital of East Azerbaijan province in northwestern Iran, plays a key role in the nation's industry and commerce. Population growth, infrastructure expansion, and urban development in both cities have led to considerable transformations of the land surface (Figure 1a, b), making their analysis through remote sensing techniques increasingly important.

In this study, Sentinel-2 Level 2A satellite data were utilised to monitor land use changes across these regions (Figure 1a, b). With a spatial resolution of 10 metres, along with geometric and atmospheric corrections, these datasets are well-suited for time-series analyses. For Mashhad, two images from tile T40SGF were employed (Figure 1b): the first acquired on 27 August 2019 and the second on 31 August 2022. This temporal window captures significant changes, including the conversion of agricultural and barren lands to built-up areas and the expansion of urban zones (Figure 1b).

For Maragheh, analyses were based on images from tile T38SPG (Figure 1a). The baseline image dates to 7 August 2019, while the subsequent image is from 6 August 2023. This four-year period allows for the examination of long-term trends in urban growth, agricultural land degradation, and the spread of built environments (Figure 1a).

The integration of multi-temporal and multi-spatial data from two distinct tiles (Figure 1a, b) provides a comprehensive framework for evaluating change detection methods, enabling assessment of algorithm performance under varying climatic, socio-economic, and developmental patterns. Such an approach can significantly support data-driven decision-making in urban planning and natural resource management.

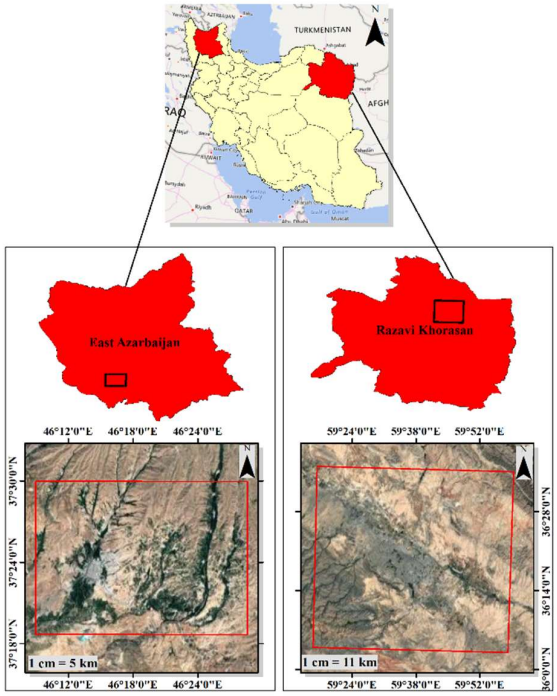

Figure 1. Study area. (a) Maragheh, (b) Mashhad.

2.2 Dataset

This study employed Sentinel-2 satellite imagery to analyze land-use changes in the cities of Mashhad and Maragheh. Multi-temporal images, combined with carefully labeled change regions, enabled the detection and simulation of urban land-use transitions.

2.2.1 Ground Truth Data Preparation

Change detection was performed for Mashhad and Maragheh, focusing on six key land-use transition classes: (1) agricultural land to built-up areas, (2) wasteland to built-up areas, (3) forest/jungle to built-up areas, (4) agricultural land degradation, (5) environmental degradation (forest/rangeland loss), and (6) miscellaneous changes (Table 1). Ground truth labeling was conducted in QGIS, where Sentinel-2 image pairs were visually inspected to identify clear changes. Uncertain cases were cross-verified using Google Earth imagery, and confirmed changes were digitized into polygons and stored as shapefiles, forming the reference dataset for model training and validation (AhmedRotich & Czimber, 2024). Figure 2a, b illustrates the labeled change detection map for Mashhad and Maragheh.

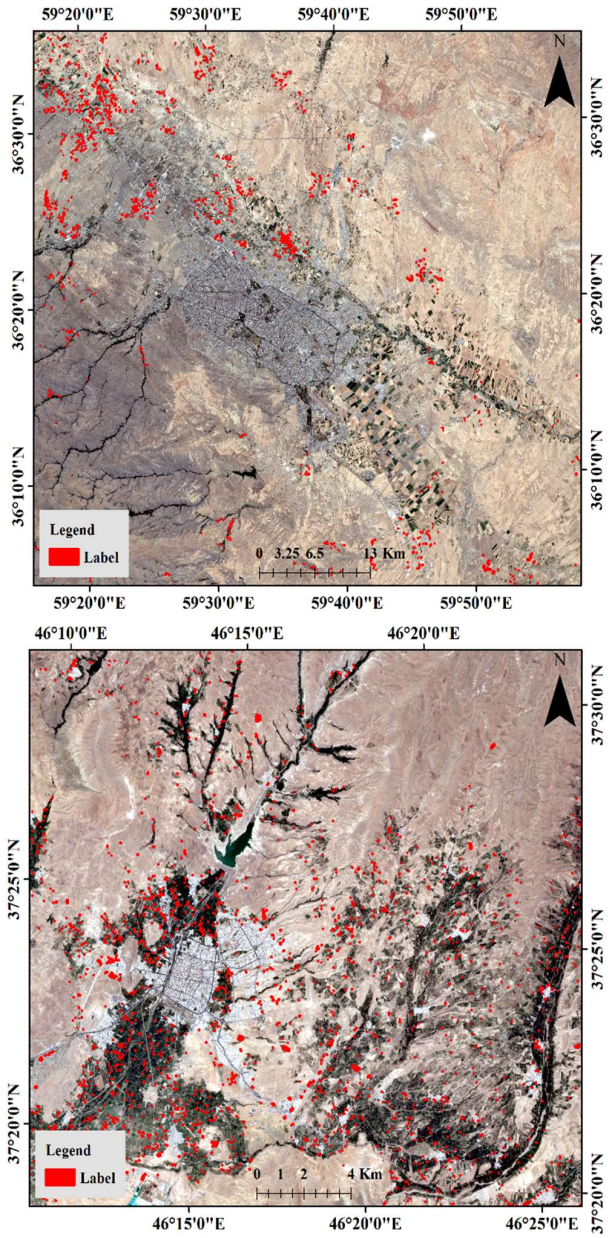

Figure 2. Reference change map generated through QGIS digitization of Sentinel-2 multi-temporal observations. (a) for Mashahad, (b) Maragheh.

2.2.2 Satellite Dataset

The study utilized multi-temporal Sentinel-2 imagery from the Copernicus program, which provides high-resolution multispectral data at 10 m, 20 m, and 60 m resolutions across 13 spectral bands (Inglada, Michel, & Hagolle, 2022). For land-use change detection, the 10 m resolution visible bands—Blue (B2), Green (B3), and Red (B4)—were selected due to their sensitivity to surface cover variations (AhmedRotich & Czimber, 2024). Level-2A products, preprocessed with Sen2Cor atmospheric correction (Phiri et al., 2020), were used to ensure data quality. Cloud-free scenes were prioritized, and geometric co-registration was applied to maintain spatial consistency across dates, ensuring reliable change detection in these urban environments. As presented in Tables 1 and 2, tile T38SPG (Maragheh) recorded 11397 changes over a two-year period, while tile T40SGE (Mashhad) exhibited 8442 changes during the same timeframe. To account for seasonal variability, additional images from different seasons were also acquired for each tile, ensuring the models could robustly interpret changes under varying seasonal conditions.

Maragheh	Mashhad	Distribution/Class
21.8 %	19.5 %	Agriculture to Building
32.7 %	23.5%	Wasteland to Building
12.8 %	6.7%	Tree/Forest to Building
6.6 %	17.7 %	Destruction of Agriculture
8.3 %	12.8 %	Destruction of Environment
17.8 %	19.8 %	Others
11397	8442	Number of Changes

Table 1. Distribution of changes for each class across the whole data.

Maragheh	Mashhad	City
T38SPG	T40SGE	**Tile**
2019-04-14 2019-08-07 2019-11-15 2019-12-25	2019-02-23 2019-05-04 2019-08-27 2019-10-16	**Acquisition Dates (Before)**
2023-04-28 2023-08-06 2023-10-15 2023-12-04	2022-04-13 2022-08-31 2022-10-15 2022-12-19	**Acquisition Dates (After)**

Table 2. Acquisition date of sentinel-2 images used in this study.

2.3 Methodology

This research develops an advanced change detection methodology specifically designed for analyzing urban land cover transitions in Mashhad and Maragheh using Sentinel-2 satellite imagery. The comprehensive framework integrates cutting-edge deep learning techniques with robust post-processing to achieve accurate change identification and classification.

2.3.1 Image Acquisition and Preprocessing

The foundation of our analysis relies on Sentinel-2 Level-2A surface reflectance products, carefully selected to ensure seasonal consistency between the two observation periods spaced one to two years apart. To overcome computational limitations while preserving spatial context, each satellite image was systematically divided into 112×112 pixel patches, generating approximately 9,604 analyzable units per scene. This tiling strategy maintains the integrity of spatial features while enabling efficient processing of the high-resolution imagery.

2.3.2 Ensemble Deep Learning Architecture

At the core of our approach lies a One-vs-Rest (OvR) ensemble architecture. This strategy decomposes the complex 6-class semantic change problem into six independent binary classification tasks. For each of the six land-use transition classes, a dedicated U-Net++ model was trained as a "specialist"

(Scientific, 2025). Each specialist model was trained to distinguish its single target class (e.g., "agricultural land to built-up areas") from all other classes combined (the "Rest").

During inference, each input image patch is processed by all six specialist models simultaneously. Each model outputs a probability score from its final sigmoid activation, indicating the confidence that the pixel belongs to its specific target class. The final semantic label is then determined by a winner-takes-all fusion: the class corresponding to the model that produced the highest probability score is assigned to that pixel. This ensemble method allows each model to become highly specialized for detecting its particular transition type, rather than requiring a single model to learn all six complex boundaries simultaneously

A primary challenge in this study was the differentiation of spectrally similar classes, such as agricultural land and wasteland, which can have overlapping spectral signatures at certain times of the year. Our framework addresses this by moving beyond single-pixel spectral values. First, the patch-based (112x112) U-Net++ architecture learns crucial spatial-contextual features and textures. The uniform texture of an agricultural plot, for example, is a strong spatial differentiator from the heterogeneous texture of degraded land.

Furthermore, to make this spatial-feature learning robust, our model was trained on a dataset comprising distinct images from multiple seasons. By exposing the model to the full range of seasonal-spectral variations (e.g., green fields in summer, fallow fields in winter), it was forced to learn season-invariant spatial representations. This training strategy ensures the model identifies classes based on their persistent textural properties, not their transient spectral state, thereby preventing misclassifications caused by seasonal changes like harvesting.

2.3.3 Advanced Post-Processing Pipeline

Following the deep learning analysis, we implemented a multi-stage post-processing workflow to refine the results. First, the predicted patches were precisely reassembled into complete change maps, which were then converted into vector format with comprehensive metadata attributes, including transition type, temporal information, and geographical identifiers. Subsequent spatial filtering removed unreliable detections by eliminating polygons that were either smaller than half a Sentinel-2 pixel or larger than 20,000 m². We also developed an advanced cloud and shadow masking system using Sentinel-2's native cloud probability layers, incorporating a 300-meter buffer adjusted according to sun azimuth angles to identify and exclude affected areas accurately.

2.3.4 Spatial Filtering and Masking

To eliminate noise and irrelevant features: Polygons with areas smaller than half a Sentinel-2 pixel or larger than 20,000 m² are discarded.(Pacheco-Pascagaza et al., 2022) Cloud and shadow regions are extracted from Sentinel-2 cloud probability layers. Using sun azimuth information, a 300-meter buffer is generated to delineate shadows. An intersection operation masks affected change polygons (Layton et al., 2023).

2.3.5 Phenological Correction Using NDVI Analysis

To distinguish genuine land cover changes from seasonal variations, we incorporated a sophisticated NDVI-based filtering mechanism. By analysing four-season NDVI composites from Planetary Computer archives for both time periods, we established reliable vegetation baselines. Areas demonstrating consistently low NDVI values (<0.3) in both periods were classified as barren, while those showing significant vegetation presence in either period underwent additional agricultural change validation. This critical step substantially reduced false positives caused by normal vegetation cycles.

2.3.6 Performance Evaluation Metrics

The model's accuracy was quantified using the following standard metrics, derived from fundamental components of the confusion matrix. Where Equation 1 defines precision, Equation 2 expresses recall, and Equation 3 gives the F1-score.

$$Precision = \frac{TP}{TP+FP} \quad (1)$$

$$Recall = \frac{TP}{TP+FN} \quad (2)$$

$$F-Score = \frac{2\times Precision\times Recall}{Precision+Recall} \quad (3)$$

Where,

- TP (True Positives): Pixels correctly identified as having undergone a specific land cover transition.
- FP (False Positives): Pixels incorrectly classified as changed when no actual transition occurred.
- FN (False Negatives): Pixels where actual land cover transitions were missed by the model

Precision measures the reliability of detected changes, where higher values indicate fewer false alarms. Recall assesses detection completeness, with higher values showing fewer missed changes. The F1-score balances these competing priorities, providing a comprehensive performance measure when both error types carry significant weight. This formulation was applied both, globally (overall change detection performance) and per-class (specific transition type accuracy).

The component-wise breakdown enables precise diagnosis of error sources, while the combined metrics provide standardized performance benchmarks comparable across different change detection studies.

This contribution has been peer-reviewed. The double-blind peer-review was conducted on the basis of the full paper.
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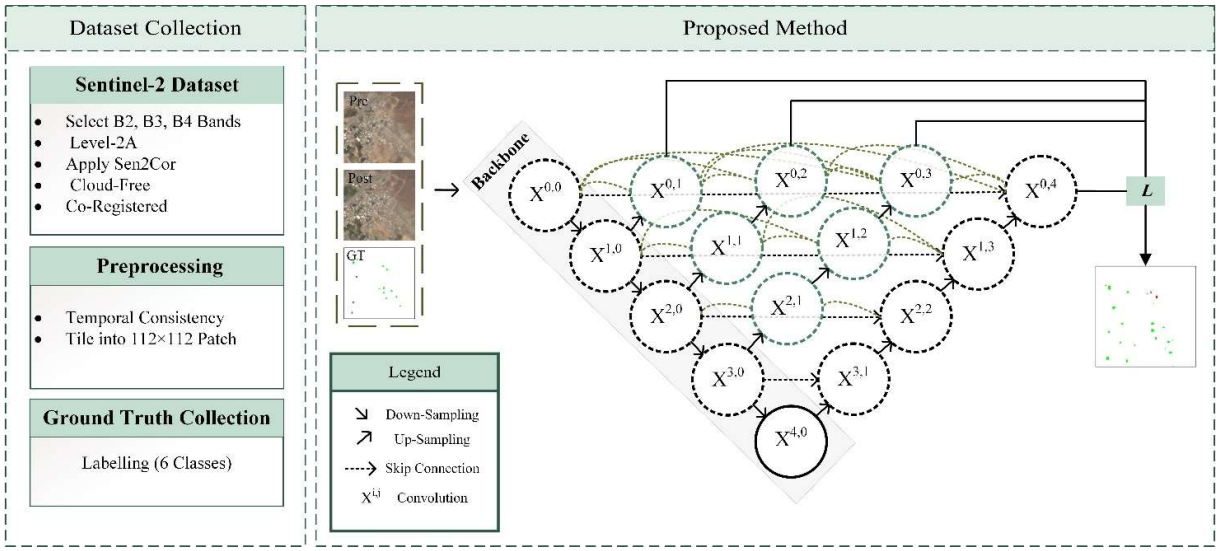


Figure 3. Workflow of proposed method.

3. RESULT

The proposed deep learning framework demonstrated robust performance in detecting land-use changes across Mashhad and Maragheh, as evidenced by quantitative metrics and visual analysis.

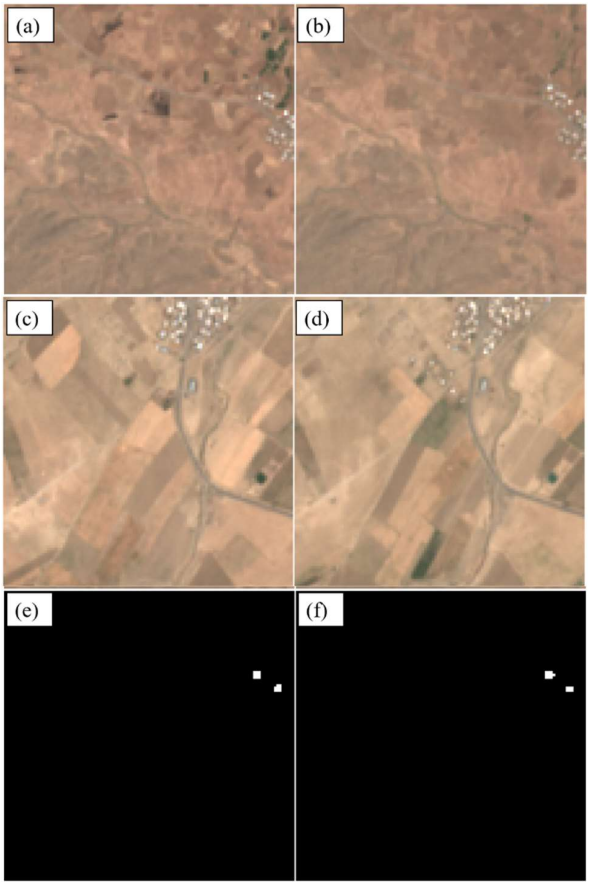
3.1 Model Training and Evaluation Framework

The ground truth dataset was partitioned into training (80%), validation (10%), and test (10%) subsets following standard machine learning protocols. This stratified division ensured robust model development while maintaining an independent evaluation set.

3.2 Binary Change Detection Performance

The model demonstrated strong capabilities in identifying major land cover transformations, as shown in Figures 3a , b, c, and d. These figures present comparative visualizations including input image pairs (pre-change and post-change), expert-annotated ground truth with changes marked in white, and model predictions, similarly indicating detected changes in white. The results reveal effective detection of large-scale urban expansion and significant landscape conversions, with good spatial correspondence between predicted changes and ground truth in areas of substantial transformation.

However, the analysis also identified several limitations in the model's performance. Precise boundary delineation proved challenging, particularly in heterogeneous transition zones where changes occur gradually. Furthermore, the model exhibited difficulties in distinguishing between spectrally similar land cover types, such as abandoned agricultural fields versus bare land. These limitations are visually apparent in the residual glitter change regions of the output maps, where environmental complexity and spectral resolution constraints of the satellite imagery contribute to detection uncertainties.



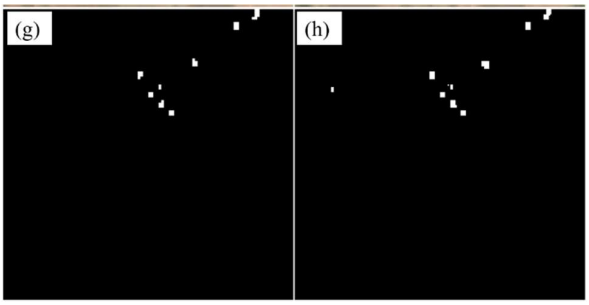
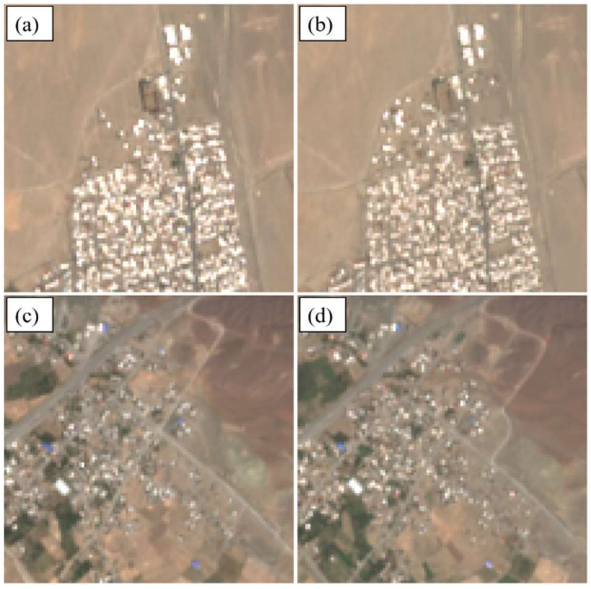


Figure 4. Model performance for Mashhad: (a, c) Pre-change Sentinel-2 image; (b, d) Post-change Sentinel-2 image; (e, g) Ground truth change map (white = pixel change); (f, h) Predicted change map.

3.2 Semantic Change Classification Analysis

Figure 5 presents the detailed semantic change map of Mashhad, revealing important patterns in classification accuracy. The model produced some systematic misclassifications, notably labeling certain areas as "Wasteland to Building" when the ground truth specified "Agriculture to Building" or "Others". These discrepancies primarily occur in cases where spectral signatures overlap significantly between different land cover categories, or where transitional areas exhibit mixed characteristics that challenge clear classification.

The semantic change analysis further indicates that edge effects and boundary uncertainties are most pronounced in peri-urban fringe areas and locations undergoing gradual land cover transitions. Approximately 12% of pixels showed divergence between ground truth and predicted change classes, with the majority of errors occurring in these ambiguous transition zones spectral responses.



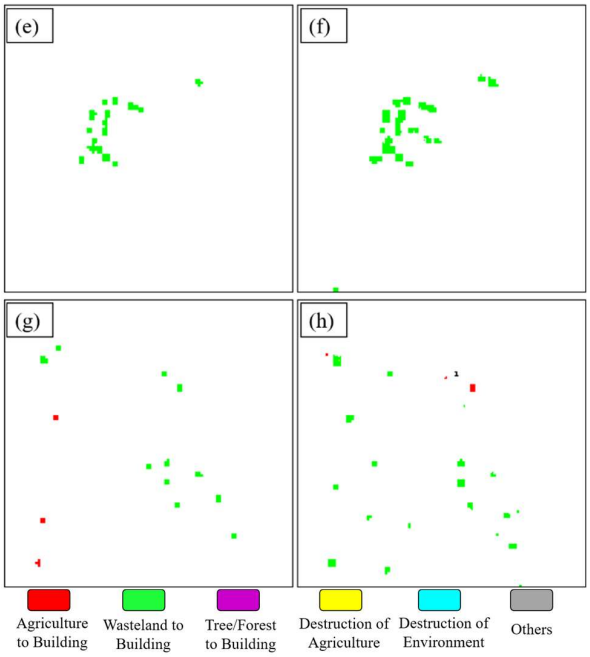
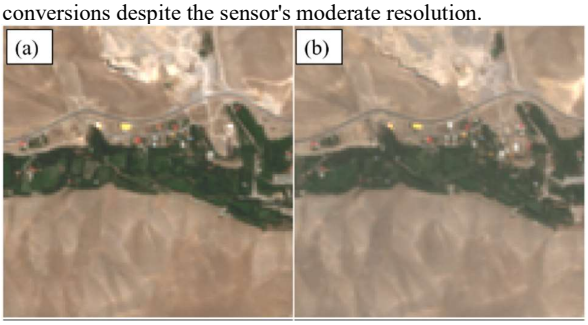


Figure 5. Model performance for Mashhad: (a, c) Pre-change Sentinel-2 image; (b, d) Post-change Sentinel-2 image; (e, g) Ground truth semantic change map (in 6 class); (f, h) Predicted semantic change map.

3.3 Model performance on the Test dataset

The evaluation process employed Sentinel-2 image pairs from Maragheh as test samples, representing pre- and post-change land cover conditions. Figure 6 presents the comparative analysis between ground truth and model predictions, following the same visualization convention established in previous figures: white pixels in the ground truth image represent expert-annotated changes, while white pixels in the predicted image indicate detected changes by the model. The model demonstrates exceptional capability in generating accurate change prediction maps from Sentinel-2 imagery, as evidenced by the high visual correspondence between predictions and ground truth. Leveraging Sentinel-2's 10-meter resolution data, the framework reliably identifies urban expansion patterns (Figures 6f/h), with predicted change pixels (white) precisely aligning with expert-annotated transitions in built-up areas (Figures 6e/g). This strong performance is particularly notable given Sentinel-2's spectral characteristics, with the model effectively utilizing the visible and NIR bands to distinguish large-scale natural-to-urban conversions despite the sensor's moderate resolution.



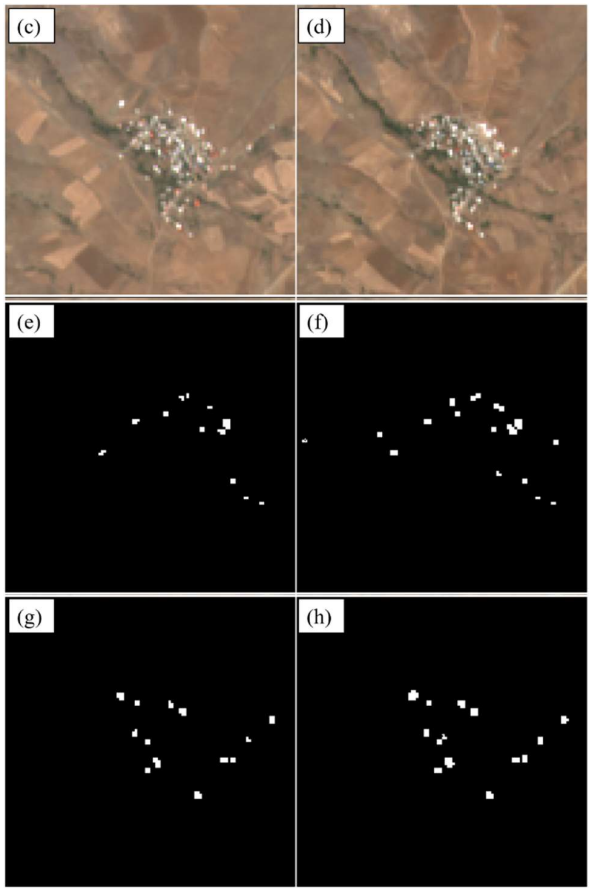
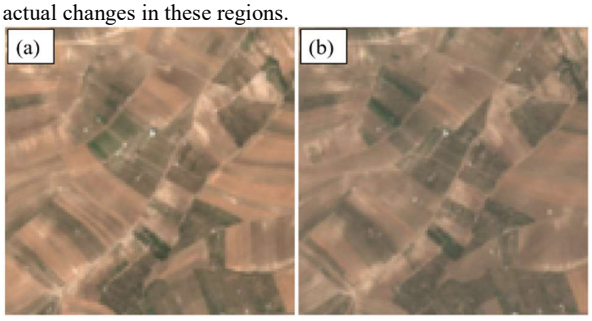


Figure 6. Model performance for Maragheh: (a, c) Pre-change Sentinel-2 image; (b, d) Post-change Sentinel-2 image; (e, g) Ground truth change map (white = pixel change); (f, h) Predicted change map.

Based on the visual analysis of the figures, the model demonstrates strong performance in detecting and classifying major land cover changes, while revealing specific areas for improvement. The prediction maps show accurate identification of clear urban expansion patterns, with white pixels in the predicted change maps (6f, h) closely matching the ground truth annotations (6e, g) for well-defined conversions to built-up areas. The model particularly excels in detecting large-scale transformations from natural landscapes to urban development, as evidenced by the consistent alignment between predicted and actual changes in these regions.



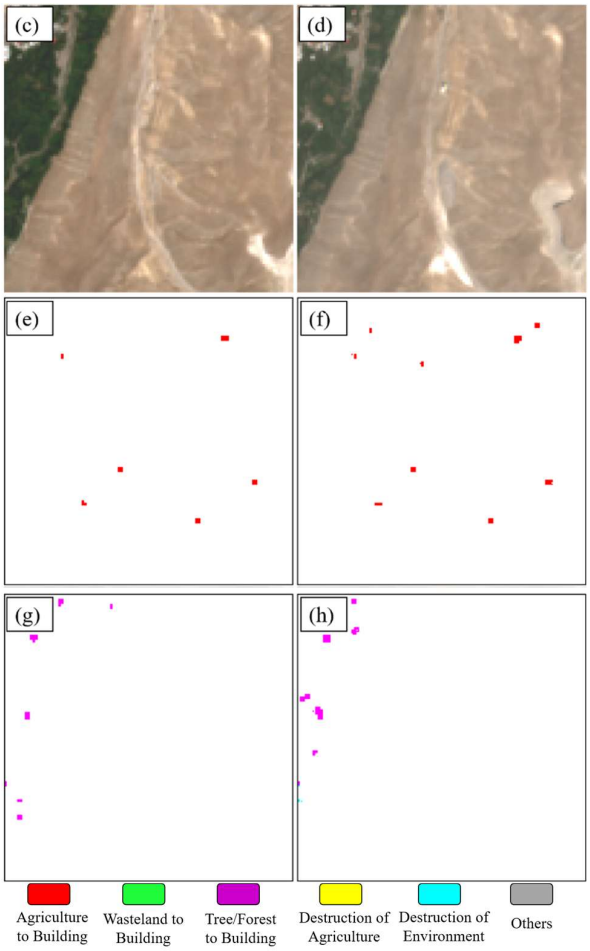


Figure 7. Model performance for Maragheh: (a, c) Pre-change Sentinel-2 image; (b, d) Post-change Sentinel-2 image; (e, g) Ground truth semantic change map (in 6 class); (f, h) Predicted semantic change map.

The observed classification variances likely stem from several factors: spectral similarities between certain land cover types during transitional phases, inherent limitations in Sentinel-2's spatial resolution for detecting fine-scale changes, and potential ambiguities in the reference data itself. These findings underscore the importance of continued refinement in both the model architecture and training methodology to better capture nuanced land cover transitions.

3.4 Training Phase Performance Evaluation

The model's change detection capability was quantitatively assessed using standard classification metrics, as detailed in Table 3. The binary detection component of the U-Net++ architecture achieved a balanced F1-score of 0.65. This score reflects a precision-oriented model, with a precision of 0.72 and a recall of 0.60. This indicates that while the model is highly reliable (72% of predicted changes were correct), it is conservative, missing 40% of genuine changes. The detailed error analysis (Table 3) supports this, revealing 1,201 correctly identified change instances against only 450 false alarms at the cost of 783 missed changes.

Following binary detection, the semantic classification performance was evaluated on the true positive change pixels. The macro-averaged results show an F1-score of 0.55, with a macro-precision of 0.54 and macro-recall of 0.58, reflecting the

increased complexity of the 6-class problem. The per-class breakdown in Table 4 highlights the model's strengths and weaknesses. It performed robustly on its primary task of identifying urban expansion, achieving F1-scores of 0.68 for "Agriculture to Building," 0.67 for "Wasteland to Building," and 0.63 for "Tree/Forest to Building." Conversely, the model struggled with more ambiguous transitions, particularly "Destruction of Agriculture" (0.39 F1) and "Destruction of Environment" (0.42 F1), suggesting these classes were the primary source of classification errors.

Metric	Value	Interpretation
Precision	0.72	Correct positive predictions ratio
Recall	0.60	Proportion of true positives found
F1-score	0.65	Balance between precision and recall
True Positives (TP)	1201	Correctly detected positive samples
False Positives (FP)	450	Incorrectly detected positive samples
False Negatives (FN)	783	Missed positive samples

Table 3. Comprehensive accuracy assessment of the binary change detection model.

Class	F1-score	Precision	Recall
Agriculture to Building	0.68	0.64	0.72
Wasteland to Building	0.67	0.63	0.71
Tree/Forest to Building	0.63	0.68	0.59
Destruction of Agriculture	0.39	0.34	0.46
Destruction of Environment	0.42	0.37	0.48
Others	0.55	0.56	0.54
Macro Average	0.55	0.54	0.58

Table 4. Comprehensive accuracy assessment of the semantic change detection model (excluding class no change and only on true positives samples from binary).

The moderate performance metrics suggest several potential areas for improvement: (1) enhanced spectral feature extraction to reduce false positives, (2) improved spatial context modeling to minimize missed detections, and (3) more balanced training data representation across all change categories. These modifications could help address the current limitations while maintaining the model's demonstrated strengths in detecting clear land-use transitions.

4. CONCLUSION

This research successfully developed and validated a novel deep learning framework for automated land-use change detection using Sentinel-2 satellite imagery, with specific application to the rapidly urbanizing regions of Mashhad and Maragheh, Iran. The proposed U-Net++ ensemble architecture demonstrated competent performance in identifying major land cover transitions, particularly conversions from agricultural and wasteland to built-up areas, as evidenced by the overall F1-score of 0.65. The model's effectiveness was further enhanced through the strategic incorporation of seasonal NDVI analysis and cloud-shadow masking techniques, which significantly improved the reliability of the generated change maps.

Key findings from this study reveal two primary technical challenges: (1) difficulties in discriminating between spectrally similar land cover classes during transition periods, and (2) limitations in achieving precise change boundary delineation. These observations are supported by the quantitative evaluation metrics and visual analysis of the semantic change maps.

For future research directions, three critical pathways emerge: First, architectural optimizations should focus on improved spectral feature extraction to address classification ambiguities. Second, the integration of higher-resolution satellite data or aerial imagery could enhance boundary precision. Third, exploring multi-modal data fusion techniques, potentially incorporating SAR data or 3D urban information, may provide complementary features for more robust change detection.

The methodological advancements presented in this work contribute meaningfully to the growing field of remote sensing-based urban monitoring, offering practical tools for urban planners and environmental managers. As cities continue to expand rapidly, such automated change detection systems will become increasingly vital for sustainable urban development and natural resource conservation. Further validation across diverse geographical contexts and urban environments will help establish the generalizability of the proposed framework while identifying additional opportunities for refinement.

ACKNOWLEDGEMENTS

The authors gratefully acknowledge the support and resources provided by Basysco Remote Sensing Institute, which contributed significantly to the completion of this work..

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