AI-based multi-temporal analysis of urban dynamics using Sentinel-2 data. A case study over Osmaniye, Turkey

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Keywords: Urbanization, Sentinel-2, Deep Learning, Turkey, Disaster Monitoring

Abstract

Monitoring urban dynamics in hazard-prone regions is essential for understanding long-term urban growth and assessing the impact of disruptive events. This study presents a multi-temporal framework for urban monitoring that integrates Sentinel-2 multispectral imagery with semantic segmentation techniques. A U-Net architecture trained using World Settlement Footprint (WSF) reference data was employed to automatically extract built-up areas and reconstruct the temporal evolution of urban expansion in the city of Osmaniye (Türkiye) between 2015 and 2025. The trained model was applied to the full Sentinel-2 time series to generate yearly built-up maps and analyse changes in the urban footprint over the decade. The results reveal a clear and sustained expansion of built-up areas throughout the study period. The multi-temporal analysis also captures a distinct disruption in the urban trajectory associated with the 2023 earthquake, followed by a rapid rebound likely related to post-disaster reconstruction activities. By combining semantic segmentation with multi-temporal satellite observations, the proposed framework enables the detection of both gradual urban expansion and abrupt disaster-related changes using openly available Earth Observation data. The results highlight the potential of Artificial Intelligence and Remote Sensing for continuous urban monitoring, disaster impact assessment, and data-driven urban planning.

1. Introduction

Urbanization is a complex and continuous process that profoundly transforms land use, environmental conditions, and socio-economic structures. Over recent decades, cities worldwide have experienced accelerated growth driven by population increase, economic development, and the rising demand for housing and infrastructure. However, rapid expansion is often not accompanied by sustainable planning strategies. As a consequence, urban development frequently encroaches upon environmentally sensitive or hazard-prone areas, increasing exposure to natural risks and generating significant environmental pressures. These processes commonly lead to soil sealing, landscape fragmentation, and ecosystem degradation, ultimately reducing permeable surfaces and altering natural hydrological and ecological balances (Vu et al., 2024).

These issues are particularly critical in regions characterised by high geological hazards. In areas affected by active tectonic structures, rapid and unplanned urban expansion can substantially increase territorial vulnerability. Understanding where and how urban areas develop, especially in morphologically unstable zones, is therefore essential for assessing exposure to seismic risk and supporting risk-informed territorial management. Continuous monitoring of urban dynamics has consequently become a proactive approach towards sustainable planning and disaster risk reduction.

Traditional in situ surveys and cadastral datasets often lack the temporal continuity, spatial coverage, and update frequency required for long-term monitoring or rapid post-event assessments. In this context, Earth Observation (EO) has emerged as a powerful tool for analysing urban transformations from space. The increasing availability of open-access multispectral imagery, such as that provided by the Sentinel-2 mission, enables synoptic, repeatable, and cost-effective monitoring of urban environments over extended temporal scales. Multispectral optical data support detailed land-cover analysis and facilitate the reconstruction of historical urban expansion patterns, providing valuable information for urban planning and environmental management.

Recent advances in Artificial Intelligence (AI), particularly in the field of Deep Learning (DL), have further enhanced the capability to analyse large EO datasets. Convolutional Neural Networks (CNNs) have demonstrated strong performance in extracting spatial features from medium- and high-resolution satellite imagery, often outperforming traditional pixel-based or object-based classification approaches. Among these techniques, semantic segmentation architectures such as U-Net enable dense, pixel-level classification of imagery, allowing accurate delineation of built-up areas and a detailed representation of urban morphology (Memar et al., 2024; Sikdar et al., 2023). The integration of EO data with DL models therefore represents a promising approach for analysing urban dynamics across large spatial and temporal scales.

These capabilities are particularly relevant in the context of disaster monitoring and post-event assessment. Multi-temporal analysis of satellite imagery acquired before and after seismic events enables the rapid identification of affected areas, the evaluation of structural damage, and the observation of reconstruction processes. Changes in built-up structures, vegetation cover, or the appearance of temporary settlements can be detected and mapped, providing valuable information to support emergency response and reconstruction planning.

Within this framework, the present study focuses on the city of Osmaniye, located in southern Turkey. The urban development of the city has been strongly influenced by its geographical set-

https://doi.org/10.5194/isprs-archives-XLIX-B3-2026-1307-2026

ting, characterised by the interaction between mountainous reliefs, the valleys of the Ceyhan River, and surrounding plains. While the historic urban core remains relatively compact, recent demographic pressure has led to increasing peripheral expansion. At the same time, Osmaniye lies in close proximity to the East Anatolian Fault, one of the most active tectonic structures in the region (Yagci et al., 2024). The devastating earthquake sequence that struck southern Turkey in 2023 represents a major turning point in the recent evolution of the city, offering a unique opportunity to analyse both long-term urban growth patterns and post-disaster reconstruction dynamics (Russo et al., 2025).

Building upon these premises, this work proposes a multi-temporal framework for analysing urban dynamics in Osmaniye over the period 2015–2025. By integrating Sentinel-2 multispectral imagery with a U-Net semantic segmentation model, the proposed workflow enables consistent mapping of built-up areas across a decade of satellite observations.

Beyond the specific neural network architecture adopted, the main contribution of this study lies in the development of a multi-temporal EO framework that enables the joint analysis of long-term urbanization processes and abrupt disaster-related disruptions using high-resolution Sentinel-2 time series.

The main objectives of this study are threefold: (i) to quantify the spatial and temporal evolution of urban expansion in Osmaniye over the last decade; (ii) to evaluate the capability of a DL segmentation framework to generalise across multi-temporal satellite data; (iii) to investigate how the 2023 earthquake influenced urban dynamics, particularly in terms of disruption and subsequent reconstruction processes.

While several studies have focused primarily on post-disaster damage detection using very high resolution imagery, fewer works have explored how high-resolution satellite time series can be exploited to jointly analyse long-term urban expansion and disaster-related disruptions within a unified analytical framework. In this context, the proposed approach leverages multi-temporal Sentinel-2 observations to capture both gradual urban growth patterns and abrupt changes associated with extreme events.

By relying entirely on open-access satellite data and reproducible methodologies, the proposed framework demonstrates how AI and EO can provide robust and scalable tools for monitoring urban growth in hazard-prone regions, ultimately supporting sustainable urban planning, disaster risk reduction, and post-event recovery strategies.

2. Related Work

Remote sensing has long been recognized as an effective tool for monitoring urban environments and assessing the impacts of natural hazards. Satellite imagery provides synoptic spatial coverage and temporal continuity, allowing researchers to observe urban expansion, land-use transformations, and infrastructure changes across large geographic areas. Early studies demonstrated the potential of EO data for assessing earthquake impacts and urban vulnerability, highlighting how multispectral and radar imagery can support damage mapping and post-disaster response (Dell'Acqua and Gamba, 2012; Brunner et al., 2010; Dong and Shan, 2013). These approaches showed that satellite observations can provide valuable information on structural damage and urban exposure, particularly when ground surveys are difficult or time-consuming.

With the increasing availability of higher-resolution satellite imagery and expanding EO archives, machine learning methods have progressively replaced traditional rule-based and manual interpretation techniques. Automated classification algorithms have enabled more efficient extraction of built-up areas and urban features from multispectral imagery. However, these approaches often rely on handcrafted features and may struggle to capture the spatial complexity of heterogeneous urban landscapes.

In recent years, the rapid development of Deep Learning (DL) has significantly improved the capability to analyse satellite imagery for urban monitoring and disaster assessment. Convolutional Neural Networks (CNNs) have demonstrated strong performance in extracting complex spatial patterns from optical images, enabling automated detection of buildings, land-use classes, and damaged structures. For instance, Ji et al. (2019) showed that CNN-based features outperform traditional texture descriptors for detecting collapsed buildings in post-earthquake satellite imagery. The growing success of DL methods has stimulated extensive research aimed at developing automated frameworks capable of mapping urban damage and infrastructure changes directly from aerial or satellite data.

A major milestone in the adoption of DL for disaster analysis was the creation of large benchmark datasets designed for building damage assessment. In particular, the xBD dataset introduced by Gupta et al. (2019) provides a large collection of pre-event and post-event satellite imagery annotated with building-level damage categories across multiple disasters. The availability of such datasets has enabled the training and evaluation of neural networks capable of learning generalizable damage features across different hazard scenarios. Subsequent studies demonstrated that CNN models trained on these datasets can generalize reasonably well to new disaster events, especially when fine-tuned with local data (Valentijn et al., 2020). More recently, advanced architectures such as transformer-based models have also been explored for large-scale building damage assessment, achieving competitive performance on benchmark datasets (Kaur et al., 2023).

The devastating earthquakes that struck southern Turkey and northern Syria on 6 February 2023 provided a real-world testbed for these methodological advances. Several studies have leveraged satellite imagery and DL models to analyse building damage and post-event reconstruction dynamics in the affected regions. For example, Serifoglu Yilmaz et al. (2023) developed a radiometric change-analysis framework combining Sentinel-1 and Sentinel-2 imagery to detect damaged buildings after the Kahramanmaraş earthquakes, achieving overall accuracies between approximately 74% and 84%. Other works applied DL models originally trained on global datasets to very high-resolution imagery of the affected cities, demonstrating the potential of transfer learning for rapid post-disaster mapping (Soleimani-Babakamali et al., 2025). These studies highlight the growing role of EO-based AI frameworks in supporting emergency response and damage assessment at large spatial scales.

Despite these advances, most existing research has primarily focused on detecting building damage immediately after a disaster using very high-resolution imagery. Comparatively fewer studies have explored how multi-temporal satellite data and DL

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can be integrated to analyse both long-term urban expansion and abrupt disaster-induced changes within the same analytical framework. In particular, satellite missions such as Sentinel-2 offer high temporal revisit frequency and long-term data continuity, making them particularly suitable for analysing urban dynamics over extended time periods.

Within this context, the present study contributes to the growing body of research on AI-driven EO analysis by integrating multi-temporal Sentinel-2 imagery with a U-Net semantic segmentation framework to investigate urban expansion and post-earthquake reconstruction processes in the city of Osmaniye, Türkiye. By analysing a decade-long time series (2015–2025), the proposed approach aims to capture both gradual urban growth patterns and the disruption caused by the 2023 earthquake, providing new insights into the evolution of urban environments in seismically active regions.

3. Study Area and Data

The study focuses on the city of Osmaniye, located in southern Turkey in the eastern Mediterranean region of Anatolia (Figure 1). The city lies close to the East Anatolian Fault (EAF), one of the most active tectonic structures in the area, marking the boundary between the Anatolian, Arabian, and Eurasian tectonic plates. This tectonic setting makes the region particularly prone to seismic activity and associated risks.

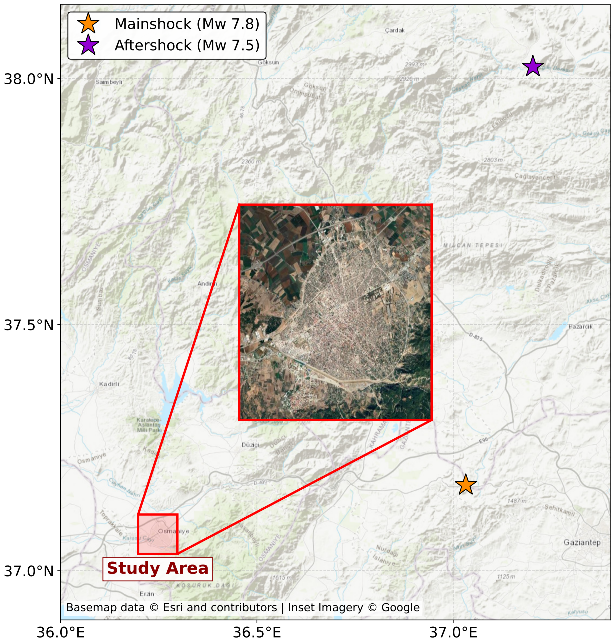

Figure 1. Location of Osmaniye (southern Türkiye) and epicenters of the 2023 Kahramanmaraş earthquakes. The inset highlights the study AoI.

On 6 February 2023, a major earthquake sequence struck southeastern Türkiye, with a magnitude 7.8 event near Kahramanmaraş followed approximately nine hours later by a magnitude 7.5 earthquake near Elbistan. The rupture propagated along several segments of the EAF system, affecting large areas of southern Türkiye and northern Syria. The earthquakes caused widespread destruction across multiple provinces and resulted in significant human and economic losses. As one of the strongest seismic events recorded in the region since 1939, this disaster highlighted the vulnerability of rapidly expanding urban areas located near active tectonic structures.

Osmaniye represents an interesting case study in this context (Russo et al., 2025; Yagci et al., 2024). The city has experienced steady population growth and urban expansion over recent decades, while its geographical setting combines mountainous terrain, river valleys associated with the Ceyhan River, and surrounding plains. The urban structure is characterised by a relatively compact historical core hosting administrative and commercial activities, surrounded by expanding peri-urban zones and agricultural land. Urban growth has primarily occurred toward the surrounding plains, while mountainous areas have partially constrained expansion in certain directions.

These characteristics make Osmaniye a suitable testbed for analysing the interaction between long-term urbanization processes and sudden disaster-related disruptions, such as those caused by the 2023 earthquake.

3.1 Earth Observation Data

Multi-temporal multispectral satellite imagery was acquired from the Sentinel-2 mission through the Google Earth Engine (GEE) platform. Level-2A products providing Bottom of Atmosphere (BOA) reflectance were selected for the period 2015–2025 in order to reconstruct a decade-long time series of urban evolution.

To reduce seasonal variability and atmospheric artefacts, images with minimal cloud coverage and better spectral contrast between different land cover classes were selected during the spring period of each year. Four spectral bands with a spatial resolution of 10 m were used to construct the input dataset: Blue, Green, Red, and Near-Infrared. The combination of visible and near-infrared wavelengths enables effective discrimination between built-up areas, vegetation, and bare soil, making these bands particularly suitable for urban land-cover analysis.

All Sentinel-2 images were clipped to the Area of Interest (AoI) corresponding to the administrative boundaries of Osmaniye and subsequently used to construct the multi-temporal dataset employed in the DL workflow.

3.2 Reference Dataset

Reference data for built-up area extraction were provided by the World Settlement Footprint (WSF) dataset (Marconcini et al., 2020), developed by the German Aerospace Center (DLR). The WSF is a global settlement layer derived from the integration of radar and optical satellite data, including Sentinel-1, Sentinel-2, and Landsat imagery, using advanced data fusion and classification techniques.

The dataset provides a binary representation of built-up areas at a spatial resolution of 10 m. In this study, the WSF 2015 and WSF 2019 products were obtained through the DLR Earth Observation Center (EOC) GeoService and used as reference masks for training and validation of the DL-based segmentation model.

3.3 Data Pre-processing and Patch Generation

Before training the DL model, the satellite imagery and reference masks were processed through a preprocessing pipeline to ensure spatial consistency across the multi-temporal dataset.

All data were projected to a common coordinate reference system and spatially aligned over the AoI.

To enable patch-based learning, the original images were resampled to a uniform spatial size of 768×768 pixels. The multispectral scenes and their corresponding masks were then subdivided into non-overlapping image tiles of 64×64 pixels using a stride equal to the patch size. This configuration provides a suitable balance between spatial context and computational efficiency during model training.

A filtering procedure was applied to remove patches containing invalid values or lacking built-up pixels in the corresponding reference mask. This step reduces class imbalance and improves the learning stability of the segmentation model. The resulting dataset consists of pairs of multispectral input tensors $\mathbf{X} \in \mathbb{R}^{64\times64\times4}$ and binary mask tensors $\mathbf{Y} \in \{0,1\}^{64\times64\times1}$, which were used as training samples for the U-Net semantic segmentation network.

4. Methodology

The proposed framework integrates multi-temporal EO data with DL techniques to automatically map built-up areas and analyse urban dynamics over time. The processing chain consists of three main stages: (i) preparation of the training dataset from multispectral Sentinel-2 imagery and WSF reference masks; (ii) training of a deep neural network for semantic segmentation; and (iii) multi-temporal inference to generate yearly urban maps and quantify urban expansion. The workflow is illustrated in Figure 2.

4.1 Deep Learning Architecture

Built-up extraction was formulated as a pixel-wise binary semantic segmentation problem. A CNN based on the U-Net architecture was adopted due to its effectiveness in dense image segmentation tasks and its widespread use in EO applications (Memar et al., 2024).

U-Net follows an encoder–decoder structure designed to capture both global contextual information and fine spatial details. The encoder progressively extracts hierarchical features from the input imagery through successive convolutional blocks composed of 3×3 convolutions followed by Rectified Linear Unit (ReLU) activations and 2×2 max-pooling operations. This process progressively reduces the spatial resolution of the feature maps while increasing their semantic depth.

The decoder reconstructs the spatial resolution through upsampling operations and convolutional layers. To preserve spatial details, skip connections are introduced to concatenate feature maps from the encoder with the corresponding decoder layers. These connections allow the network to combine high-level contextual information with fine-grained spatial features, which is essential for accurately delineating built-up structures.

In this study, the network processes multispectral input patches $\mathbf{X} \in \mathbb{R}^{64\times64\times4}$ composed of four Sentinel-2 bands (Blue, Green, Red, and Near-Infrared). The final layer applies a 1×1 convolution with a Sigmoid activation function to produce a probability map $\hat{\mathbf{Y}} \in [0,1]^{64\times64\times1}$ representing the likelihood that each pixel belongs to the built-up class.

4.2 Training Strategy

The dataset composed of multispectral image patches and corresponding reference masks was randomly divided into training (80%) and validation (20%) subsets. This split ensures that model performance is evaluated on unseen samples, reducing the risk of overfitting and improving the network's generalization capability.

Model optimisation was performed using the Binary Cross-Entropy (BCE) loss function, which measures the difference between predicted probabilities and ground-truth labels. For N pixels, the BCE loss is defined as:

$$BCE = -\frac{1}{N}\sum_{i=1}^{N}[y_i \log(\hat{y}_i) + (1-y_i)\log(1-\hat{y}_i)] \tag{1}$$

where y_i represents the reference label and $\hat{y}_i$ denotes the predicted probability for pixel i.

The network was trained using the Adam optimizer with mini-batches of 32 samples for a maximum of 200 epochs. To improve training stability and mitigate overfitting, two adaptive strategies were adopted: early stopping and dynamic learning rate adjustment. The main hyperparameters used during training are summarized in Table 1.

Table 1. Training hyperparameters of the U-Net model.

Parameter	Value
Optimizer	Adam
Initial LR	10^{-3}
Loss function	Binary Cross-Entropy (BCE)
Batch size	32
Maximum epochs	200
Early stopping patience	10 epochs
LR scheduler	ReduceLROnPlateau
LR reduction factor	0.5

4.3 Model Evaluation

Model performance was evaluated on the validation dataset using standard metrics commonly adopted in semantic segmentation tasks. The probabilistic outputs produced by the network were converted into binary segmentation maps using a fixed classification threshold of 0.5. In addition to Accuracy, which measures the proportion of correctly classified pixels, overlap-based metrics were also considered, including Precision, Recall, Intersection over Union (IoU), and the F_1 score.

The IoU metric measures the spatial overlap between predicted and reference masks and is defined as:

$$\mathrm{IoU} = \frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FP}+\mathrm{FN}} \tag{2}$$

where TP, FP, and FN denote True Positives, False Positives, and False Negatives, respectively. The F_1 score, which balances Precision and Recall, is computed as:

$$F_1 = 2 \times \frac{\mathrm{Precision} \times \mathrm{Recall}}{\mathrm{Precision} + \mathrm{Recall}} \tag{3}$$

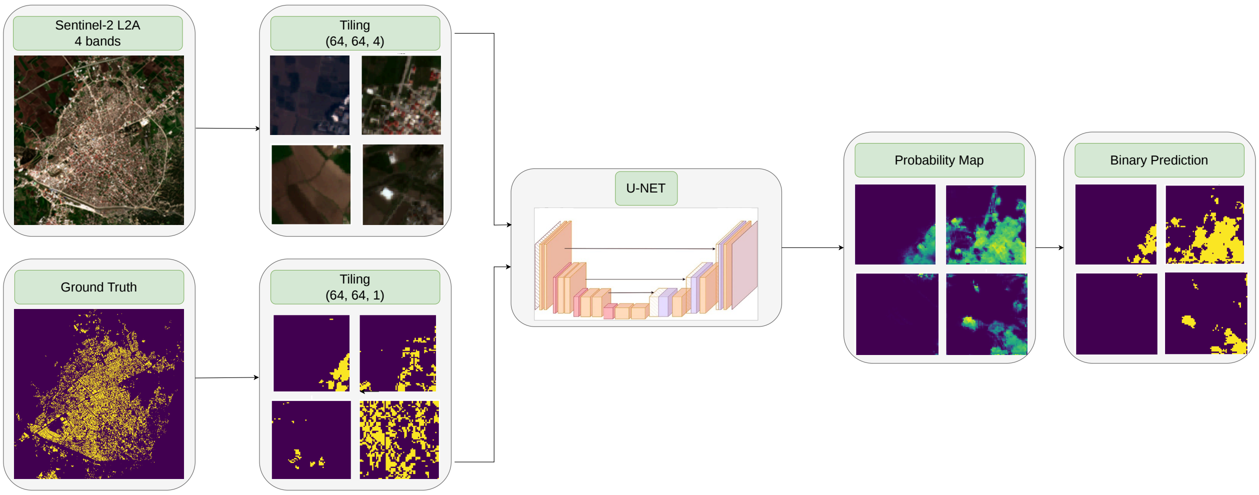

Figure 2. Overview of the proposed workflow for multi-temporal urban mapping. Sentinel-2 imagery and Ground Truth (WSF) reference data are used to generate training patches for a U-Net semantic segmentation model, which is then applied to the Sentinel-2 time series to produce yearly built-up maps and analyse urban expansion.

After validation on the reference years, the trained model was applied in inference mode to the full Sentinel-2 time series (2015–2025) to reconstruct the temporal evolution of urban areas and quantify long-term urban dynamics.

5. Results and Discussion

This section presents and discusses the results obtained from the proposed multi-temporal framework. First, the segmentation performance of the trained model is quantitatively evaluated. This is followed by a qualitative analysis of the prediction outputs and an investigation of the urban dynamics observed in Osmaniye between 2015 and 2025.

5.1 Quantitative Validation Performance

The performance of the trained model was evaluated on the validation dataset using standard metrics commonly adopted in semantic segmentation tasks. The quantitative results are summarized in Table 2. Overall, the obtained metrics indicate a strong agreement between the predicted segmentation masks and the reference WSF data. In addition to Accuracy, overlap-based metrics such as Precision, Recall, F_1 score, and IoU provide a more detailed evaluation of segmentation quality, reflecting the model's ability to correctly identify built-up areas while limiting misclassifications.

Table 2. Performance metrics of the model for built-up area segmentation evaluated on the validation dataset.

Metric	Value
Accuracy	0.8727
Precision	0.5754
Recall	0.5820
F_1 score	0.5787
IoU	0.4071

Although the IoU and F_1 values may appear moderate, these results are consistent with the characteristics of high-resolution multispectral imagery ($10\,m$). At this spatial resolution, a single pixel often captures a heterogeneous composition of urban elements, including buildings, vegetation, roads, and bare soil, which reduces the sharpness of class boundaries and introduces uncertainty in the reference representation. Furthermore, different land-cover types such as built-up surfaces, bright soils, and construction areas may exhibit similar reflectance patterns in the visible and near-infrared bands. This spectral similarity limits class separability and can lead to increased misclassification in complex urban and peri-urban environments. The balance between Precision and Recall indicates that the model does not strongly favor either omission or commission errors. False positives are mainly associated with spectrally similar surfaces such as bright soils, exposed rock formations, or heterogeneous agricultural areas at the urban fringe. Conversely, false negatives typically occur in sparsely built-up zones where buildings are partially covered by vegetation or appear fragmented at the sensor resolution.

A comparison with similar approaches reported in the literature is presented in Table 3. For example, (Dixit et al., 2022) evaluated several DL architectures for urban extraction from Sentinel-2 imagery, reporting F_1 scores between 0.54 and 0.57 depending on the adopted network architecture. Although these results were obtained on different study areas and datasets, the performance achieved in this study falls within a comparable range, indicating that the proposed framework achieves results consistent with recent deep learning approaches for built-up area segmentation.

Table 3. Comparison of segmentation performance with selected DL approaches from the literature.

Study	Model	F_1 score	IoU
Dixit et al. (2022)	ResNet18	0.5428	0.637*
Dixit et al. (2022)	SegUnet	0.5728	0.654*
This study	**U-Net**	**0.5787**	**0.407****

* Mean IoU (average of built-up and background classes).

** Class IoU (built-up class only).

5.2 Qualitative Segmentation Assessment

A qualitative inspection of the segmentation outputs further supports the robustness of the trained model. Figure 3 presents two representative inference examples on validation patches, illustrating the Sentinel-2 RGB input, the reference WSF mask,

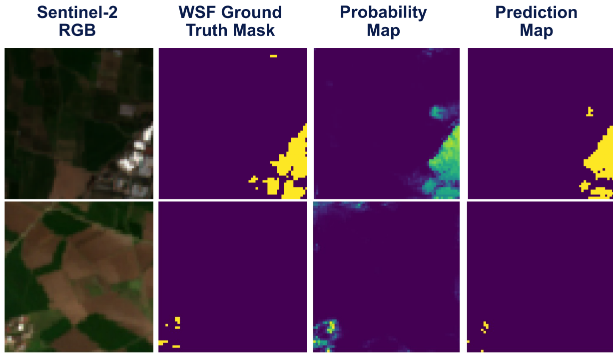

Figure 3. Examples of model predictions over validation patches in Osmaniye.

the predicted probability map generated by the network, and the final binary segmentation.

The probability maps highlight areas with a higher likelihood of built-up presence while maintaining lower confidence values over surrounding agricultural or vegetated surfaces. This behaviour reflects the model's ability to capture the spectral and spatial characteristics associated with urban structures.

After binarization, the predicted masks reproduce the spatial distribution of the reference built-up areas with a coherent representation of urban features. In both examples, the predicted segmentation closely follows the structure of the WSF ground-truth mask, indicating that the network successfully learned meaningful patterns associated with built-up surfaces despite the presence of mixed land-cover conditions typical of high-resolution satellite imagery.

5.3 Temporal Generalization Across the Sentinel-2 Time Series

To assess temporal robustness, the U-Net model was applied in inference mode to the full Sentinel-2 archive covering the period 2015–2025. This experiment evaluates the capability of the model to produce consistent segmentation results across a multi-year satellite time series. Overall, the predicted segmentation maps show consistent detection of built-up areas throughout the time series, despite variations in illumination conditions, atmospheric effects, and seasonal vegetation dynamics. This behaviour suggests that the network learned stable spectral and spatial characteristics associated with urban structures.

Figure 4 presents a representative example of model predictions for two different years (2020 and 2025) over the same image patch extracted from the study area. For each epoch, the Sentinel-2 RGB composite is displayed together with the predicted probability map and the final binarized segmentation.

The comparison highlights the ability of the network to consistently identify built-up structures across different years. The probability maps exhibit coherent spatial patterns, while the binary predictions preserve the spatial configuration of urban features. In this example, the segmentation also suggests an increase in built-up areas between the two epochs, consistent with the urban growth trends observed in the multi-temporal analysis.

These results indicate that the model generalizes effectively across the Sentinel-2 time series and can be reliably applied to monitor urban dynamics over extended periods.

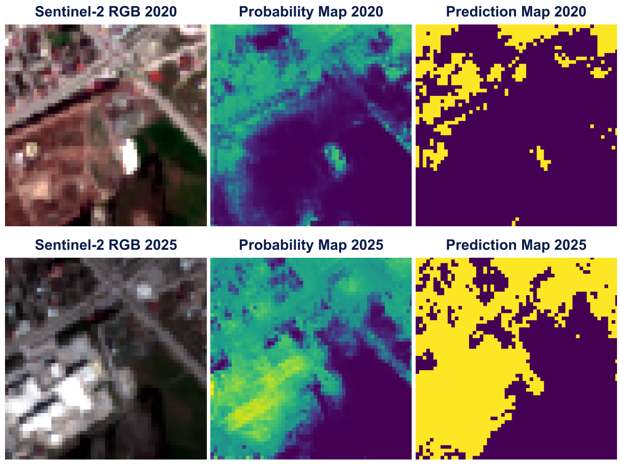

Figure 4. Example of model predictions for two different years (2020 and 2025) over the same geographic patch in Osmaniye.

5.4 Multi-temporal Urban Dynamics (2015–2025)

Applying the trained model to the full Sentinel-2 time series enabled the reconstruction of the urban expansion trajectory of Osmaniye over the decade 2015–2025. For each year, the number of pixels classified as built-up was computed and compared with the total number of pixels within the AoI, providing an indirect estimate of the temporal evolution of urban surface coverage. Figure 5 illustrates the evolution of built-up pixels between 2015 and 2025. The results reveal a clear expansion of the urban footprint throughout the analysed period, with urban coverage increasing from approximately 13.3% in 2015 to about 35.1% in 2025.

The temporal trajectory can be broadly divided into three phases. Between 2015 and 2018, Osmaniye experienced rapid urban expansion, likely driven by residential development and the conversion of surrounding agricultural land. From 2018 to 2022, the growth rate slowed slightly, suggesting a phase of consolidation and densification of the existing urban fabric.

A significant anomaly occurs in 2023, coinciding with the major earthquake that affected southern Türkiye. Prior to the seismic event, urban coverage reached its highest level within the decade. Immediately after the earthquake, a noticeable decrease in built-up pixels is observed, likely reflecting building collapse, structural damage, and the accumulation of debris that altered the spectral characteristics of urban surfaces. The decline continues into 2024, followed by a strong rebound in 2025. This sharp increase suggests an intense reconstruction phase and possibly accelerated urban development following the disaster.

These observations are consistent with previous studies investigating urban growth dynamics in Osmaniye and other Turkish cities. Remote sensing analyses of land-use change in Osmaniye have reported a significant increase in settlement areas over recent decades, highlighting sustained urban expansion driven by demographic and infrastructural development (Yagci et al., 2024).

Within this broader urbanization trend, the temporary decrease observed in 2023 can be interpreted as a short-term perturbation caused by the earthquake, while the strong increase detected in 2025 likely reflects reconstruction processes and renewed urban development following the disaster.

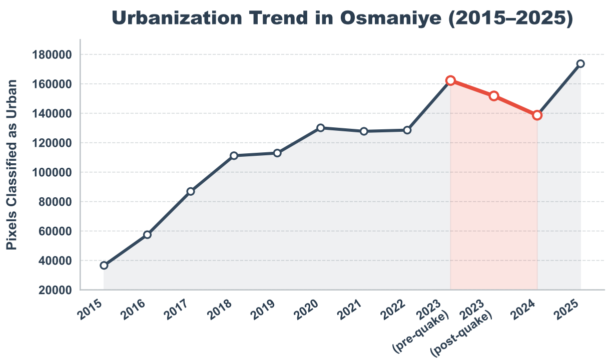

Figure 5. Temporal evolution of built-up area in Osmaniye between 2015 and 2025 derived from the number of pixels classified as urban.

5.5 Spatial Patterns of Urban Expansion

To further analyse the spatial distribution of urban growth, a change detection analysis was performed by comparing predicted segmentation masks from different years of the Sentinel-2 time series.

Figure 6 shows the spatial distribution of urban changes between 2020 and 2025 for the same image patch previously illustrated in Figure 4. The change map was obtained through a pixel-by-pixel comparison of the binarized segmentation outputs generated by the U-Net model for the two epochs. The resulting map highlights areas of urban expansion, unchanged urban regions, changed non-urban areas, and localized zones where built-up pixels are no longer detected. Newly urbanized areas are mainly concentrated along the peripheral portions of the scene, indicating outward growth of the built-up footprint between the two years.

Conversely, most pixels remain unchanged, reflecting the stability of both consolidated urban areas and surrounding non-urban land cover. Small clusters of pixels classified as urban loss may correspond to demolition, reconstruction processes, or minor classification inconsistencies caused by spectral variability.

Overall, the spatial distribution of changes confirms the outward expansion of the urban fabric observed in the temporal trend analysis (Figure 5). In particular, the newly developed area visible in the lower-left portion of the scene, identified as urban expansion in the change map, corresponds to a modern public building complex, identifiable as a hospital, clearly observable in the 2025 imagery. The absence of urban loss signals in this area suggests that these structures were not significantly affected by the earthquake, likely reflecting the adoption of more recent and resilient construction standards.

5.6 Discussion and Limitations

Overall, the results indicate that the proposed framework provides an effective and scalable approach for monitoring urban dynamics using openly available EO data.

Nevertheless, several limitations should be acknowledged. First, the supervised training relied on WSF reference masks available only for a limited number of reference years. Although the model demonstrates strong temporal generalization across the Sentinel-2 time series, the absence of independent

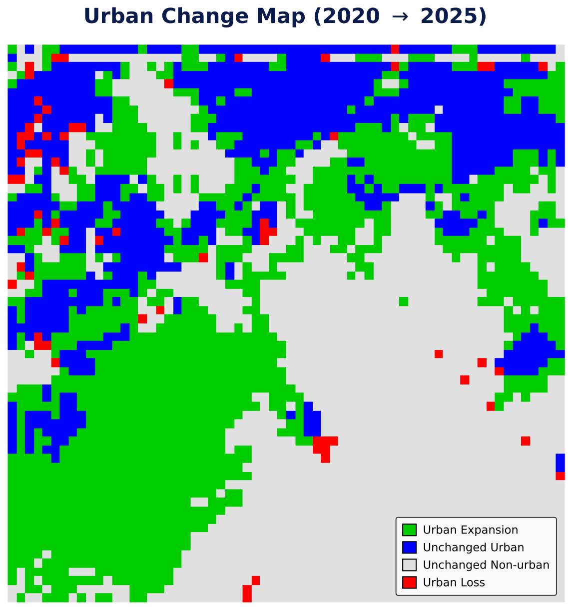

Figure 6. Urban change map between 2020 and 2025 derived from the pixel-wise comparison of the predicted segmentation masks for the same validation patch shown in Figure 4.

ground-truth data for later epochs prevents a strict quantitative validation of the predictions beyond the training period.

Second, the moderate precision values indicate residual uncertainty in spectrally complex peri-urban environments. In high-resolution multispectral imagery, built-up surfaces may exhibit spectral similarities with bright bare soil, construction sites, or heterogeneous agricultural areas, which can lead to occasional misclassifications.

Future developments could address these limitations by integrating complementary datasets such as Sentinel-1 Synthetic Aperture Radar (SAR) imagery, which is less sensitive to illumination conditions and vegetation cover. Furthermore, extending the framework towards multi-class semantic segmentation would allow the differentiation of urban subcategories, including residential areas, industrial zones, rubble fields, or temporary shelters in post-disaster contexts.

6. Conclusions

This study presented a framework for monitoring urban dynamics through the integration of multi-temporal EO data and semantic segmentation techniques. Using Sentinel-2 multispectral imagery and WSF reference data, a U-Net architecture was trained to automatically extract built-up areas and reconstruct the evolution of urban expansion in the city of Osmaniye between 2015 and 2025. The results show that the proposed approach can reliably identify urban structures from high-resolution satellite imagery and produce spatially consistent segmentation maps across the Sentinel-2 time series. The multi-temporal analysis revealed a marked expansion of the urban footprint over the decade, while also capturing a clear disruption associated with the 2023 earthquake. In particular, a temporary decrease in detected built-up areas was observed after the event, followed by a strong recovery likely related to reconstruction activities. From an operational perspective, the proposed workflow relies exclusively on open-access satellite data and reproducible processing techniques, making it scalable and transferable to other regions exposed to rapid urbanization or natural hazards. These results highlight the potential of combining AI and EO for continuous urban monitoring and post-disaster assessment. Future developments will focus on extending the framework toward multi-class semantic segmentation and integrating complementary datasets, such as Sentinel-1 SAR imagery or higher-resolution and hyperspectral observations (e.g., COSMO-SkyMed and PRISMA), to further improve robustness in complex urban environments.

Acknowledgments

The authors would like to acknowledge the Italian Space Agency (ASI) for funding support provided through the PhD scholarship of Pietro Di Stasio under the contract N. 2024-24-HH.0 CUP: F83C24000890005, and for the Traineeship of Antonino Pigna.

References

Brunner, D. et al., 2010. Earthquake damage assessment of buildings using VHR optical and SAR imagery. *IEEE Transactions on Geoscience and Remote Sensing*, 48(5), 2403–2420.

Dell’Acqua, F., Gamba, P., 2012. Remote sensing and earthquake damage assessment: Experiences, limits, and perspectives. *Proceedings of the IEEE*, 100(10), 2876–2890.

Dixit, M. et al., 2022. 6+: A novel approach for building extraction from a medium resolution multi-spectral satellite. *Sustainability*, 14(3), 1615.

Dong, L., Shan, J., 2013. A comprehensive review of earthquake-induced building damage detection with remote sensing techniques. *ISPRS Journal of Photogrammetry and Remote Sensing*, 84, 85–99.

Gupta, R. et al., 2019. Creating xbd: A dataset for assessing building damage from satellite imagery. *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition workshops*, 10–17.

Ji, M. et al., 2019. A comparative study of texture and convolutional neural network features for detecting collapsed buildings after earthquakes using pre-and post-event satellite imagery. *Remote Sensing*, 11(10), 1202.

Kaur, N. et al., 2023. Large-scale building damage assessment using a novel hierarchical transformer architecture on satellite images. *Computer-Aided Civil and Infrastructure Engineering*, 38(15), 2072–2091.

Marconcini, M. et al., 2020. Outlining where humans live, the World Settlement Footprint 2015. *Scientific Data*, 7(1), 242.

Memar, B. et al., 2024. A U-Net Architecture for Building Segmentation Through Very High Resolution Cosmo-Skymed Imagery. *IGARSS 2024-2024 IEEE International Geoscience and Remote Sensing Symposium*, IEEE, 4653–4657.

Russo, L. et al., 2025. A Deep Learning framework for building damage assessment using VHR SAR and geospatial data: demonstration on the 2023 Türkiye Earthquake. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*.

Serifoglu Yilmaz, C. et al., 2023. Automated detection of damaged buildings in post-disaster scenarios: a case study of Kahramanmaraş (Türkiye) earthquakes on February 6, 2023. *Natural Hazards*, 119(3), 1247–1271.

Sikdar, A. et al., 2023. Deepmao: Deep Multi-Scale Aware Overcomplete Network for Building Segmentation in Satellite Imagery. *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 487–496.

Soleimani-Babakamali, M. H. et al., 2025. Deep ensemble learning for rapid large-scale postearthquake damage assessment: Application to satellite images from the 2023 Türkiye earthquakes. *ASCE OPEN: Multidisciplinary Journal of Civil Engineering*, 3(1), 04025003.

Valentijn, T. et al., 2020. Multi-hazard and spatial transferability of a cnn for automated building damage assessment. *Remote Sensing*, 12(17), 2839.

Vu, A. T. et al., 2024. Applying object-based approach to monitor urban expansion in Ha Long city, Vietnam, during 2000-2023 from multi-date Landsat satellite imagery. *European Journal of Remote Sensing*, 57(1), 2398108.

Yagci, C. et al., 2024. A Case Study of the Impact of University Establishment on Urbanization in Turkey’s Medium-Sized City of Osmaniye. *Turkish Journal of Remote Sensing*, 6(1), 01–11. https://dergipark.org.tr/en/pub/tuzal.