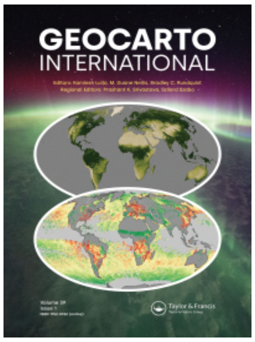

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Formal and informal settlements and corresponding demographic patterns in Gaza Strip: deep learning approach to urban sustainability

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ABSTRACT

Understanding how formal and informal settlements grow and change, and their demographic features, is key for sustainable urban development (SDG−11). This study introduces a deep learning approach integrating satellite images, population, and healthcare data to track and forecast these settlements. Using a U-Net with ResNet−18, we accurately map formal and informal settlements. The Land Change Modeler (LCM) and Multilayer Perceptron-Markov Chain (MLP-MC) predict future settlement expansions, and linear regression projects population growth. Zonal statistics and OpenRouteService (ORS) reveal demographic patterns and accessibility to healthcare facilities. Our method achieves high accuracy (89.80%) in Gaza-Strip, effectively capturing settlement dynamics from 2000–2040. Results highlight significant demographic differences and critical gaps in healthcare access between settlement types, providing practical insights for urban planners and policymakers. The approach is scalable and data-efficient, making it ideal for conflict zones and rapidly urbanizing regions. This study contributes essential knowledge for monitoring SDG−11 and enhancing human-centric urban planning.

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Deep Learning; Land Change Modeler; formal and informal settlements; demographic trends; Gaza-Strip

1 Introduction

The United Nations introduced SDG−11 in September 2015 (Küfeoğlu 2022), which emphasises the need for inclusive, safe, resilient, and sustainable cities, with a particular focus on upgrading informal settlements to ensure access to adequate and affordable housing and basic services (Habitat 2018; Monaco 2024). Informal settlements commonly known as slums or urban villages which are typically characterised by unregulated Land Use (LU), inadequate infrastructure, and precarious living conditions (Zerbo et al. 2020). While their architectural forms, density, and layouts may vary globally, these settlements often share a set of common spatial and environmental attributes, including high population density, unplanned development, and limited access to essential services (Dovey et al. 2020). To effectively monitor progress toward SDG−11, one of the key indicators is SDG−11.1.1. Which tracks the proportion of the urban population residing in informal settlements, slums, or inadequate housing (Monaco 2024; Tu et al. 2024; UN Habitat 2018). This indicator plays a critical role in evaluating the quality of urban living conditions and identifying populations at risk of social and spatial exclusion (UN Habitat 2018). Therefore, analysing spatiotemporal geographic changes and corresponding demographic patterns of formal and informal settlements over time is crucial for informed urban planning and policy-making aligned with SDG−11.

Traditional methods of analysing and monitoring these settlements, such as field surveys and census data collection, are labour-intensive and time-consuming (Zheng et al. 2009). Such traditional methods hinder the timely and scalable data collection to evaluate progress SDG−11. In contrast, remote sensing technologies offer a cost-effective and scalable solution by providing high spatial resolution (HSR) satellite imagery to identify and monitor urban growth patterns (Kadhim et al. 2016; Yao et al. 2018). Recent

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advancements in deep learning have revolutionised the field of remote sensing, enabling more accurate and efficient analysis of complex urban environments through state-of-the-art models (Jadhav et al. 2024; Yao 2022). For instance, (Han et al. 2022; Wang et al. 2020) employed the Mask R-CNN and (Zhang et al. 2024) utilised SAM to detect urban villages. Furthermore (Hu 2025) utilised ResNet to detect urban villages. Subsequent studies by (Mast et al. 2020) and (Wei 2023) further underscore the efficacy of deep learning in urban monitoring, employing semantic segmentation architectures like FCN and U-Net to map informal settlements. This study aims to utilise the U-Net architecture enhanced with a ResNet−18 backbone to perform precise pixel-level segmentation of formal and informal settlements. The U-Net model, known for its effectiveness in semantic segmentation tasks (Singh and Nongmeikapam 2023), is particularly well-suited for capturing complex spatial patterns in high resolution remote sensing imagery (Bidari et al. 2024; Cao et al. 2024; Holail 2024), while the ResNet−18 backbone enhances feature extraction through deep residual learning (Kiran et al. 2024; Xue et al. 2023). This integrated deep learning approach enables the efficient and accurate delineation of settlement types and provides a viable approach to SDG−11.1.1 measurement.

Understanding spatiotemporal geographic changes in formal and informal settlements is crucial for assessing urban development dynamics, especially in the context of SDG−11.1.1. Several recent studies (Aghajani et al. 2024; Ait El Haj et al. 2023; Qacami et al. 2023; Shafie et al. 2023) have explored the spatiotemporal dynamics of urban settlements and predict future scenarios by utilising LCM. The LCM has emerged as a powerful geospatial tool for analysing spatiotemporal LU dynamics and forecasting future LU scenarios (Aghajani et al. 2024; Qacami et al. 2023). LCM employs machine learning algorithms such as MLP and MC analysis to assess change potential and simulate spatially explicit projections (Abbas 2023). MLP is a type of artificial neural network (ANN) comprising multiple layers of interconnected neurons, typically organised into an input layer, one or more hidden layers, and an output layer (Madhiarasan and Louzazni 2022; Zhang et al. 2023). On other hand, the MC model is the core framework for modelling LU changes by aligning and comparing LU maps of two distinct periods (Aghajani et al. 2024). The MC model is a stochastic process framework that characterises transitions between states over time. MLP-MC have been effectively applied in various studies (Abbas et al. 2026; Aghajani et al. 2024; Hussain 2025). This study aims to utilise LCM for spatiotemporal geographic changes and future prediction of formal and informal settlements.

Open-source Landsat imagery has long been integral to urban studies because of its multi decadal archive, consistent acquisition, and rich spectral information, supporting large scale land use analysis and SDG monitoring (Fu 2024; Zhao and Yu 2025). However, mapping formal and informal settlements using Landsat or other medium resolution data remains challenging, as their spatial granularity often fails to capture the fine scale heterogeneity typical of dense urban environments. Although very high spatial resolution (VHSR) imagery such as QuickBird or SPOT can resolve such detail, their high cost, restricted licensing, and limited spatiotemporal coverage make them unsuitable for sustained SDG 11.1.1. Pan-sharpening offers an effective compromise by merging 30m multispectral and 15m panchromatic Landsat bands to create synthetic 15m HSR products (Chaurasia and Sharma 2025; Rahim 2024). This pan-sharpened dataset enhances spatial detail while preserving spectral quality, enabling more reliable detection of built-up areas and differentiating formal from informal settlement patterns (Matarira et al. 2022). This capability is particularly valuable for long term and large area assessments aligned with SDG 11 goals. Accordingly, this study investigates the benefits of using Pan-sharpened HSR Landsat composited unified dataset of bands and spectral indices for formal and Informal settlement segmentation.

Accurate demographic information within formal and informal settlements is critical for the assessment and monitoring of SDG−11.1.1 (Tu et al. 2024). However, current methods for collecting such data remain limited in both efficiency and accessibility (Tjia and Coetzee 2022). Traditionally, household surveys and national population censuses have been the primary means of acquiring demographic insights (Aragona and Zindato 2016). While these approaches are well-established, they are time-consuming, costly, and often outdated by the time they are analysed particularly in rapidly changing urban environments where informal settlements evolve quickly and unpredictably. The advent of earth observation technologies has significantly advanced population estimation efforts by enabling remote sensing-based approaches (Lu et al. 2006; Silván-Cárdenas et al. 2010). Nevertheless, many of these methodologies, along with their supporting datasets, are not openly accessible or standardised for direct application in SDG monitoring frameworks. The growing availability of global gridded population datasets such as the Gridded Population of the World (Lloyd et al. 2017), WorldPop (Tatem 2017), LandScan (Lebakula 2025), and the Global Human Settlement Layer (Nautiyal et al. 2020) has substantially enhanced population mapping efforts. However, a notable limitation is their inability to distinguish between formal and informal residential areas. To address this challenge, integrating WorldPop data with HSR maps of formal and informal settlements offers a promising and scalable solution. This fusion not only improves spatial contextualisation but also supports more nuanced evaluations of age and gender distribution, accessibility to healthcare facilities, and spatiotemporal demographic distribution, because this fusion has direct relevance to understanding social vulnerability and service inequality within formal and informal settlements, and thereby contributing to more effective and inclusive urban policy and planning aligned with the targets of SDG−11.

This study aims to extract and predict the spatiotemporal geographic changes of formal and informal settlements in Gaza-Strip and to examine the corresponding demographic structure by integrating open-source multispectral imageries, population and healthcare facilities data. A U-Net architecture with a ResNet−18 backbone was employed for pixel-level segmentation of formal and informal settlements. Subsequently, spatiotemporal transitions, gains, losses, net changes, and spatial change trends were analysed using the LCM. The future expansion of formal and informal settlements was projected through a hybrid MLP-MC modelling approach, while population forecasting was conducted using a linear regression model. Furthermore, spatiotemporal demographic profiles were developed through Zonal Statistics and ORS by integrating data on settlements, population, and healthcare facilities to uncover spatial patterns and demographic trends.

The principal contributions of this study are summarised as follows:

- A comprehensive and effective framework is proposed for large scale spatiotemporal geographic changes and demographic trends assessment of formal and informal settlements fusing opensource multispectral and population and healthcare facilities data, providing a critical methodological advancement for the evaluation of SDG−11.1.1.
- Pan-sharpened HSR Landsat composited unified dataset of bands and spectral indices is generated for large scale spatiotemporal geographic changes of formal and informal settlements.
- The proposed framework is demonstrated in a diverse and complex urban scenario i.e. spatiotemporal geographic change analysis and future prediction of formal and Informal settlements, future population prediction and spatiotemporal demographic trends analysis of formal and Informal settlements with population to provide insights into SDG−11.

2 Study area and data

2.1 Study area

The Gaza-Strip is a narrow coastal enclave located in the eastern Mediterranean region, bordered by Israel to the north and east, Egypt to the south, and the Mediterranean Sea to the west as depicted in Figure 1. It lies approximately between 31°.13 to 31°.36 North latitude and 34°.13 to 34°.34 East longitude. The territory covers an area of 365 square kilometres, making it one of the most densely populated regions in the world. As of recent estimates, the population exceeds 2.142 million, with a density surpassing 5,868 persons per square kilometre, leading to significant challenges in infrastructure, resource management, and urban planning. Gaza-Strip has been at the centre of prolonged geopolitical conflicts, experiencing multiple wars and military escalations, notably in 2008, 2012, 2014, and 2023, which have caused severe damage to its built environment, economic infrastructure, and social systems. A significant proportion of its residents are Palestinian refugees, with over 5.9 million registered with the United Nations Relief and Works Agency (UNRWA 2024). The prolonged impacts of urban warfare have accelerated the formation of informal areas, as displacement, destruction of housing stock, and rapid population redistribution have forced communities to construct temporary or unregulated shelters in previously undeveloped spaces (Abukashif and Riza 2019). These conditions influence the spatial signatures captured in satellite imagery

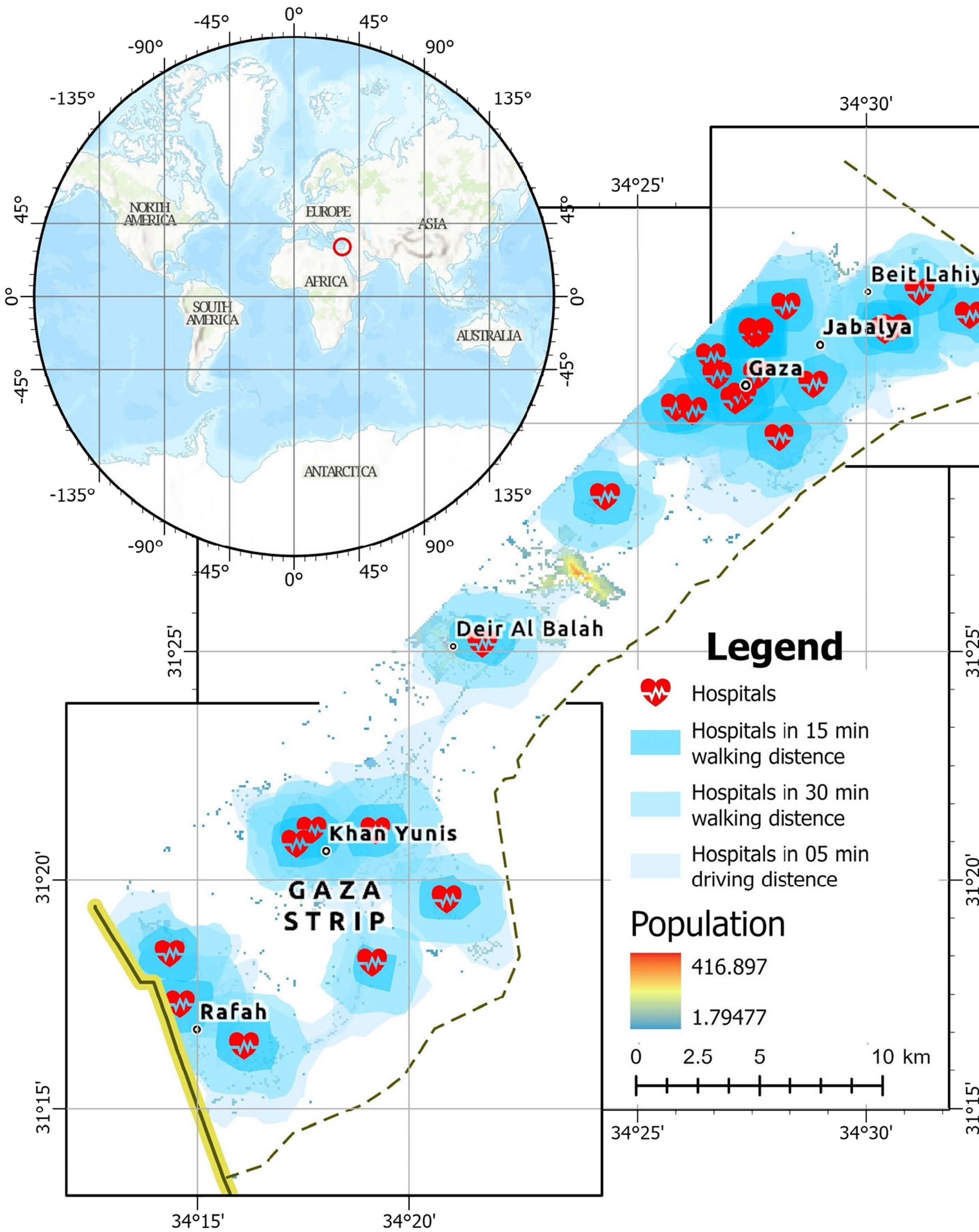

Figure 1. Study area (Gaza-Strip).

and justify the need for clear classification between formal and informal settlement types in the conflict-affected context.

2.2 Data

The process of dataset acquisition and preprocessing began with using Google Earth Engine (GEE), where HSR imageries from Landsat 7 and Landsat 8 satellites were obtained for five specific years: 2000, 2005, 2010, 2015, 2020 and calculate spectral indices. Population dataset was acquired from the World Population Hub for each targeted year.

2.2.1 Pan-sharpened HSR landsat composited unified dataset of bands and spectral indices

To ensure the accuracy of satellite imagery, a cloud masking technique was applied, which removes cloud cover and unwanted artifacts, thereby improving the quality of the data (Yin et al. 2020). Once cloud-free imagery was prepared, the band selection process was conducted, where spectral bands (B1 to B7) were selected based on their relevance to environmental analysis (Pande 2024). These bands, available in Landsat data, capture information across visible, and near-infra-red, providing crucial inputs for computing environmental indices (Sebbah et al. 2021), such as built-up area extraction index (BAEI), Index-based Built-up Index (IBI), Modified Built-up Area Index (MBAI), Normalised Difference Built-up Index (NDBI), Normalised Built-up Index (NBI) and the Normalised Difference Bare Area Index (NDBAI). After band selection, the pan-sharpening technique was applied in ArcGIS Pro 3.4 to selected bands to enhance the spatial resolution of the multispectral imagery from 30 metres to 15 metres. Pan-sharpening fuses the high-resolution panchromatic band with lower-resolution multispectral bands, resulting in a sharper and more detailed image (Feng et al. 2024; Wang et al. 2024; Wang et al. 2024).

Following pan sharpening, several spectral indices were calculated in GEE to derive meaningful insights about formal and informal settlements based on their unique spectral characteristics. Key indices included the BAEI (Ismaeel and Satish Kumar 2024), IBI (Xu 2008) and MBAI (Benkouider et al. 2019) for extract built-up areas, the NDBI (Ismaeel and Satish Kumar 2024) and NBI (Kaur and Pandey 2022) for urban area identification, and the NDBAI (Hamoodi and Mahdi 2021;Hongmei and Xiaoling 2005) for analysing barren lands (Sebbah et al. 2021). These indices provide a quantitative basis for studying environmental and urban changes over time. The selected bands and calculated spectral indices were then composited into a unified dataset for each target year, which simplified subsequent analysis and ensures consistency across time-series datasets to classify formal and informal settlements and other areas.

2.2.2 Healthcare facilities data

The data on health facilities in the Gaza-Strip was acquired from the Humanitarian Data Exchange (HDX) platform, a reputable and widely recognised source for humanitarian-related datasets. This dataset provides comprehensive information on the geographical distribution, operational status, and service capacities of health facilities within the Gaza-Strip.

2.2.3 Population data

The population count dataset (WorldPop 2020a) for the years 2000, 2005, 2010, 2015, 2020 and population dynamics of age and gender distribution (WorldPop 2020b) was acquired for the year 2020 from the World Population Hub, which provides high-resolution population estimates at a 100-metre spatial resolution.

3 Methods

3.1 Research framework

This research was conducted in four main stages, as illustrated in Figure 2. The 1st stage involved data acquisition and preprocessing, 2nd stage involved deep learning based formal and informal settlements segmentation, 3rd stage involved spatiotemporal change analysis & future prediction of formal & informal settlements, 4th and final stage involved age and sex distribution, accessibility to healthcare facilities, and spatiotemporal demographic distribution in formal & informal settlements.

3.2 Future population prediction

GEE was utilised to predict the future population for the years 2030 and 2040 using a linear regression approach, integrating WorldPop data. This methodology involved acquiring historical population datasets from WorldPop.org, which provides high-resolution gridded population estimates. A linear regression

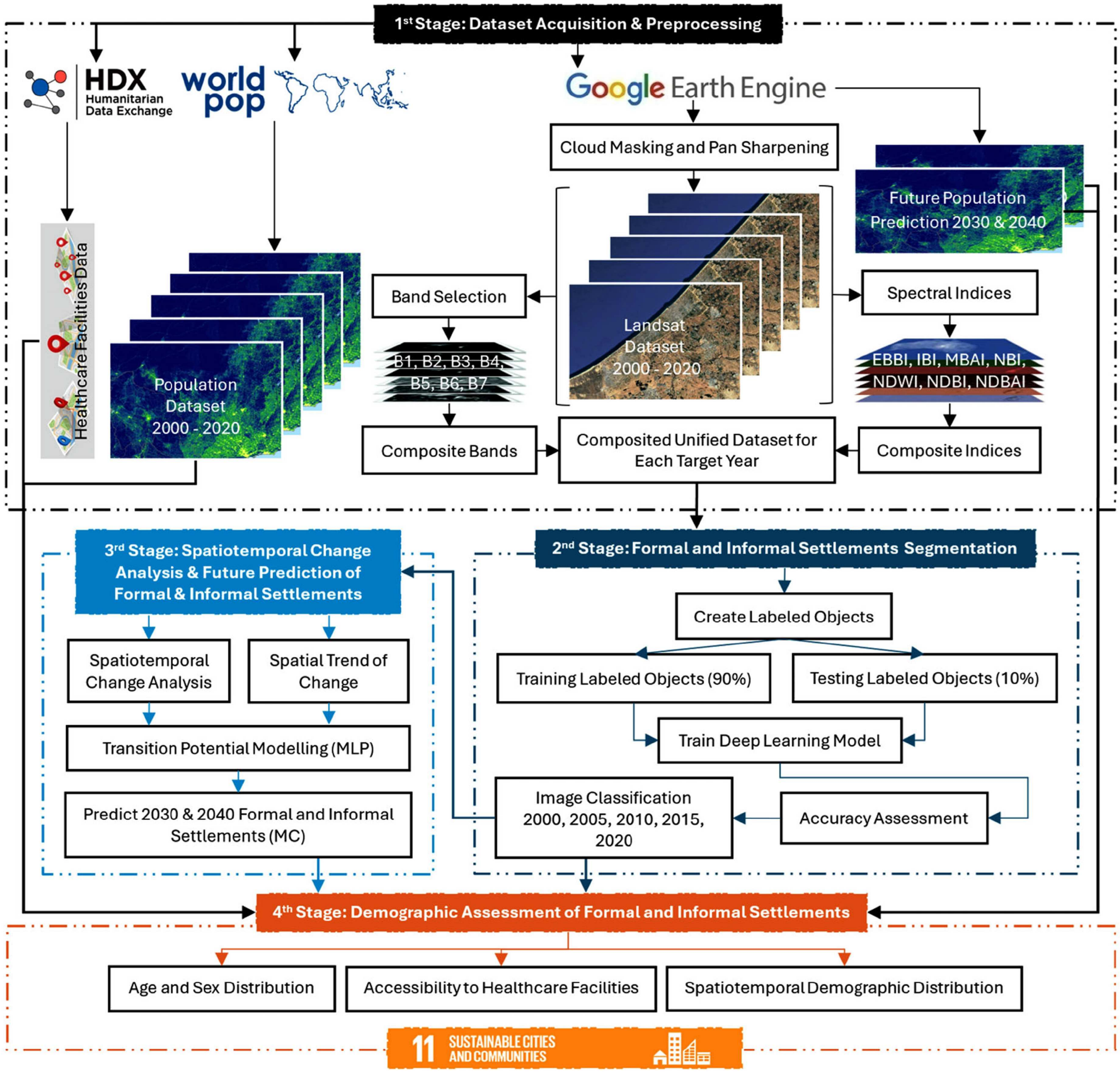

Figure 2. Research framework for large scale spatiotemporal change and demographic trends assessment of formal and informal settlements and SDG–11.1.1 evaluation.

model was then employed to establish a temporal relationship between population data points over the available years. The model's parameters were derived based on observed trends, enabling the extrapolation of future population estimates. Through this approach, spatially explicit population projections were generated for 2030 and 2040, allowing for an assessment of expected population growth patterns.

3.3 Deep learning based formal and informal settlements segmentation

The proposed methodology for segmentation of formal and informal settlements in ArcGIS Pro 3.4 using deep learning methods follows a structured approach, starting from labelled object creation to model training, performance evaluation, and image segmentation.

3.3.1 Labelled object creation

The initial step involved generating labelled objects from the pan-sharpened HSR Landsat composited unified dataset of bands and spectral indices in TIFF format into three distinct classes, formal settlements,

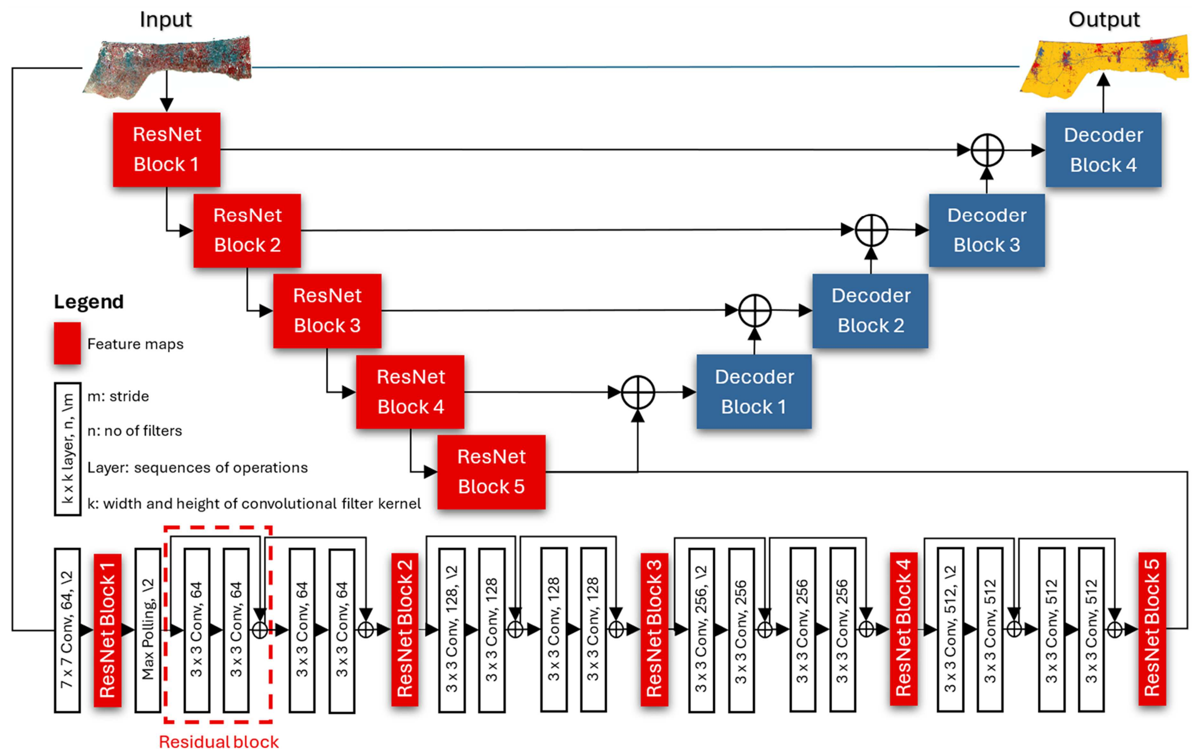

Figure 3. Architecture of U-Net model with ResNet–18 Encoder Backbone.

informal settlements and other areas. Labelled objects were created by digitising each target class using the Training Sample Manager, where each sample is organised, validated and assigned to a predefined class. Deep learning models require input images with consistent dimensions, so using Export Training Data for Deep Learning Tool, the imagery was divided into tiles of size 64×64 pixels to balance computational efficiency and the preservation of essential spatial features (Sawant and Ghosh 2024). A stride of 32×32 pixels was used to introduce overlapping between tiles, enhancing the model's ability to capture edge features and reduce boundary artifacts during training (An et al. 2020). The tiles were indexed according to a map space reference system to preserve their spatial geolocation, and metadata was stored in a classified tile format to ensure consistency and traceability of labelled data (ArcGIS Pro 2024). The labelled data was divided into 90% for training and 10% for testing, following standard practices in deep learning to ensure a robust evaluation of model performance (Tobler 2021). By allocating a larger portion for training, the model was exposed to diverse examples, while a smaller portion was reserved for testing to evaluate generalisation. Export Training Data for Deep Learning Tool converts the imagery into model-ready image chips and corresponding annotation files for deep learning workflows

3.3.2 Model training

The core of the methodology involves training deep learning model for pixel-level classification. The U-Net model was employed, which is widely recognised for its efficiency in semantic segmentation tasks, especially when working with biomedical and geospatial imagery (Ronneberger et al. 2015; Sawant and Ghosh 2024). U-Net's encoder-decoder structure, with skip connections, allows it to capture both high-level contextual information and fine-grained details, which is critical for accurately distinguishing between formal and informal settlements. To enhance feature extraction, ResNet–18 was used as the encoder backbone of the U-Net model (Holail 2024; Sawant and Ghosh 2024). ResNet employs skip connections to mitigate the vanishing gradient problem and allows the training of deeper models, thereby improving feature learning without introducing excessive computational complexity (Borawar and Kaur 2023). ResNet–18, a lightweight variant with 18 layers, strikes an optimal balance between computational efficiency and classification accuracy, making it a popular choice in segmentation tasks for remote sensing imagery (Cao et al. 2024; Hao et al. 2024). Figure 3 depicts the architecture of U-Net model with ResNet−18 encoder backbone. The model was trained using 30 epochs to ensure adequate learning without overfitting (Holail 2024). The batch size was set to 8, balancing computational resource usage and convergence stability during training.

3.3.3 Performance evaluation of the model

The performance of the trained model was evaluated using standard metrics, including Overall accuracy (OA), Precision (PR), Recall (RE), and F1-score (F1) (Sawant and Ghosh 2024; Sokolova and Lapalme 2009). Together, these metrics provide a comprehensive evaluation of model performance as expressed in (Equation (1) to Equation (4)).

$$Overall\ Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \tag{1}$$

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

$$F1Score = \frac{2 \times TP}{(2 \times TP) + FP + FN} \tag{4}$$

3.3.4 Image segmentation (pixel classification)

Following the successful training phase, the deep learning model was finally applied to classify Landsat imageries into formal settlements, informal settlements and other areas for the years 2000, 2005, 2010, 2015, and 2020.

3.4 Spatiotemporal change analysis of formal and informal settlements

Spatiotemporal change analysis of formal and informal settlements was conducted for the years 2000, 2005, 2010, 2015, and 2020 using deep learning based segmented imagery for each corresponding year. This analysis aimed to examine the dynamics of LU transitions over time, with a particular focus on formal and informal settlements. The LCM module within the Terrset 2020 software was employed to facilitate this spatiotemporal change analysis (Qacami et al. 2023). The spatiotemporal change analysis was performed by assessing the classified LU maps between two time periods, where the first period represents the initial time point (i.e. 2000) and the second period represents a subsequent time point (i.e. 2005) and so on. The LU maps generated for each time period served as the foundational data for identifying and quantifying transitions between different LU categories (Lambin 2001). This analysis primarily focuses on transitions from one class to another class, detecting gains and losses, net changes, and spatial trend of changes in formal and informal settlements.

3.5 Future prediction of formal and informal settlements

3.5.1 Transition potential modelling

Following the spatiotemporal change analysis, in this study, during transition potential modelling, suitable sub-models were initially identified. The sub-models included six specific sub-models, including transitions from informal settlements to formal settlements, informal settlements to other areas, formal

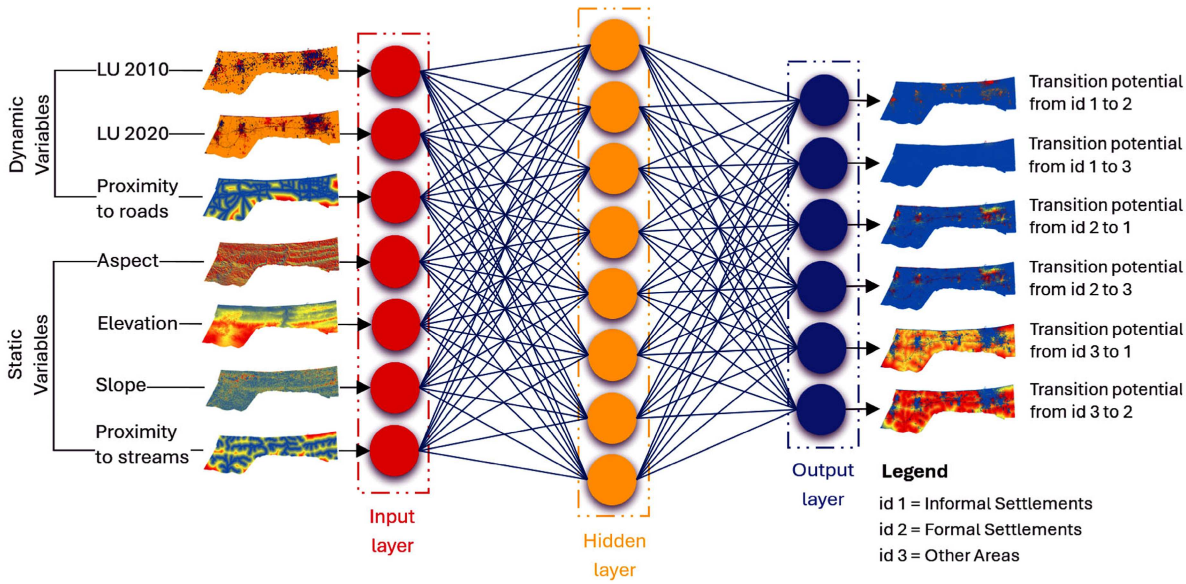

Figure 4. Architecture of multi-layer perceptron (dynamic variables) changed over the time, (static variables) don't changed over the time.

settlements to informal settlements, formal settlements to other areas, other areas to informal settlements and other areas to formal settlements. Following the selection of appropriate sub-models, both static variables (slope, aspect, elevation, proximity to streams) and dynamic (LU 2010, LU 2020, proximity to roads) variables with significant influence on LU changes were incorporated into the model, as depicted in Figure 4 (Aghajani et al. 2024). This modelling process involves evaluating each pixel of the image to determine its likelihood of transitioning from one LU type to another (Salarin et al. 2022). The LCM incorporates a diverse array of different approaches to facilitate transition potential modelling, including MLP, DF, LR, WNL, SVM, and Sim Weight. The MLP was utilised in this study owing to its exceptional performance in comparison to alternative approaches (Abbas 2023; Aghajani et al. 2024; Karul and Soyupak 2003; Saha et al. 2022).

3.5.2 Future change prediction

After completing the transition potential modelling, the final stage focused on predicting future LU changes. In this stage, the outputs from the transition potential modelling served as inputs of future change prediction stage (Aghajani et al. 2024). Using the MC Model, transition probabilities between different LU categories were computed, enabling the projection of future LU changes.

3.5.3 Accuracy evaluation of the model

Validation plays a critical role in the predictive modelling process (Lopez et al. 2023). To evaluate the accuracy of the model, first predicted LU image for 2020 to compare it with the actual segmented LU image of 2020. After that an accuracy assessment was performed in ArcGIS Pro 3.4 using confusion matrix (Aghajani et al. 2024), including user accuracy (UA), producer accuracy (PA) and overall accuracy (OA). As expressed in (Equation 5 to Equation 7).

$$User\ Accuracy = \frac{correctly\ classified\ pixels\ in\ each\ class}{Total\ classified\ pixels\ in\ that\ class} \times 100\% \tag{5}$$

$$Producer\ Accuracy = \frac{correctly\ classified\ pixels\ in\ each\ class}{Total\ reference\ pixels\ in\ that\ class} \times 100\% \tag{6}$$

$$Overall\ Accuracy = \frac{Total\ correctly\ classified\ pixels}{Total\ number\ of\ reference\ pixels} \times 100\% \quad (7)$$

3.6 Demographic analysis of formal and informal settlements with population

To acquire a more comprehensive understanding of formal and informal settlements for the evaluation of SDG−11, it is imperative to establish correlations between the derived thematic layer of formal and informal settlements and demographic datasets of population counts and age and sex distribution. The high spatial resolution derived formal and informal settlements layer facilitate its efficient integration with demographic datasets through zonal statistics method, thereby enhancing analytical precision and supporting robust SDG−11.1.1 assessment, which aims to ensure access to adequate, safe, and affordable housing for all.

In this study, the thematic maps of formal and informal settlements were integrated with the WorldPop population datasets (Tatem 2017) to enhance spatial analysis. The derived formal and informal settlement maps were generated at a spatial resolution of 15 metres, whereas the WorldPop datasets had a coarser resolution of 100 metres. To effectively align these datasets, the dataset representing formal and informal settlements was spatially resampled to 100 metres to enhance analytical consistency.

Finally, the zonal statistics tool was employed to derive the age and sex distribution of populations residing within formal and informal settlements in 2020, as well as population living within a 2 km buffer surrounding healthcare facilities. Additionally, ORS was employed to calculate accessibility zones based on both walking and driving times. Specifically, within 15-minute and 30-minute walking distances, as well as 5-minute and 10-minute driving distances from these facilities based on Gaza-Strip total area and according to the WHO accessibility to health services modelling (WHO 2024). The total population within each accessibility zone was then calculated to assess spatial disparities in access to essential services. Afterward, the spatiotemporal demographic distribution in formal and informal settlements from 2000–2040 was then derived.

4 Results

4.1 Spatiotemporal changes of formal and informal settlements between 2000 to 2020

4.1.1 LU transitions in between 2000 to 2020

Following the model's performance evaluation, which achieved an overall accuracy of 0.8980 (Text S1), the deep learning based segmented imageries presented in Figure 5 and details in Table S2 effectively illustrates the spatiotemporal and geographical transitions of LU in the Gaza-Strip between 2000 and 2020. The primary transitions include formal settlements transforming into informal settlements, other areas converting into informal settlements, and informal settlements being upgraded into formal settlements.

During 2000–2005, 9.41 km^2 of formal settlements transitioned into informal settlements, with similar patterns continuing in subsequent periods (9.52 km^2 in 2005–2010, 12.42 km^2 in 2010–2015, and 9.31 km^2 in 2015–2020). Likewise, the conversion of other areas into informal settlements increased in 2005–2010 (4.67 km^2) but showed a slight decline in the later periods.

On the positive side, informal settlements were upgraded into formal settlements, with the highest conversion observed in 2015–2020 (9.66 km^2). However, significant portions of formal settlements transitioned into other areas, with a peak in 2010–2015 (25.18 km^2), suggesting major land restructuring during this period.

The total area transformed peaked at 61.12 km^2 in 2010–2015, while the lowest transformation (40.01 km^2) occurred in 2015–2020, possibly indicating reduced urban expansion or LU changes due to external factors such as conflicts or policy interventions.

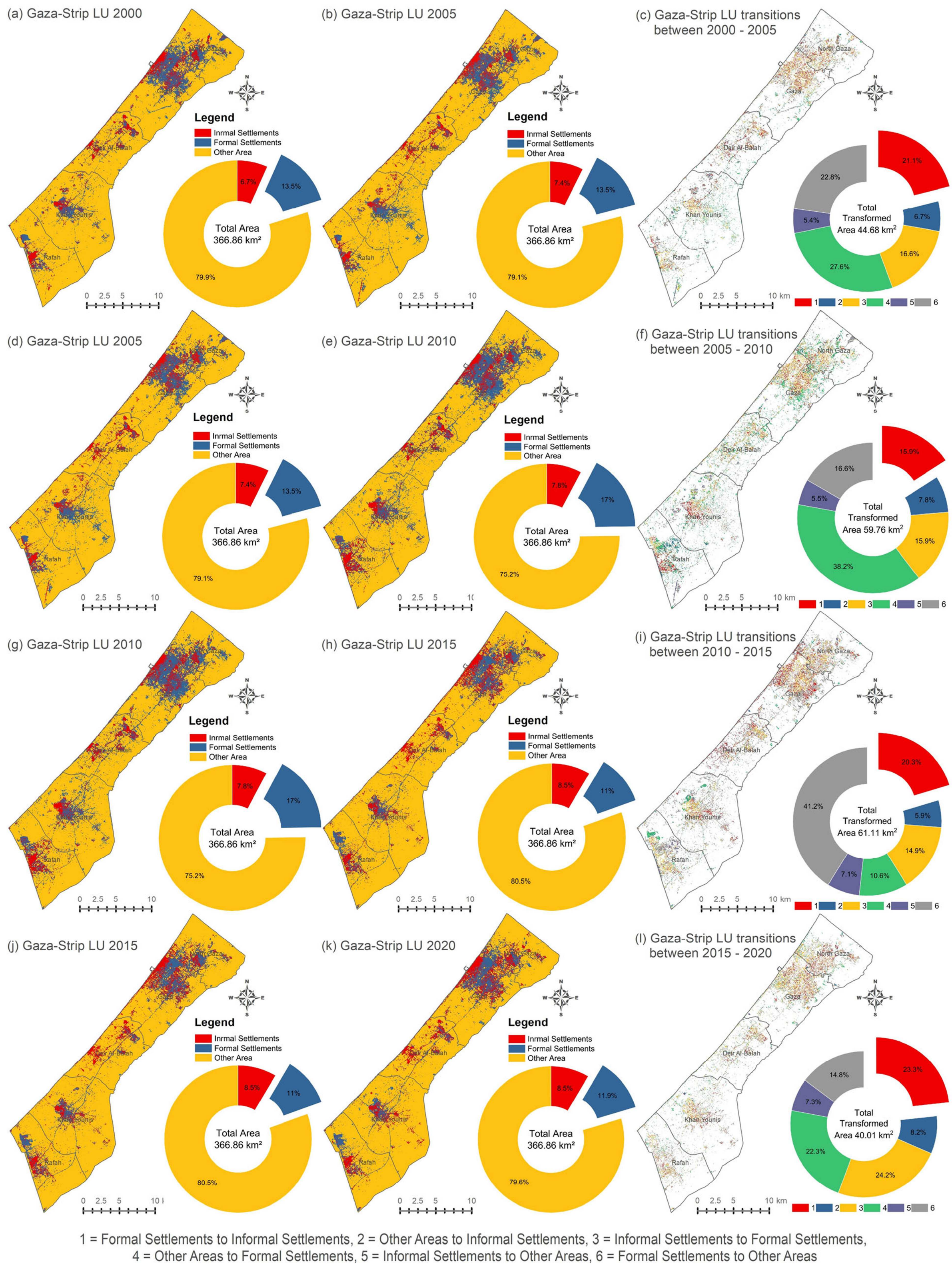

Figure 5. U-Net with Resnet−18 backbone based segmented imageries highlighting LU transitions (measured in percentage) between 2000 to 2020 in Gaza-Strip.

4.1.2 Gains, losses and Net changes in formal and informal settlements between 2000 to 2020

The gains, losses, and net changes in formal and informal settlements in the Gaza-Strip from 2000 to 2020, segmented into four distinct periods 2000–2005, 2005–2010, 2010–2015, and 2015–2020. The imageries presented in Figure 6 and details in Table S3 highlights fluctuations in LU transitions, reflecting the impact of urban growth, conflict, and LU policies on housing and settlement structures.

In formal settlements, land area gains were highest in 2005–2010 (32.35 km²) due to Israel's disengagement from Gaza-Strip in 2005 (Britannica, 2005), followed by 2000–2005 (19.73 km²) and 2015–2020 (18.59 km²). However, 2010–2015 saw the lowest gain (15.57 km²) and the highest loss (37.60 km²), leading to a significant negative net change (-22.03 km²). In contrast, 2005–2010 experienced the largest net positive change (12.88 km²), indicating an expansion in formal housing. The 2015–2020 period saw a modest recovery (3.37 km² net gain) following the previous drastic losses.

For informal settlements, the total gains ranged from 12.39 km² to 16.04 km², with the highest increase recorded in 2010–2015 (16.04 km²). Similarly, losses varied, with the highest loss occurring in 2010–2015 (13.43 km²). The net changes were positive throughout all four periods, indicating continued growth of informal settlements. However, the net gain significantly declined in 2015–2020 (0.03 km²), suggesting a stabilisation or potential saturation in informal settlement expansion.

Overall, the data reflects an unstable housing environment where formal settlements experienced severe fluctuations, whereas informal settlements grew consistently but slowed in recent years.

4.1.3 Spatial trend of changes in formal and informal settlements between 2000 to 2020

The spatial trend maps (Figure 7) illustrate the spatiotemporal and geographical shifts in formal and informal settlements across the Gaza-Strip from 2000 to 2020. The colour gradient from blue (low change) to red (high change) represents the intensity of LU transitions, indicating areas experiencing significant expansion in settlement growth.

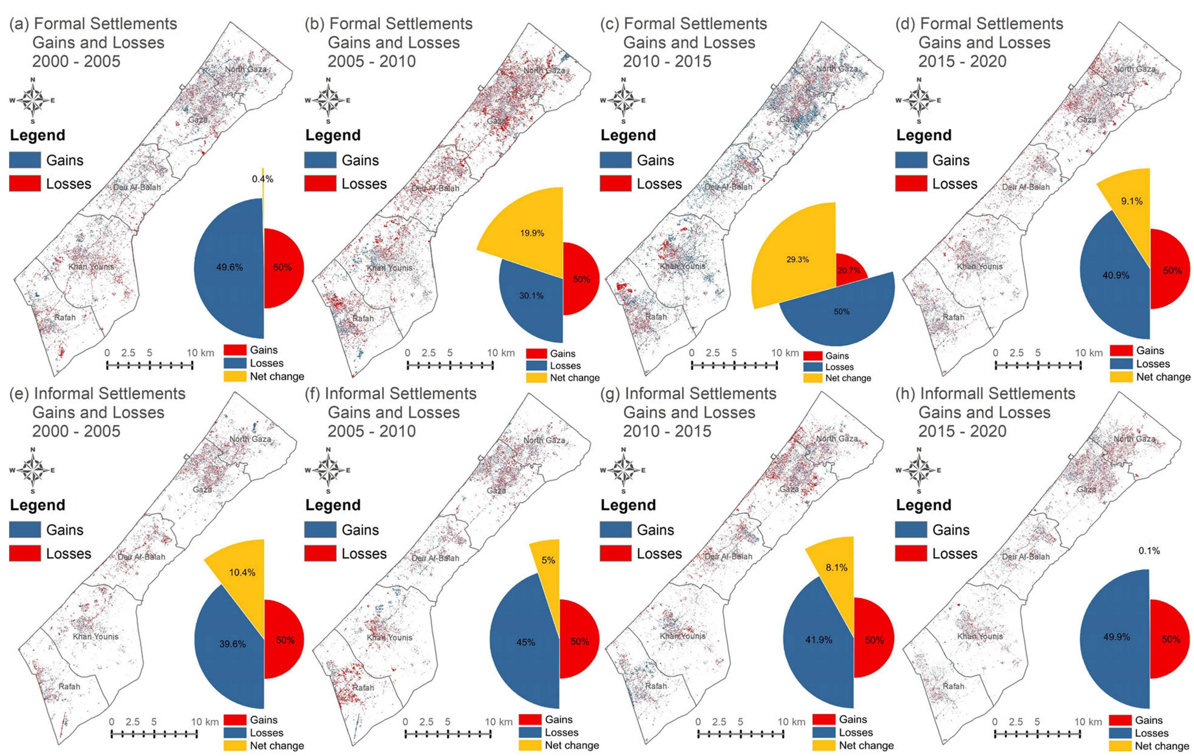

Figure 6. Gains, Losses and Net changes in formal and informal settlements (measured in percentage) between 2000 to 2020 in Gaza-Strip.

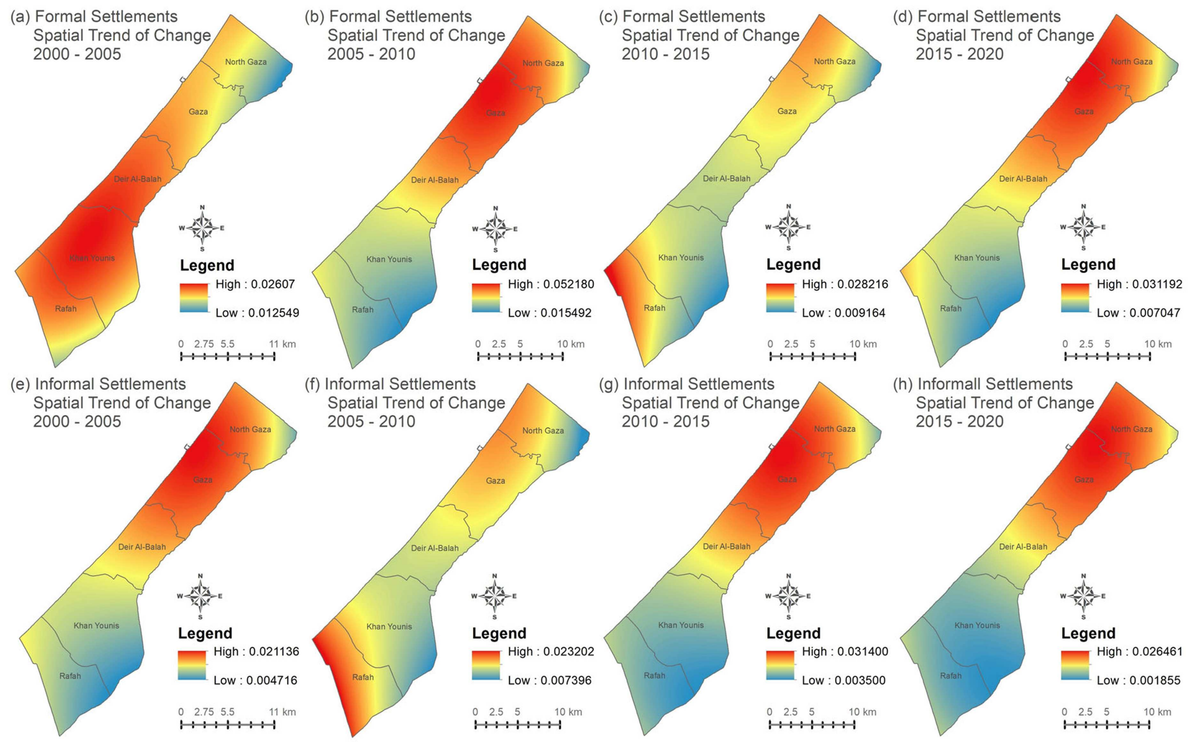

Figure 7. Spatial trend of changes in formal and informal settlements between 2000 to 2020 in Gaza-Strip.

In formal settlements, the trend maps (Figure 7a–d) reveal a consistent northward shift, with high-change areas primarily concentrated in Gaza City and North Gaza, while Khan Younis and Rafah in the south exhibit lower change intensity. The 2005–2010 period (Figure 7b) shows the most substantial spatial expansion, particularly in Gaza City and North Gaza, aligning with the highest gains recorded during this period. However, in 2010–2015 (Figure 7c), a significant contraction is evident, as losses in formal settlements outweigh gains. The 2015–2020 period (Figure 7d) suggests a slight recovery in formal settlements, though the expansion remains concentrated in the northern regions.

In informal settlements, the maps (Figures 7e–h) indicate a predominantly northward trend, with higher growth rates in Gaza City and North Gaza across all timeframes. However, unlike formal settlements, informal settlements exhibit a steadier expansion pattern. The period 2010–2015 (Figure 7g) represents the most substantial informal settlement growth, aligning with the period of greatest formal settlement losses. The 2015–2020 period (Figure 7h) shows reduced informal settlement expansion, with low-intensity growth in Khan Younis and Rafah, indicating a possible saturation of informal housing areas or regulatory interventions restricting further spread.

4.2 Future predicting of formal and informal settlements for 2030 and 2040

Following the model's accuracy evaluation, which achieved an overall accuracy of 0.9555 (Text S2), The actual and predicted imageries presented in Figure 8 and details in Table S5 effectively illustrates the expected LU changes in the Gaza-Strip from 2020 to 2040, focusing on formal settlements, informal settlements, and other areas. The projections indicate a gradual increase in both formal and informal settlements, with a corresponding decrease in other areas.

Between 2020 and 2030, formal settlements are expected to expand from 43.74 km^2 (11.9%) to 47.13 km^2 (12.8%), indicating a net increase of 3.40 km^2 (0.9%). Similarly, informal settlements are predicted to grow from 31.12 km^2 (8.5%) to 32.75 km^2 (8.9%), reflecting an increase of 1.63 km^2 (0.4%). Conversely, other areas are expected to shrink from 292.02 km^2 (79.6%) to 286.99 km^2 (78.2%), losing 5.03 km^2 (1.4%) of their extent.

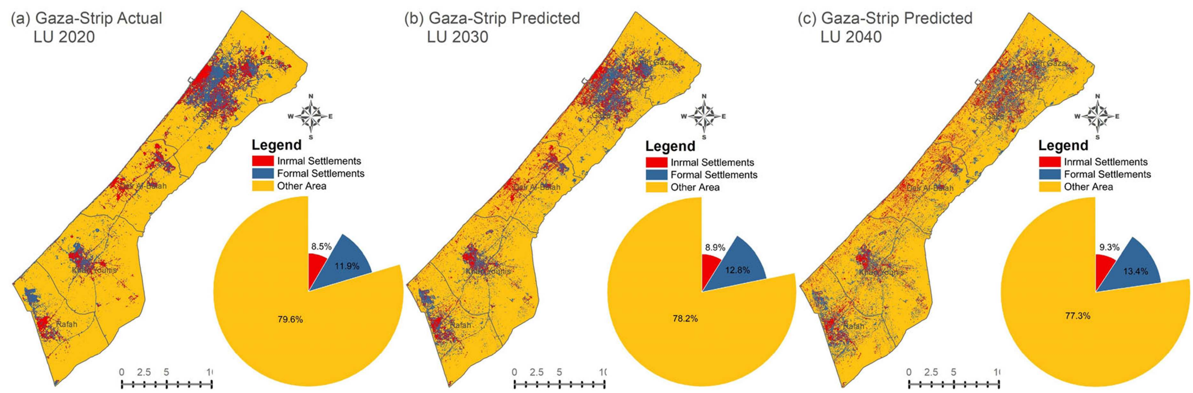

Figure 8. (a) Actual LU 2020, (b) Predicted LU 2030, and (c) Predicted LU 2040 of Gaza-Strip (measured in percentage).

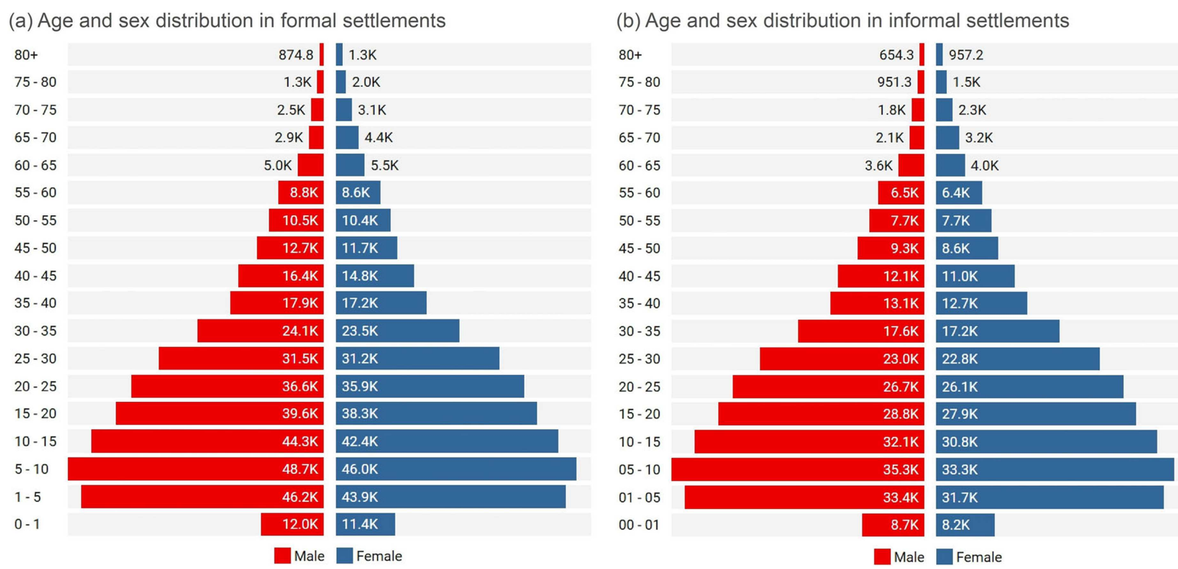

Figure 9. Age and sex distribution in formal and informal settlements in Gaza-Strip.

Between 2030 and 2040, the expansion of both formal and informal settlements continues, with formal settlements increasing to 49.08 km² (13.4%), marking a growth of 1.94 km² (0.6%), while informal settlements expand to 34.29 km² (9.3%), gaining 1.53 km² (0.4%). The reduction in other areas persists, declining further by 3.48 km² (0.9%), indicating a continued trend of urban expansion.

Overall, the findings suggest a consistent increase in urban land cover, particularly within formal settlements, accompanied by a gradual but persistent growth in informal settlements, which presents challenges to sustainable urban development. On the other hand, the Gaza-Strip has experienced repeated large-scale conflicts, population displacement, infrastructure destruction, and rapid restructuring of residential areas till date. The proposed framework effectively captured and predict long term spatio-temporal trends in formal and informal settlement dynamics, it does not explicitly account for sudden conflict induced destruction that drastically reshape urban morphology of Gaza-Strip.

4.3 Demographic trends assessment in formal and informal settlements

4.3.1 Demographic age and gender distribution in formal and informal settlements in 2020

The graphs presented in Figure 9 and details in Table S6 illustrates the demographic age and sex distribution in the Gaza-Strip in 2020, categorised into formal and informal settlements, which presents a distinct demographic profile that reflects urban settlement dynamics and socio-economic conditions. The population pyramid for both settlement types is broad-based, indicating a youth-dominated demographic structure.

In formal settlements (Figure 9a), the highest population proportions are observed within the 0–5, 5–10, and 10–15 age groups, with a slight male predominance (48.7 K males vs. 46.0 K females in the 5–10 age bracket). The youth bulge remains evident through the 15–25 age groups, indicating a high birth rate and sustained youthful population growth (UN-Habitat 2024). In contrast, the elderly population (65+) remains minimal, with a gradual decline in numbers across older age brackets. The sex ratio remains balanced throughout most age categories, with minor male predominance in younger cohorts.

Conversely, in informal settlements (Figure 9b), the youth-dominated structure is even more pronounced, with the 0–5 and 5–10 age groups displaying the highest population shares (35.3 K males vs. 33.3 K females in the 5–10 bracket). This trend highlights higher birth rates and family sizes within informal settlements compared to formal areas (UN-Habitat 2024). However, a more noticeable decline in older age groups (65+) is observed, likely due to harsher living conditions, limited healthcare access, and socioeconomic vulnerabilities (Sabah 2025).

The comparative analysis between the two settlement types suggests that informal settlements maintain a younger population structure, whereas formal settlements demonstrate a slightly more balanced age distribution.

4.3.2 Demographic distribution in formal and informal settlements and varying patterns of accessibility to healthcare facilities in 2020

The demographic distribution across formal and informal settlements in the Gaza-Strip in 2020 reveals significant disparities in population accessibility to healthcare facilities as depicted in Figure 10 and detailed in Table S7. The data categorises populations within varying distances from hospitals, including 2km buffer (Figure 10a), walking distances within 15 min and 30 min (Figure 10b), and driving distances within 5 min and 10 min (Figure 10c).

In formal settlements, the populations within a 2 km buffer around hospitals are generally higher than in informal settlements, reflecting a more structured urban layout that facilitates healthcare accessibility. For instance, Al Nasser Paediatric Hospital serves 158,253 people within 2 km, compared to 75,531 people in informal settlements. Similarly, Al Shifa Hospital, the largest medical facility in Gaza, covers 152,018 residents in formal settlements within 2 km, whereas informal settlements have 95,997 within the same distance. These patterns suggest that formal settlements benefit from a denser hospital distribution, ensuring better accessibility for residents.

Conversely, in informal settlements, hospitals serve a higher population within larger distance buffers, indicating limited accessibility in closer proximity. For example, Al Durra Hospital serves 295,123 people in informal settlements within a 30-minute walking distance, whereas formal settlements have only 132,193 within the same range. This suggests that informal settlement residents travel longer distances to access healthcare, exacerbating vulnerability to health risks.

Additionally, hospitals located in central urban areas, such as Al Shifa Hospital and European Hospital, show significantly higher populations within short walking distances, reinforcing the spatial imbalance between settlement types. Rural and peripheral hospitals, such as Al Wafa Hospital and Algerian Hospital, serve a comparatively smaller number of individuals, further highlighting the geographical disparities in healthcare coverage.

4.3.3 Spatiotemporal demographic distribution in formal and informal settlements in 2000–2040

The spatiotemporal demographic distribution in formal and informal settlements in the Gaza-Strip from 2000 to 2040 reveals significant shifts in population density, Figure 11 illustrating evolving urban trends over the time. The demographic classification is divided into low, moderate, and high population density levels, providing insight into settlement transformations over four decades.

In formal settlements, the proportion of low-density areas fluctuates between 30% and 40% from 2000 to 2020, but it rises to 50% by 2040, indicating a trend towards urban expansion and population

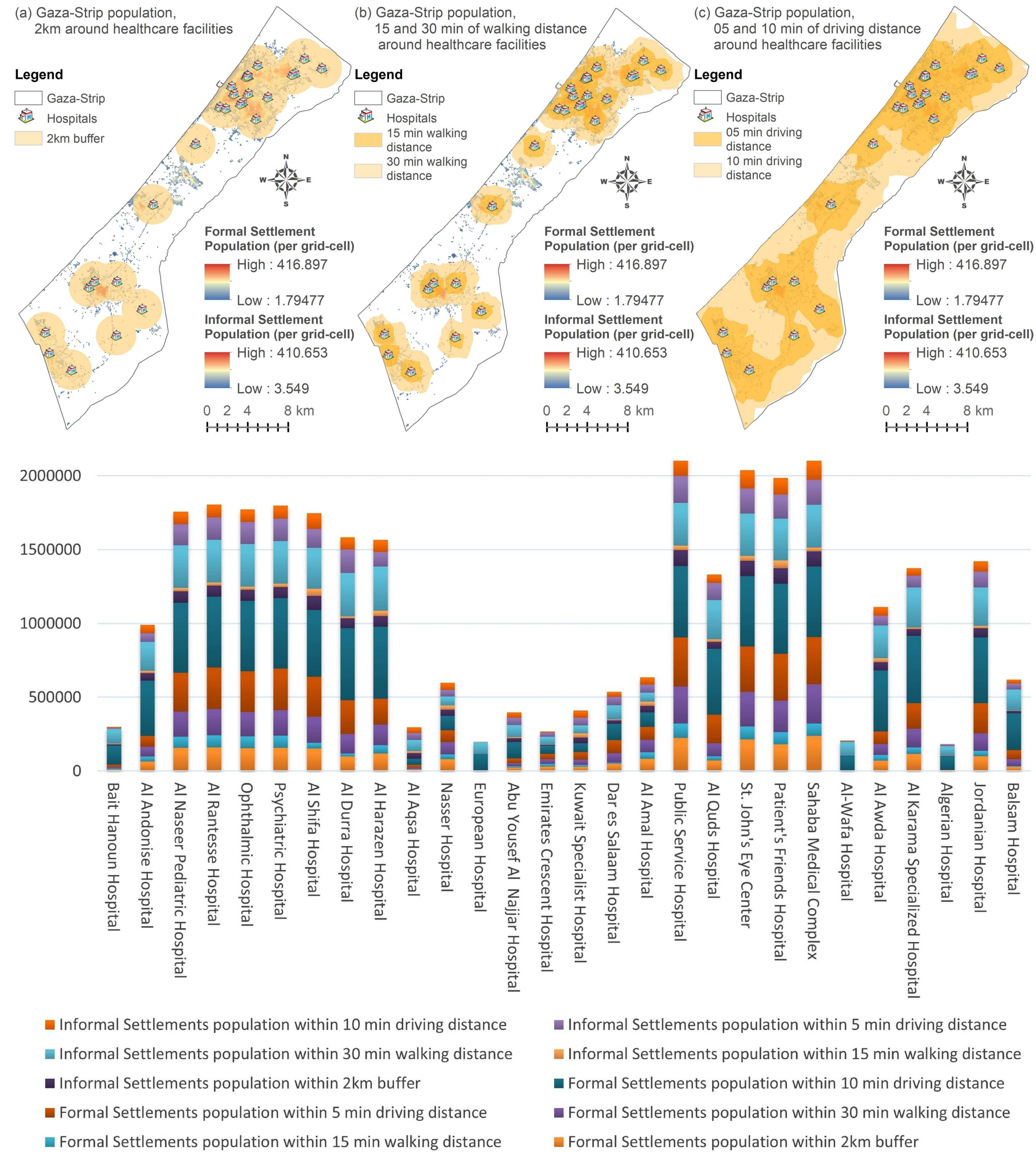

Figure 10. No of population in formal and informal settlements around health care facilities in different patterns in Gaza-Strip.

dispersion. Moderate-density areas initially decline from 37% (2000) to 30% (2020) before slightly increasing to 32% by 2040, suggesting a stable urban core with controlled growth. However, high-density regions show a continuous decrease, dropping from 23% in 2000 to just 18% in 2040, which implies reduced overcrowding due to improved urban planning and infrastructure development.

Conversely, informal settlements exhibit a more unstable pattern. The low-density proportion drops sharply from 40% (2000) to 24% (2020) before rising again to 50% in 2040, suggesting temporary densification followed by future decongestion. Meanwhile, moderate-density areas fluctuate but peak at 48% in 2025, before stabilising at 30% in 2040, indicating that some informal areas transition into more structured urban zones. However, high-density areas peak at 34% in 2010 and 2020 before declining

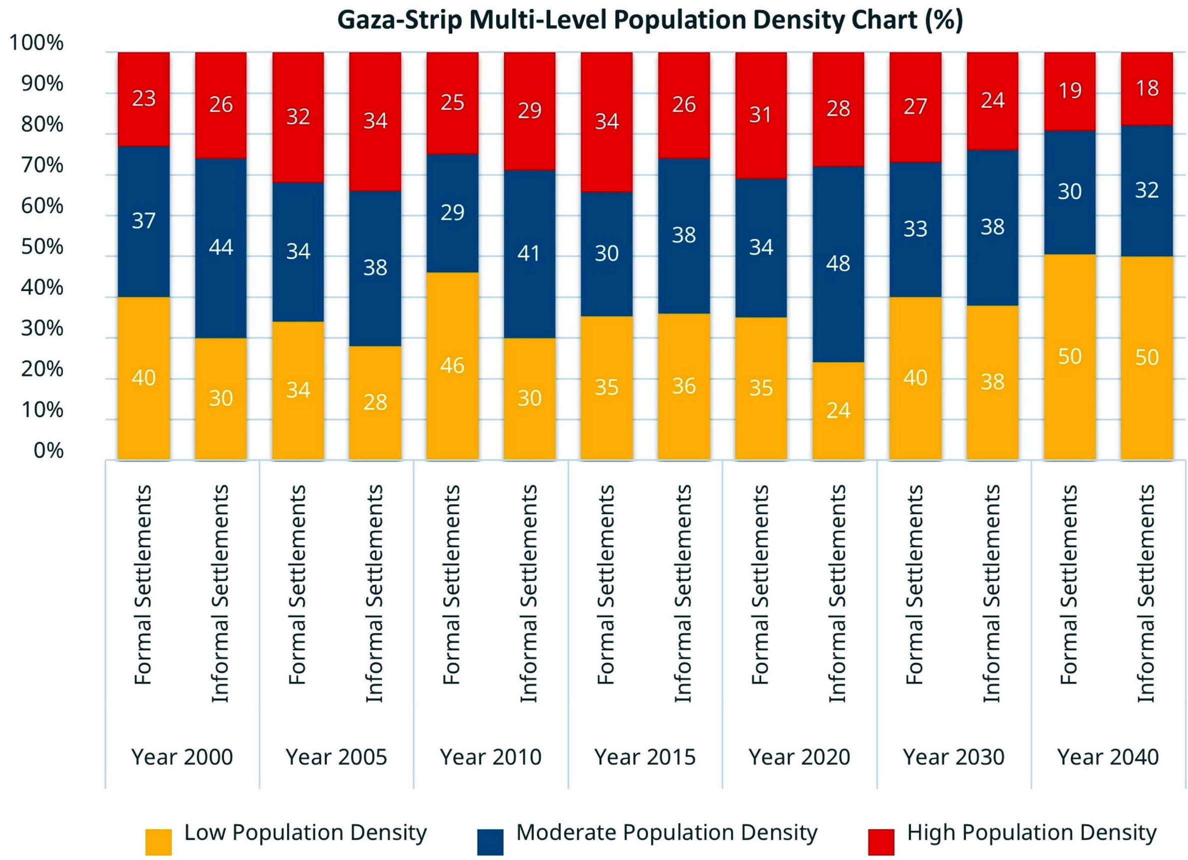

Figure 11. Multi-level population density chart (measured in percentage) of Gaza - Strip.

significantly to 19% in 2030 and 18% in 2040, reflecting efforts to reduce overcrowding and upgrade informal settlements.

The overall trend suggests that formal settlements experience a steady expansion of low-density areas, while informal settlements initially face worsening crowding before gradually improving post–2020. These patterns align with urban development policies and SDG–11.1.1, which emphasises reducing slum conditions and ensuring safe, sustainable living environments (UN-Habitat 2024).

5 Discussions

5.1 Effectiveness of the proposed framework

Mapping formal and informal settlements presents a considerable challenge due to their often-similar urban LU characteristics. Additionally, these settlement types are frequently spatially intermixed across diverse regions. Achieving broader, detailed and standard large scale spatiotemporal geographic and demographic delineation of formal and informal settlements requires the development of a robust, efficient, and generalisable methodology. Previous approaches have limitations regarding dataset availability and scope of the study. Those frameworks and methods that rely on VHSR imagery and focus on limited scope of study often achieve very higher accuracy, however their applicability at larger scales is constrained due to costly subscription requirements. Moreover, the limited scope of their study outputs restricts the broader and detailed of information they can provide. In this context and in support of monitoring progress toward the SDG–11.1.1, The proposed model U-Net architecture with a ResNet–18 backbone demonstrated superior performance in large scale spatiotemporal formal and informal settlements segmentation through the effective fusing of proposed pan-sharpened HSR Landsat composited unified dataset of bands and spectral indices, and achieved competitively high accuracy as illustrated in

Table 1. Comparison of state-of-the-art methods for geographic mapping of informal settlements in terms of experimental setups, accuracy, datasets used, and study scopes.

Study	Source	Input data	OA	Study scope
RF (Wurm et al. 2017)	close	SAR Imagery 6 m	88.58%	slum mapping (non-spatiotemporal study)
CNN (Verma et al. 2019)	close	VHSR Imagery 0.5 m	94.20%	slum mapping (non-spatiotemporal study)
FCN (Wurm et al. 2019)	close	VHSR Imagery 0.5 m	90.62%	slum mapping (non-spatiotemporal study)
Mask R-CNN (X. Wang et al. 2020)	close	VHSR Imagery 0.54 m	74.48%	urban village identification (non-spatiotemporal study)
CNN + LSTM (B. Chen 2022)	close	VHSR Imagery 2 m	92.61%	urban village classification (non-spatiotemporal study)
HR-RSF-UV (D. Chen 2022)	close	VHSR Imagery 2.5 m	96.23%	urban villages recognition (non-spatiotemporal study)
CNN + RF (Peng 2023)	close	VHSR Imagery 0.8 m	91.37%	densely populate informal settlements identification (non-spatiotemporal study)
Hierarchical Recognition Method (Tu et al. 2024)	close	VHSR Imagery 5 m	93.94%	large-scale geographic and demographic characterisation of informal settlements (non-spatiotemporal study)
Our Proposed model "U-Net architecture with a ResNet–18 backbone"	**open**	**HSR Imagery 15 m**	**89.80%**	**large-scale spatiotemporal changes and demographic trends assessment of formal and informal settlements (Spatiotemporal study)**

Table 1 & S1. The pan-sharpen and spectral indices approach produced sufficiently fine spatial detail for distinguishing formal and informal settlement textures at large scales, while the U-Net architecture with a ResNet–18 backbone provided robust, transferable segmentation performance without requiring the licensing costs associated with VHSR commercial imagery. The model has established a clear foundation for subsequent change analysis, future prediction, and corresponding demographic trends assessment.

While the comparison in Table 1 is not strictly equivalent owing to variations in experimental settings, it still effectively demonstrates the robustness of the proposed framework in the context of accuracy, dataset availability and study scope. In terms of data availability and study scope, the proposed framework effectively mitigates common limitations associated with data constraints, thereby enhancing its capacity to support large-scale, time-series assessments aligned with SDG–11.1.1. Recent studies on slum mapping highlighted that the application of deep learning to open-access satellite imagery represents one of the most scalable and cost-effective approaches for large-scale spatiotemporal mapping of informal settlements (Büttner et al. 2025; Li 2025). The framework is designed to leverage openly accessible datasets, ensuring both scalability and replicability across diverse geographic contexts. This flexibility and accessibility position the framework as a valuable tool for facilitating comprehensive SDG monitoring and evidence-based urban planning.

5.2 Spatiotemporal changes indicated a persistent rise in informal settlements

By integrating pan-sharpened HSR Landsat imagery with a U-Net architecture utilising a ResNet–18 backbone, the segmented results indicate a persistent rise in informal settlements over the last two decades from 2000–2020, as illustrated in Figure 5 and detailed in Table S2. The change analysis reveals the peak land transformation in 2010–2015, followed by a decline in 2015–2020, suggests fluctuating urbanisation patterns influenced by conflict, socio-political, and economic factors (Abukashif and Riza 2019). While formal settlements showed expansion in some periods, they suffered severe setbacks, particularly in 2010–2015, due to the extensive destruction of Gaza-Strip's built environment by Israel. Notably, approximately 800 buildings were destroyed in 2012 (Operation Pillar of Defence 2012), followed by the total destruction of about 12,620 housing units in 2014 (OCHA 2015), severely disrupting the continuity and growth of formal settlement structures. In contrast, informal settlements expanded steadily until 2015, reflecting an increased dependence on slum areas for housing. As illustrated in Figure 7 the spatial trend analysis of settlement transitions from 2000–2020 reveals a northward trend in both formal and informal settlement expansions, with Gaza City and North Gaza experiencing the most significant changes (Abukashif and Riza 2019). While formal settlements saw an initial expansion 2005–2010, a severe decline 2010–2015, and partial recovery 2015–2020, informal settlements demonstrated steady growth until 2015, followed by stabilisation. With high accuracy as illustrated in Table S4 the MLP-MC based projected urban LU changes from 2020–2040 reveals a continuous trend of urban expansion, with formal settlements increasing at a steady pace, while informal settlements also continue to grow at a slower rate as illustrated in Figure 8 and detailed in Table S5.

5.3 Demographic analysis uncovered different demographic spatial patterns and trends

By integrating segmented settlement layers with population and healthcare facilities data, the demographic analysis uncovered distinct spatial patterns and trends across formal and informal settlements. As shown in Figure 9 and details in Table S6, the age and sex distribution indicate a predominantly youthful population in both settlement types (NPR 2023; Ola 2024; Tu et al. 2024), with informal settlements in 2020 marked by higher birth rates and a smaller proportion of elderly residents. This concentration of youth in informal areas points to pressing needs in education, healthcare, housing, and employment, while age-related disparities highlight inequalities in living conditions, life expectancy, and access to essential services. Figure 10 and Table S7 further illustrates how demographic trends intersect with healthcare accessibility, revealing that formal settlements generally have better proximity to hospitals, whereas informal areas face significant barriers with worse proximity in reaching healthcare services. This urban structure limits healthcare access for informal residents, exacerbating social and health inequalities (Alkhaldi and Alrubaie 2025; Sabah 2025). Additionally, Figure 11 and Table S8 presents the spatio-temporal dynamics of demographic shifts from 2000 to 2040, revealing a complex interplay between urban expansion, population density, and settlement transformation. While formal settlements exhibit a steady increase in low-density residential development, informal settlements experience phases of rapid densification that gradually stabilise over time.

5.4 Limitations and future directions

Despite the promising and comprehensive outcomes, this study has limitations that present opportunities for future enhancement. The proposed framework relies primarily on remote sensing, population, and healthcare facilities data; however, it lacks the integration of granular spatiotemporal socioeconomic and infrastructure datasets, which are essential for a comprehensive and multidimensional evaluation of SDG−11.1.1 (Rasoulian et al. 2025). This limitation is particularly relevant for conflict-affected regions like the Gaza-Strip, where such detailed spatiotemporal datasets particularly on socioeconomic conditions and infrastructure networks are either scarce, fragmented, or not publicly available through standard global repositories due to political instability and restricted data access, which constrains the depth of urban analysis in conflict-affected regions. In future research, the framework can be further strengthened by incorporating detailed spatiotemporal socioeconomic indicators and infrastructure data. Such enhancements would provide a more holistic understanding of urban inequality and vulnerability, thereby enabling more effective policy planning and intervention strategies aligned with the broader goals of sustainable urban development.

6 Conclusion

This study demonstrates the effectiveness of a deep learning based approach specifically, the U-Net architecture with a ResNet−18 backbone in segmenting formal and informal settlements using a pan-sharpened HSR Landsat composited unified dataset of bands and spectral indices. It represents a novel attempt to analyse large scale spatiotemporal geographic changes and demographic trends assessment of formal and informal settlements fusing opensource multispectral and population and healthcare facilities data through a deep learning approach. In this study, a U-Net architecture with a ResNet−18 backbone was proposed to accurately distinguish between formal and informal settlements. The model utilised a novel fused dataset comprising pan-sharpened HSR Landsat composited unified dataset of bands and spectral indices. The approach was evaluated in the Gaza-Strip, demonstrating robust performance with a high-test accuracy of 0.8980, underscoring its effectiveness and potential for broader application in urban settlements mapping. By leveraging the actual mapped and predicted formal and informal settlements layers, and corresponding actual and predicted population data, the study successfully assessed spatial and temporal formal and informal settlements patterns alongside demographic dynamics, contributing valuable insights for monitoring progress toward SDG−11.

This study shows that informal settlements experience significantly poorer proximity to hospitals compared with formal settlements. Planners should prioritise decentralised healthcare units, mobile clinics, and improved transport links to reduce service inequities and strengthen community resilience. The projected growth and densification of informal settlements highlight the need for anticipatory urban management. Policymakers should adopt early warning spatial planning measures such as reserving land for affordable housing, strengthening tenure regularisation programmes, and improving basic service provision to manage informal growth before it becomes unplanned or unsafe. The proposed framework offers a scalable, accurate, and cost-effective solution and insights to support sustainable urban planning, policy making, and data driven decision making in complex urban environments.

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Author contributions

CRediT: **Hasnain Abbas:** Conceptualisation, Methodology, Software, Validation, Formal analysis, Investigation, Data Curation, Visualisation, Writing — Original Draft, Writing — Review & Editing; **Xiang Zhang:** Data Curation, Writing — Review & Editing; **Chenglong Yu:** Writing — Review & Editing; **Yao Yao:** Conceptualisation, Supervision, Resources, Funding acquisition, Writing — Review & Editing.

Disclosure statement

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability statement

Landsat dataset: open dataset at https://earthengine.google.com/, World Pop dataset: open dataset at https://hub.worldpop.org/, Healthcare dataset: open dataset at https://data.humdata.org/, Data acquisition and preprocessing code: open code at https://github.com/abbas7695.

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