MONITORING URBAN DYNAMICS AND THEIR IMPACT ON HANOI'S GREEN ECOSYSTEM USING INTEGRATED LANDSAT AND SENTINEL-1 OBSERVATIONS

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Abstract. Urban areas serve as hubs of socio-economic activities, with significant transformations in cities like Hanoi shaping Vietnam's urban development. This study examines Hanoi's urban dynamics from 2000 to 2023 using the Google Earth Engine (GEE) platform, integrating Landsat optical and Sentinel-1 radar imagery. The Normalized Difference Built-Up Index (NDBI) and radar VV backscatter thresholds were applied for urban land classification, achieving 93% accuracy and a Kappa coefficient of 0.80. Results reveal a dramatic urban expansion of 30,697.8 hectares between 2000 and 2023. This urban expansion has significantly impacted green ecosystem, leading to a net vegetation loss of 4,319 hectares over 23 years. The most affected districts include Nam Tu Liem (13.2% CAGR, -690 ha), Hoai Duc (9.46% CAGR, -649 ha), Ung Hoa (12.64% CAGR, -1,439 ha), and Ha Dong (9.03% CAGR, -588 ha). In contrast, Ba Vi (19.26% CAGR, +807 ha), Gia Lam (10.53% CAGR, +664 ha), and Son Tay (12.85% CAGR, +230 ha) recorded notable vegetation gains. This study highlights the trade-offs between urban expansion and environmental sustainability, demonstrating the effectiveness of integrating optical and radar data for urban monitoring while providing crucial insights into the spatial dynamics of vegetation change in rapidly developing cities.
Keywords: *Google Earth engine, remote sensing, urbanization, NDBI, Synthetic Aperture Radar*

Introduction

Urbanization is an inevitable trend accompanying industrialization and modernization, profoundly impacting socio-economic development and reshaping urban and rural landscapes. Over the past three decades, Vietnam has experienced rapid urbanization, transitioning from a predominantly rural society to one with a growing network of urban centers. As of December 2023, Vietnam had a total of 902 urban areas, classified into various categories based on their administrative and developmental characteristics. These included two special urban areas (Hanoi and Ho Chi Minh City), 22 first-class urban areas, 36 second-class urban areas, 45 third-class urban areas, 94 fourth-class urban areas, and 703 fifth-class urban areas. The national urbanization rate was recorded at approximately 42.7% (SPH, 2023a). Urbanization has brought numerous benefits, such as economic growth, improved infrastructure, and enhanced living standards, but it also poses challenges, including environmental degradation, loss of agricultural land, and increased pressure on urban ecosystems (Bousquet, 2015; Smith and Scarpaci, 2000; Tuan, 2022).

Hanoi, as Vietnam's capital city, exemplifies the dual opportunities and challenges posed by urbanization. As a political, administrative, and economic center, Hanoi has

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undergone significant urban expansion, particularly following the jurisdictional boundary expansion in 2008 (Vu et al., 2024). By 2023, the city's population reached 8.58 million, with urban residents accounting for 49.3% of the total population. The average population density stood at 2,454 people/km². Densely populated districts such as Dong Da had a population density of 37,688 people/km², nearly five times the city average (SPH, 2023b). Over 20 years, Hanoi has seen substantial urban expansion, with 30,697.8 hectares of new urban land added between 2000 and 2023 (Nguyen et al., 2020; Tuan, 2022). However, this rapid growth has introduced challenges such as traffic congestion, air and water pollution, and degradation of natural ecosystems, necessitating robust monitoring systems to ensure sustainable urban development (Fan et al., 2019).

Remote sensing offers extensive spatial and temporal coverage, enabling accurate and efficient monitoring of urban growth, land-use change, and environmental impacts. Compared to time-consuming and costly field surveys, it allows continuous observation of urban areas over time (Taubenböck et al., 2009; Haas, 2016; Luong et al., 2025). Spectral indices derived from optical imagery—such as the Normalized Difference Built-Up Index (NDBI) (Zha et al., 2003), Normalized Difference Vegetation Index (NDVI) (Rouse et al., 1973), and Impervious Surface Index (ISI))—have been widely applied to map urban areas and quantify impervious surfaces. More advanced indices like the Index-Based Built-Up Index (IBI) integrate multiple spectral bands to improve built-up area detection (Xu, 2008). However, optical imagery faces limitations in detecting built-up areas in regions with high vegetation cover or under conditions of cloud contamination. The integration of Synthetic Aperture Radar (SAR) and optical remote sensing data offers a powerful approach to overcoming limitations, particularly those related to cloud cover and spectral ambiguity in dense urban environments (Vaglio Laurin et al., 2013; Chini et al., 2018; Mahyoub et al., 2019; Nicolau et al., 2021; Verma et al., 2023). Moreover, Google Earth Engine (GEE), a cloud-based geospatial analysis platform (Gorelick et al., 2017), has proven effective in urban studies, particularly for monitoring urban expansion and assessing land-use change (Cao et al., 2020; Wahap and Shafri, 2020). Recent applications of GEE have further demonstrated its potential for near real-time monitoring and decision support in rapidly urbanizing regions (Carneiro et al., 2021; Hamud et al., 2021; Shang et al., 2021; Shao et al., 2023).

Despite the growing body of literature on urbanization, there remains a lack of long-term, high-resolution studies that simultaneously capture the spatial dynamics of urban growth and its ecological consequences. The primary objective of this study is to investigate the spatiotemporal patterns of urban expansion in Hanoi from 2000 to 2023 and assess its impact on green ecosystems, using an integrated approach that combines SAR and optical remote sensing data. The novelty of this research lies in the synergistic fusion of multi-sensor datasets within the GEE platform, enabling efficient, high-resolution analysis of urban dynamics and ecological change over more than two decades.

Accordingly, the study addresses the following research questions: (1) What are the spatial and temporal patterns of urban expansion in Hanoi between 2000 and 2023 as detected through SAR and optical remote sensing data? (2) How has urban growth during this period affected the extent and distribution of green ecosystems within the city and its surroundings? (3) To what extent can the integration of SAR and optical data within the GEE platform enhance the monitoring and analysis of urban dynamics in rapidly developing urban areas?

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Materials and methods

The study area

Hanoi, the capital of Vietnam, is located in the northwestern part of the Red River Delta, between 20°34' to 21°18' North latitude and 105°17' to 106°02' East longitude. It is centrally situated in the fertile Red River Delta region, sharing borders with eight provinces: Thai Nguyen and Vinh Phuc to the north; Ha Nam and Hoa Binh to the south; Bac Giang, Bac Ninh, and Hung Yen to the east; and Hoa Binh and Phu Tho to the west (*Fig. 1*). Hanoi lies approximately 120 km from the port city of Hai Phong and 87 km from Nam Dinh, forming a strategic triangle of major urban centers in the Red River Delta. Covering a total area of 3,358.6 km², Hanoi constitutes approximately 1% of Vietnam's total natural land area, ranking 41st in size among the 63 provinces and cities in the country. Notably, it is one of 17 capital cities worldwide with an area exceeding 3,000 km².

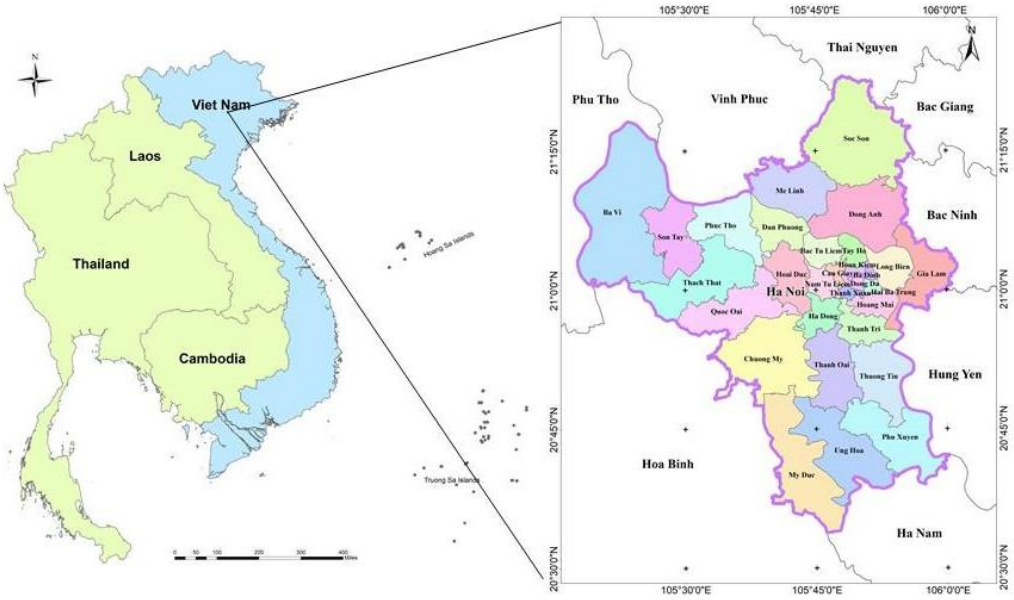

Figure 1. *The study area*

Hanoi is one of Vietnam's five centrally governed cities, alongside Ho Chi Minh City, Hai Phong, Đa Nang, and Can Tho. Among these, Hanoi and Ho Chi Minh City are classified as special-level administrative units and first-tier urban areas. As of 2023, Hanoi has a population of approximately 8.5 million people, with an average population density of 2,398 people/ha. The city's administrative framework consists of 30 districts, including 12 urban districts, 17 rural districts, and one township, further divided into 579 communes, wards, and towns (SPH, 2023b). These include 383 communes, 175 wards, and 21 towns, making Hanoi the only centrally governed city in Vietnam to include a township as part of its administrative divisions.

Over the years, significant changes in Hanoi's administrative boundaries have shaped its development trajectory. These changes have resulted in a mix of densely populated urban areas and sparsely populated rural regions, reflecting the city's rapid urbanization process.

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Materials

This study utilized a combination of optical and radar satellite imagery (*Table 1*), supplemented by statistical data, to analyze urban land changes in Hanoi from 2000 to 2023.

Table 1. *Satellite imagery used in the study*

No.	Satellite	Year	Data Type	Spatial Resolution (m)	Temporal Resolution (Days)	Number of Images Used
1	Landsat-5 TM	2000	Multispectral	30	16	53
2	Landsat-5 TM	2005	Multispectral	30	16	61
3	Landsat5TM	2010	Multispectral	30	16	47
4	Landsat-8 OLI/TIRS	2015	Multispectral	30	16	70
5	Landsat-8 OLI/TIRS	2020	Multispectral	30	16	60
6	Landsat-8 OLI/TIRS	2023	Multispectral	30	16	60
7	Sentinel-1 GRD	2015	VV backscatter (ASC)	10	12	30
8	Sentinel-1 GRD	2020	VV backscatter (ASC)	10	12	33
9	Sentinel-1 GRD	2023	VV backscatter (ASC)	10	12	25

Landsat

The study utilized optical satellite imagery from Landsat-5 TM (Thematic Mapper) and Landsat-8 OLI (Operational Land Imager) provided by NASA and the United States Geological Survey (USGS). The Landsat imagery features a spatial resolution of 30 meters for multispectral bands, a temporal revisit cycle of 16 days, and spectral diversity sufficient to monitor land-use and land-cover changes.

Sentinel-1

Radar data from Sentinel-1, provided by the European Space Agency (ESA), were used to complement optical datasets and overcome their limitations. This study utilized Level-1 Sentinel-1 GRD (Ground Range Detected) products in C-band within the GEE platform**.**

The VV polarization and ascending orbit were prioritized for its ability to identify and analyze urban features in Hanoi. VV polarization, sensitive to flat and hard surfaces such as rooftops and roads, effectively distinguishes urban areas from natural surfaces (Miranda et al., 2015; Deepthi et al., 2018). In the ascending orbit, Sentinel-1 scans the Earth from west to east during the afternoon, providing optimal conditions for capturing strong backscatter signals from built-up areas. This configuration is particularly effective in highly urbanized regions like Hanoi, where dense infrastructure generates strong radar reflections.

Population

The population data for Hanoi and its 30 districts were sourced from official statistical records, as reported in the SPH (2023b).

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Methods

The workflow of this study, as illustrated in *Fig. 2*, consists of two parallel processes for processing optical and radar satellite data. The outputs from these streams are integrated to generate comprehensive build-up area maps for Hanoi spanning the period 2000–2023.

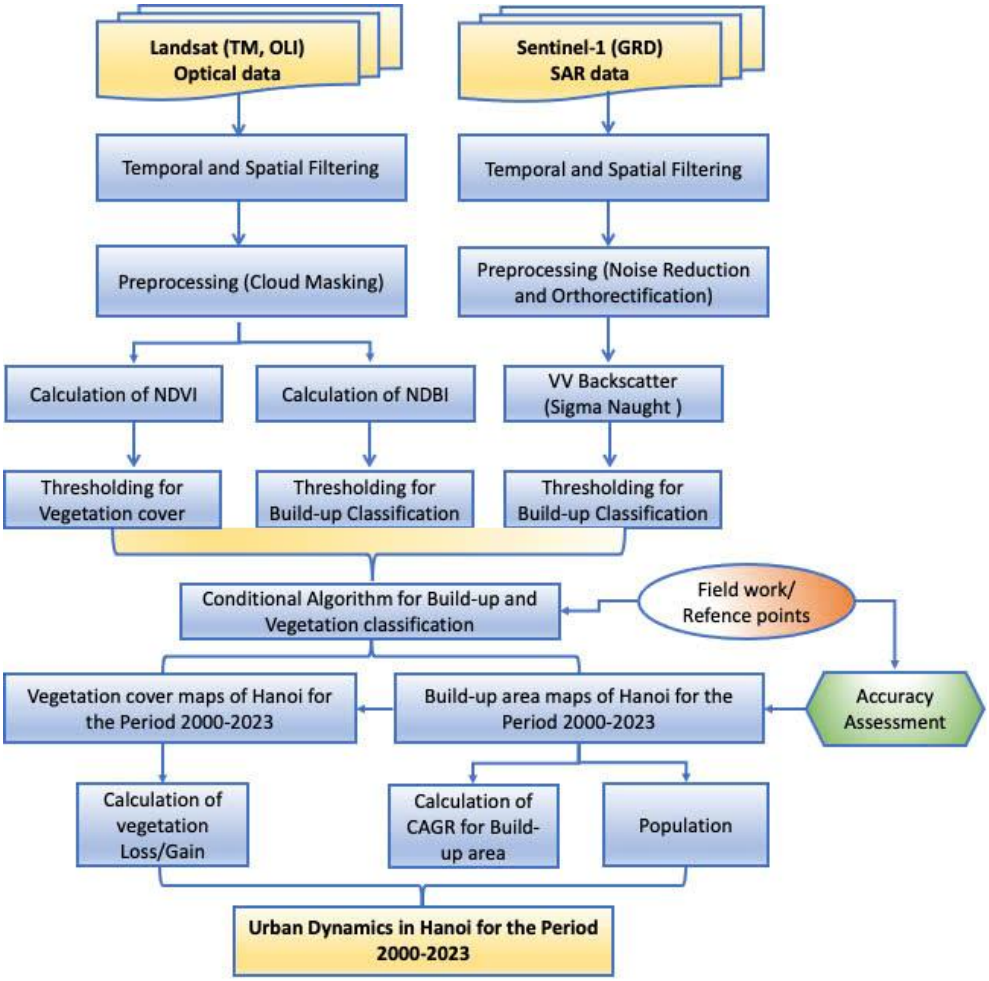

Figure 2. *The workflow of the study*

In this study, GEE was used to process satellite data and derive key indices for urban land analysis. GEE is an advanced cloud computing platform designed for the analysis of remote sensing data, environmental parameters, and meteorological data at local to global scales. The platform integrates a vast repository of free satellite imagery and geospatial datasets, including those from NASA, USGS, and ESA.

The workflow of the methodology involved key steps, as follows:

Classification of built-up areas using optical data

The Normalized Difference Built-Up Index (NDBI) was utilized to distinguish urban areas from non-urban areas, as it effectively highlights built-up regions by differentiating them from vegetation and water bodies. The following major processing steps were undertaken to derive NDBI:

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1. *Data acquisition:* Landsat (TM and OLI) images from 2000 to 2023 were selected on GEE, with annual composites generated from January to December.
2. *Temporal and spatial filtering:* Temporal filtering involved selecting images based on their acquisition year, while spatial filtering ensured the focus remained on the Hanoi study area.
3. *Preprocessing:* GEE's built-in cloud masking functions, based on the Quality Assessment (QA) band, were employed to ensure only cloud-free pixels (less than 20% cloud coverage) were included in the analysis.
4. *Index calculation:* The NDBI was calculated using the spectral bands of Landsat data, employing the formula (Zha et al., 2003):

$$\mathrm{NDBI} = \frac{(\mathrm{SWIR} - \mathrm{NIR})}{(\mathrm{SWIR} + \mathrm{NIR})} \quad \text{(Eq.1)}$$

where
SWIR: Shortwave Infrared,
NIR: Near-infrared.

This approach builds upon the theoretical framework and empirical findings of previous studies using spectral indices for urban mapping (Zha et al., 2003; Xu, 2008; As-Syakur et al., 2012), with threshold values adjusted to suit the specific characteristics of the study area. In this study, a threshold value of NDBI > –0.02 was applied to distinguish built-up areas from non-urban land cover. This threshold was derived through a combination of histogram analysis, entropy measures, spatial correlation, and gray-scale properties. Specifically, the method involved analyzing the shape of NDBI histograms to identify inflection points that effectively separated urban from non-urban classes, guided by observed spectral behavior and spatial distribution patterns. To evaluate classification accuracy, a reference dataset consisting of 1,000 samples was used. The performance of the NDBI-based urban classification was assessed by comparing the classification output to this reference dataset, as detailed in the Accuracy assessment section below.

Classification of built-up areas using SAR data

To derive built-up areas, SAR data from Sentinel-1 underwent the following processing steps:

1. *Data acquisition*: Sentinel-1 VV-polarized, ascending orbit images (2015–2023) over Hanoi were selected, with annual composites generated from January to December.
2. *Temporal and spatial filtering:* Similar to the Landsat workflow, temporal and spatial filters were applied to restrict data to the Hanoi region and relevant time periods.
3. *Preprocessing:* The steps include cleaned and calibrated data, and noise filtering.
4. *Thresholding for Urban classification:* In urban environments, built-up surfaces such as buildings, roads, and dense infrastructure produce strong backscatter signals—typically ranging from –10 dB to –5 dB—due to the presence of corner reflectors, surface roughness, and complex structural geometries (Ban et al., 2015; Chini et al., 2018; Verma et al., 2023). This distinct physical contrast in radar backscatter provides the theoretical foundation for applying VV polarization thresholds in urban classification. Based on this principle, a threshold of VV > –5 dB was selected through histogram analysis of backscatter values from verified

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urban and non-urban reference areas. High-resolution imagery from Google Earth and field observations supported the threshold selection process by enabling visual interpretation and refinement of urban boundaries. The resulting classification outputs were validated using a reference dataset of 1,000 ground truth points, as described in the Accuracy assessment section below.

Integration of Landsat and Sentinel-1 data

As described earlier, for Landsat data, urban land was classified using a threshold of NDBI > −0.02, which effectively distinguishes urban areas from non-urban areas in Hanoi. However, NDBI alone tends to misclassify barren land or other non-urban surfaces with reflectance properties similar to urban areas, as illustrated in *Figs. 3a and 3b*. To overcome this limitation, Sentinel-1 radar data was integrated into the classification process. Urban areas were identified using a threshold of VV > −5 dB from Sentinel-1 ascending polarization data, which accurately captures highly reflective surfaces such as built-up areas. Nevertheless, Sentinel-1 data alone may misclassify vegetated regions due to overlapping radar backscatter characteristics. This misclassification is mitigated by integrating Landsat-derived NDBI values, resulting in a more robust urban classification, as demonstrated in *Figs. 3c, 3d, and 3e*.

Therefore, the conditional algorithm for identifying a pixel as built-up is based on the following conditions:

$$Build-up\ classification: \begin{cases} \mathbf{1} & if\ (NDBI > -0.02) \wedge (VV > -5\ dB) \\ \mathbf{0} & otherwise \end{cases} \quad \text{(Eq.2)}$$

The logical conjunction (∧) ensures a pixel is classified as built-up only if both conditions are satisfied, leveraging the strengths of both data sources to minimize errors.

Figure 3 illustrates the individual classification results from NDBI and Sentinel-1 data, as well as the combined approach.

The integration of the two datasets demonstrates significant improvements in classification accuracy, addressing limitations in each individual method. The combined approach provides a robust framework for urban land classification and offers enhanced reliability in mapping complex urban landscapes.

For the years prior to 2015 (specifically 2010, 2005, and 2000), built-up area classification was conducted using NDBI derived from Landsat imagery, combined with the 2015 built-up classification layer as a reference baseline. In the absence of Sentinel-1 data for earlier periods, this approach offered a practical solution based on the widely accepted assumption that urban expansion is largely unidirectional—built-up areas typically expand or remain stable, with limited likelihood of reverting to non-urban land cover. Accordingly, areas identified as non-built-up in 2015 were also classified as non-built-up in prior years, thereby reducing potential misclassification due to the lower spatial resolution and spectral limitations of historical imagery. This assumption is particularly valid in the context of Hanoi's sustained urbanization, where urban land, once established, is rarely converted back to agriculture or natural vegetation. Constraining earlier classifications with the 2015 built-up layer helps to minimize false positives and enhances temporal consistency, especially in areas affected by cloud cover, haze, or sensor limitations. However, this approach also introduces potential limitations, such as the inability to detect temporary land-use changes, redevelopment, or rare cases of urban

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shrinkage, where built-up areas may have been abandoned or reverted to other land uses before 2015.

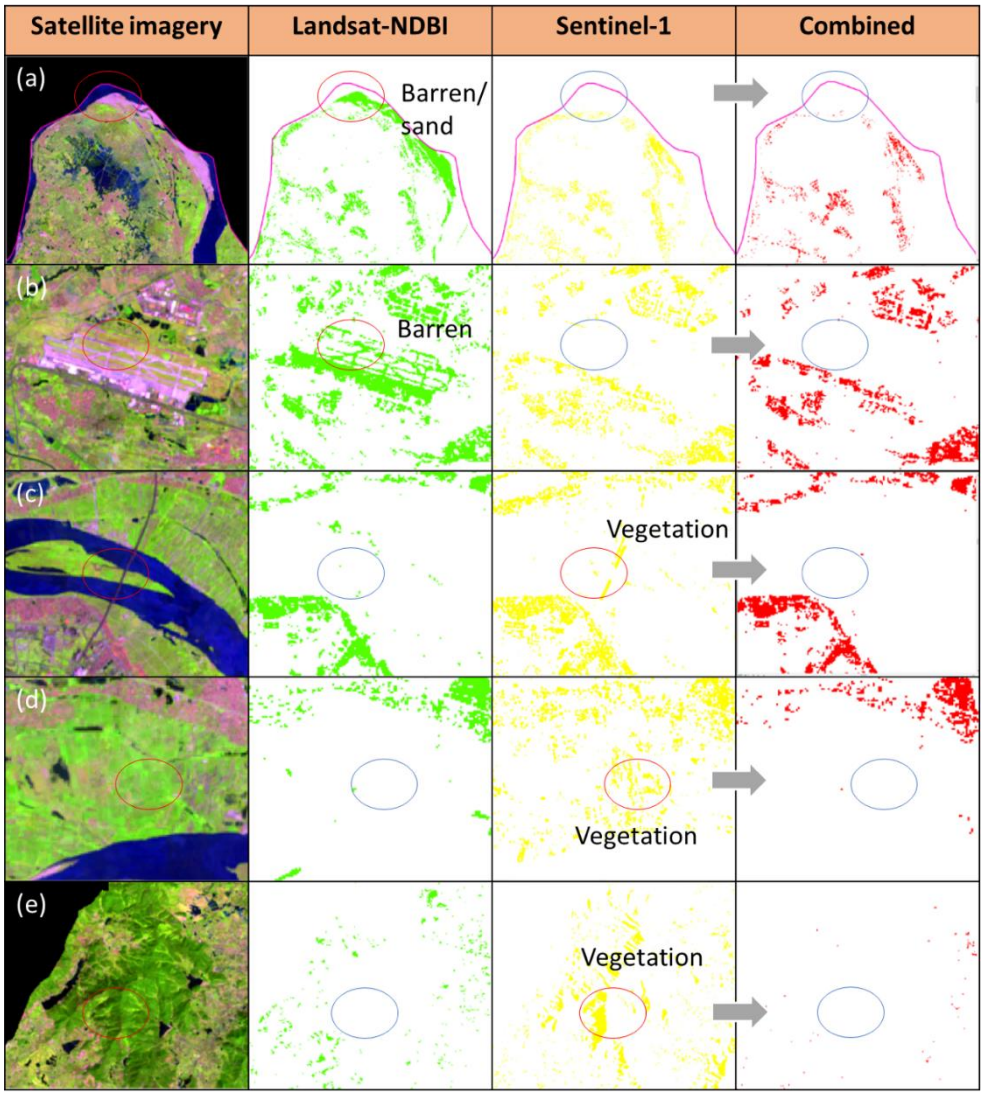

Figure 3. *Representation of single and combined indices for urban classification*

Accuracy assessment

The accuracy assessment of the urban land classification was conducted to evaluate the performance of three classification methods: Landsat-derived NDBI, Sentinel-1 SAR data, and a combined approach integrating both datasets. A reference dataset comprising 1,000 samples derived from fieldwork or high-resolution imagery is used to validate the combined classification, representing the ground truth for urban and non-urban areas (*Fig. 4*). The classification results from the three methods were compared against the reference data.

To calculate accuracy metrics, a confusion matrix was generated for each method. The metrics included Overall Accuracy, Kappa Coefficient, Precision, Recall (Sensitivity), Specificity, and F1 Score. The results of the accuracy assessment for each method are summarized in *Table 2*.

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Figure 4. *Reference sample points with field work images*

Table 2. *The accuracy assessment matries*

No.	Method	F1 Score	Kappa Coefficient	Overall Accuracy	Precision	Recall (Sensitivity)	Specificity
1	Landsat	0.73	0.64	0.86	0.77	0.70	0.92
2	Sentinel-1	0.61	0.39	0.69	0.47	0.87	0.63
3	Combined	0.86	0.81	0.93	0.92	0.81	0.97

The combined method outperformed the individual datasets with an F1 Score of 0.86, a Kappa Coefficient of 0.81, and an Overall Accuracy of 93%. This indicates the synergistic effect of integrating optical (Landsat) and radar (Sentinel-1) data, achieving higher precision (0.92), recall (0.81), and specificity (0.97) compared to standalone datasets. Landsat alone demonstrated a reasonably high performance, with an F1 Score of 0.73 and an Overall Accuracy of 86%. It also maintained a strong balance between precision (0.77) and recall (0.70), reflecting its reliability in identifying urban land cover while showing a Kappa Coefficient of 0.64, indicative of moderate agreement between classifications and reference data. In contrast, Sentinel-1 alone exhibited the lowest performance metrics among the three methods, with an F1 Score of 0.61, Overall Accuracy of 69%, and a Kappa Coefficient of 0.39. Despite its strength in recall (0.87), indicative of strong sensitivity in identifying true positives, its precision (0.47) and specificity (0.63) were lower, pointing to challenges in distinguishing urban areas from other land cover types.

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Compound Annual Growth Rate (CAGR)

To quantify the annual growth in urban land area across Hanoi's districts, the Compound Annual Growth Rate (CAGR) method was utilized. CAGR provides a standardized way to measure the consistent rate of growth over a specified period, making it particularly suitable for analyzing temporal land use changes. The formula for calculating CAGR is as follows:

$$CAGR = \left(\left(\frac{EV}{BV}\right)^{\frac{1}{n}} - 1\right) x\ 100 \quad \text{(Eq.3)}$$

where
EV: The final value (e.g., land area in 2023),
BV: The initial value (e.g., land area in 2000),
n: The time period in years (e.g., 23 years from 2000 to 2023).

This approach ensures that variations in growth are smoothed out, providing a clear picture of the long-term trend, even when yearly fluctuations may exist. The CAGR method has been widely applied in urban studies to assess changes in land use, population, and infrastructure growth (Wolff et al., 2020; Carneiro et al., 2021; Pacillo, 2022; Liu and Pan, 2023).

Identifying the impact of urbanization on the green ecosystem

To assess the impact of urbanization on the green ecosystem, this study determines vegetation cover changes in Hanoi from 2000 to 2023 by integrating built-up area data with vegetation maps. The methodology involved two key steps: (1) identifying vegetation loss by comparing the 2000 vegetation cover with the 2023 built-up area map to determine where green spaces have been replaced by urban infrastructure, and (2) identifying vegetation gain by comparing the 2023 vegetation cover with that of 2000 to detect areas where natural regeneration has occurred.

The classification of vegetation loss and gain is defined as follows:

$$Vegetation\ cover: \begin{cases} \boldsymbol{Loss} & if\ Vegetation\ cover\ in\ 2000 \rightarrow Build-up\ area\ in\ 2023 \\ \boldsymbol{Gain} & If\ non-vegetation\ \ in\ 2000 \rightarrow Vegetation\ cover\ \ in\ 2023 \end{cases} \quad \text{(Eq.4)}$$

In this study, vegetation loss is defined as areas where vegetation cover present in 2000 was replaced by built-up land by 2023. Conversely, vegetation gain refers to areas that were non-vegetated in 2000 but exhibited vegetation cover by 2023, as detected through NDVI analysis. Vegetation cover was identified using an NDVI threshold of > 0.3, effectively excluding non-vegetated surfaces. It is important to note that in dense urban districts, vegetation gain typically reflects localized or small-scale greening—such as the addition of street trees, pocket parks, green roofs, or spontaneous vegetation growth in open spaces. As such, vegetation gain in these contexts should not be interpreted as large-scale ecological restoration, but rather as incremental or ornamental improvements in urban greenery.

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Results and discussion

Build up area of Hanoi

Firstly, the NDBI was derived from processed Landsat imagery using the GEE platform for the period 2000 to 2023. The resulting NDBI maps (*Fig. 5*) distinguish urban areas from non-urban regions, providing an initial depiction of the significant spatial transformations in Hanoi's urban landscape during this time.

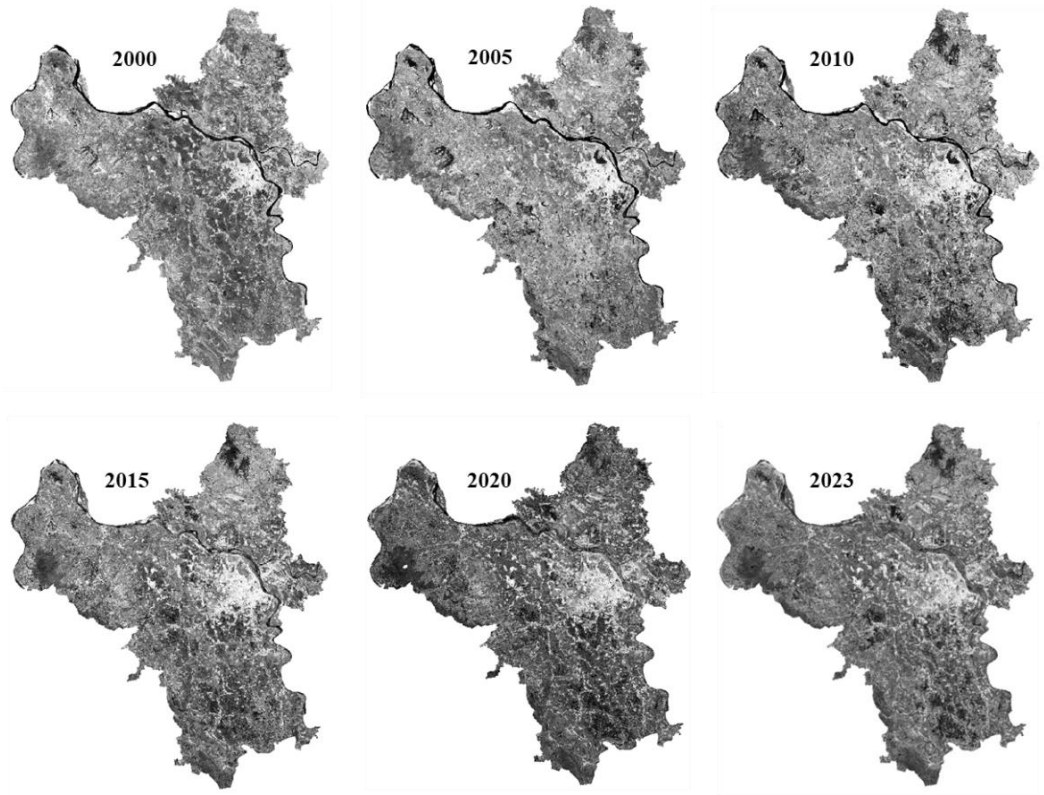

Figure 5. *Landsat-derived NDBI from 2000 to 2023*

However, NDBI relies on the spectral differences between Shortwave Infrared (SWIR) and Near-Infrared (NIR) bands, which can lead to misclassification when built-up areas exhibit similar reflectance characteristics to bare soil, rocks, or sparsely vegetated regions. Additionally, although Landsat surface reflectance products include atmospheric corrections, residual effects from cloud cover and aerosols may still compromise NDBI accuracy, particularly in tropical or monsoon-prone regions like Hanoi, where such conditions are prevalent. To improve classification accuracy, Sentinel-1 SAR data were integrated. The Sentinel-1 ascending VV polarization data (*Fig. 6*) were thresholded at values greater than -5 dB to delineate urban areas.

By integrating radar-based classification with optical Landsat imagery, urban land area maps for Hanoi were generated, covering the period from 2000 to 2023. These maps provide a detailed representation of the spatial distribution and temporal dynamics of urban expansion across Hanoi's administrative boundaries (*Fig. 7*).

Figure 7 shows that the distribution of built-up areas in Hanoi is uneven, with a concentration primarily in inner-city districts. Over time, the city has experienced a

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significant shift in the spatial distribution of urban zones, with the expansion of existing urban areas and the emergence of new urban zones in suburban and peripheral regions. Urban development has spread outward from the city center, particularly toward the north, northeast, and northwest, leading to an increase in urban density in inner-city areas and slower growth in suburban and rural regions.

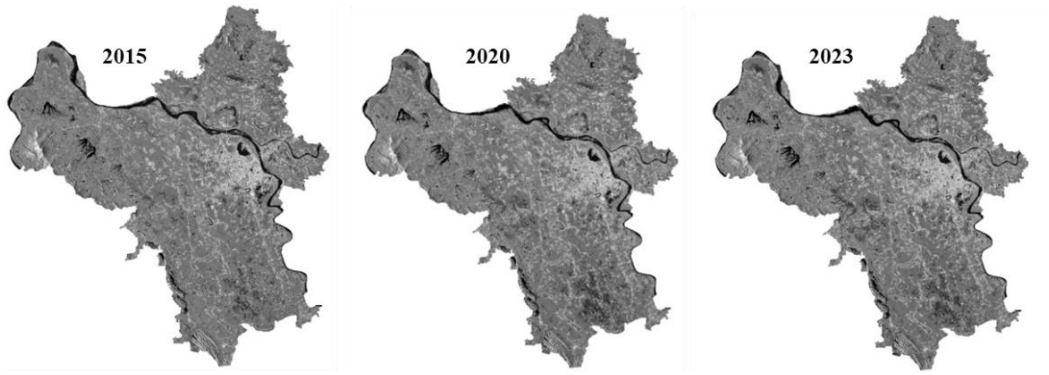

Figure 6. *Sentinel-1 VV backscatter*

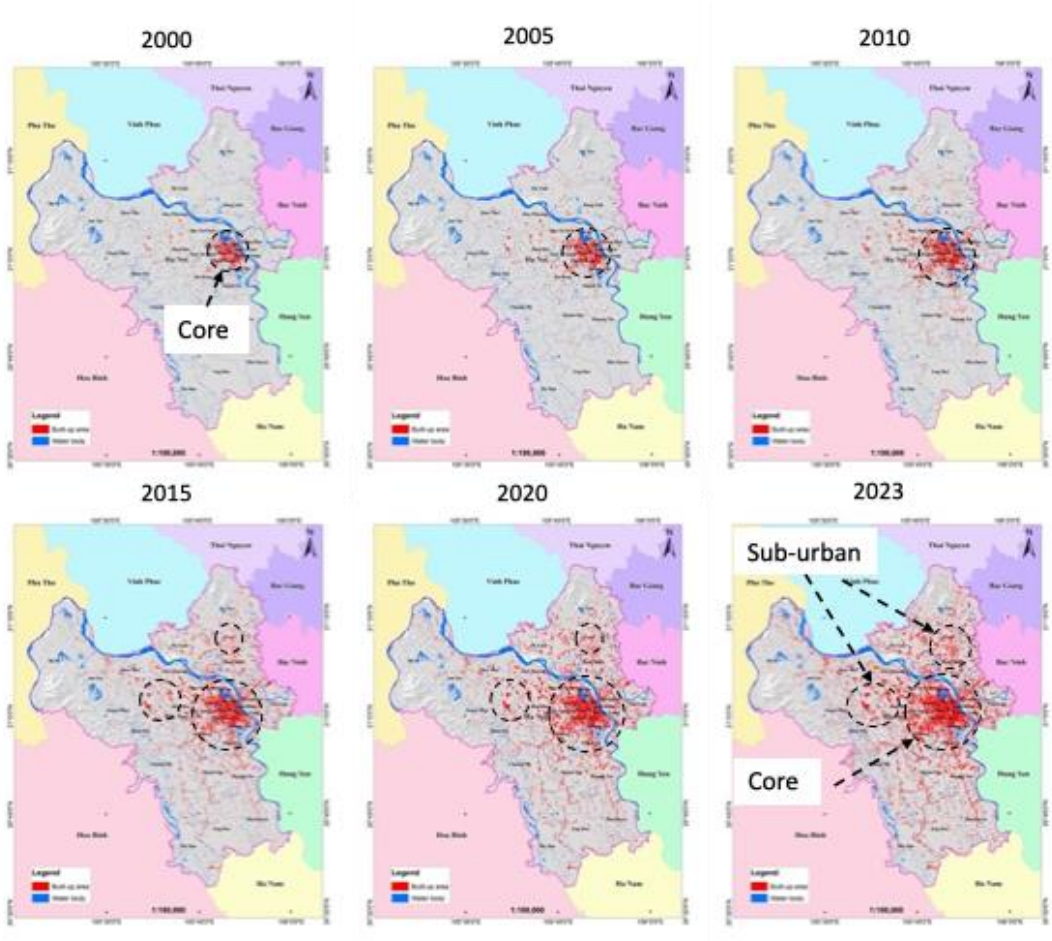

Figure 7. *Expansion of built-up areas (red) in Hanoi from 2000 to 2023*

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In 2000, the urban land area of Hanoi was approximately 4,832.74 hectares, accounting for a small fraction of the city's total land area. By 2005, this area had increased to 6,982.88 hectares, reflecting gradual urban growth. The year 2010 marked a major urbanization boom, with the urban land area rising sharply to 11,278.69 hectares (*Table 3*).

Table 3. *Build-up area in Hanoi (2000–2023)*

Year	Build-up area (ha)
2000	4,832.74
2005	6,982.88
2010	11,278.69
2015	21,766.67
2020	28,860.48
2023	35,530.54

This surge in urbanization can be attributed to large-scale land-use conversion from agricultural to construction land during real estate booms and increased real estate activity. Additionally, this expansion was driven by a significant population influx from rural to urban areas, following the administrative boundary expansion of Hanoi in August 2008 (Hien et al., 2020; Vu et al., 2024).

By 2023, the urban land area had reached 35,530.54 hectares, indicating a net increase of 30,697.8 hectares over the 23-year study period. The spatial dynamics of urban land changes from 2000 to 2023 demonstrate that urban land expansion predominantly occurred in surrounding areas, particularly to the north, northeast, and northwest of the city. These trends align with infrastructure development, such as new residential areas, transportation corridors, and industrial zones.

Overall, from 2000 to 2023, Hanoi's urban land area grew by approximately 30,697.8 hectares**,** representing a sixfold increase. This growth underscores the dynamic and complex nature of urbanization in Hanoi, characterized by rapid expansion from the traditional core areas to the suburban fringe. While this presents significant opportunities for economic development, it also raises challenges for urban planning, resource management, and sustainable development.

Urban land area changes

The maps of urban land changes were generated using a cross-construction method, which compares the classification results of urban land status at two specific time points. This approach enabled a systematic assessment of urban land changes in the study area, conducted at five-year intervals over the period from 2000 to 2023. The results, presented in *Fig. 8*, reveal a clear upward trend in urban land area, reflecting the significant expansion of built-up regions during this time frame.

In 2000, urban land in Hanoi was predominantly concentrated in central districts such as Dong Da, Hoan Kiem, Hai Ba Trung, and Ba Dinh, covering approximately 4,832.74 hectares. By 2010, new urban zones had emerged in districts such as Cau Giay, Tu Liem, Hoang Mai, Long Bien, Gia Lam, and Ha Dong, while suburban districts including Dong Anh, Me Linh, and Soc Son began to witness initial urban development. During this period, the urban land area expanded significantly, more than doubling within a decade (11,278.69 hectares).

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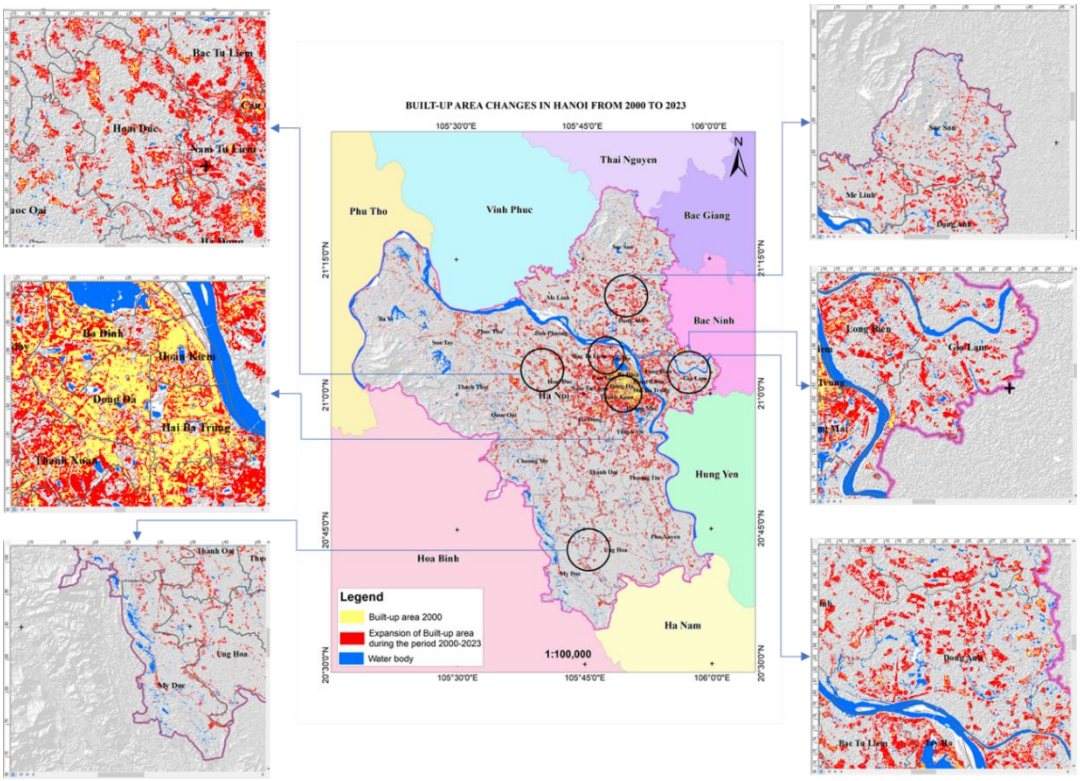

Figure 8. *Build-up area changes in Hanoi from 2000 to 2023*

By 2023, inner-city districts like Dong Da and Ba Dinh had reached near saturation in terms of urban land development, whereas districts such as Gia Lam, Hoai Duc, and Dong Anh experienced substantial growth, establishing themselves as major contributors to Hanoi's suburban urbanization. The northern, northwestern, and northeastern regions of the city emerged as key hotspots for urban growth, driven by extensive infrastructure development and land conversion for residential and industrial purposes. This dramatic increase in total urban land area highlights Hanoi's rapid expansion and transformation over the two decades.

Compound Annual Growth Rate (CAGR) and disparities among districts

The CAGR index was calculated to assess the rate of urban land expansion across Hanoi's districts over the study period, utilizing the combined Landsat and Sentinel-1 derived built-up maps (*Fig. 9*).

The analysis of land area, and population in Hanoi's districts reveals significant variations between urban cores, suburban zones, and peripheral areas. Urban districts, such as Dong Da (995 ha, 376,709 people), Hai Ba Trung (1,026 ha, 304,101 people), and Thanh Xuan (917 ha, 293,292 people), feature small land areas but high population, with Dong Da reaching approximately 376,709 people, reflecting its status as a highly urbanized central district. Administrative and commercial hubs like Ba Dinh (921 ha, 226,315 people) and Hoan Kiem (535 ha, 141,687 people) have lower population but play critical roles in non-residential activities. Meanwhile, suburban districts such as Bac Tu Liem (4,524 ha, 354,364 people) and Nam Tu Liem (3,217 ha, 282,444 people) are rapidly urbanizing, showcasing larger land areas and increasing populations due to

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expanding infrastructure and urban sprawl. In contrast, peripheral districts like Ba Vi (42,180 ha, 305,933 people) and Soc Son (30,551 ha, 357,652 people) have vast land areas but much lower population reflecting its predominantly rural character. Districts like Dong Anh (18,568 ha, 437,308 people) and Gia Lam (11,664 ha, 292,943 people) stand out for their relatively high populations and proximity to the city center, positioning them as hotspots for future urban expansion.

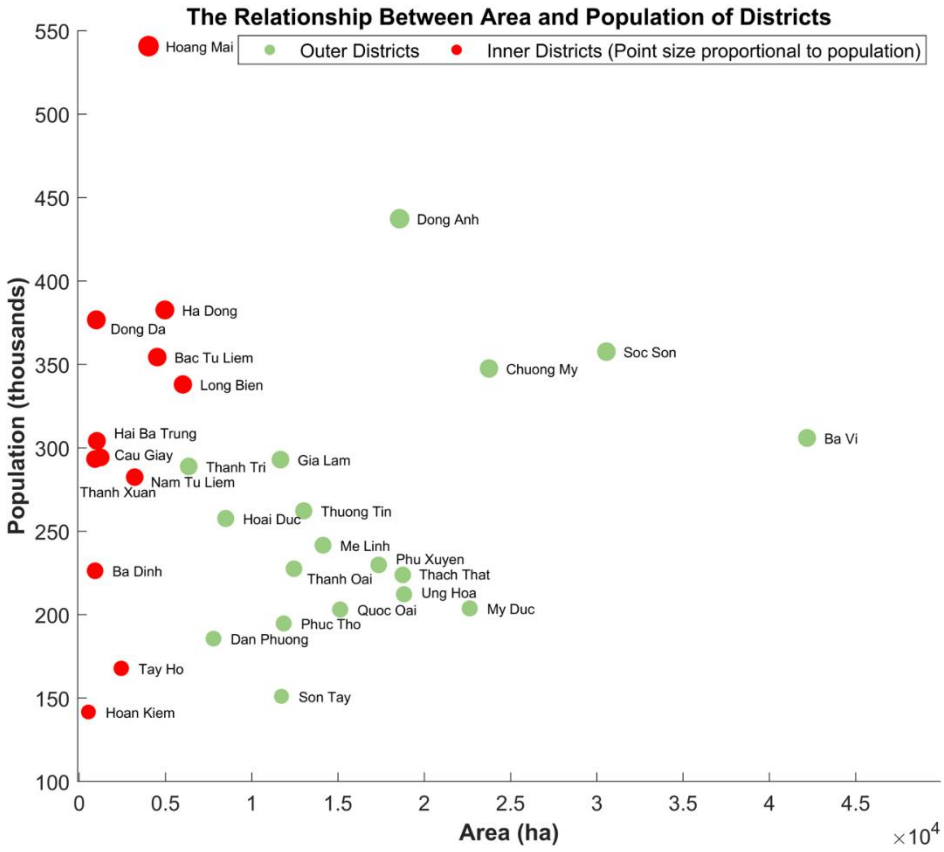

Figure 9. *The relationship between the land area and population of districts in Hanoi*

Furthermore, this study delves into the development of urban areas and population density across districts. *Figure 10* offers critical insights into the spatial and temporal dynamics of urbanization, identifying districts with rapid growth as well as those approaching saturation.

The chart highlights the stark disparities in urban development between Hanoi's districts, with clear differences in land area growth (CAGR) and population density. Peripheral districts such as Ba Vi (19.27% CAGR, ~7 p/ha) and My Duc (16.13% CAGR, ~9 p/ha) exhibit the highest growth rates in urban area expansion but maintain sparse populations, reflecting early stages of urban development and significant potential for future urbanization. Similarly, districts like Chuong My (13.42%, ~14 p/ha) and Soc Son (14.87%, ~11 p/ha) demonstrate rapid land conversion with limited current population density. In contrast, central districts, including Dong Da (1.45%, ~378 p/ha), Hai Ba Trung (1.79%, ~296 p/ha), and Hoan Kiem (1.68%, ~264 p/ha), show minimal urban area growth due to spatial saturation, coupled with extremely high population densities that pose challenges for infrastructure and quality of life. Suburban districts, such as Bac Tu

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Liem (12.90%, ~78 p/ha), Nam Tu Liem (13.15%, ~87 p/ha), and Long Bien (10.74%, ~56 p/ha), represent transitional zones with growing urban footprints and moderate population densities, driven by suburban expansion and ongoing infrastructure development. Districts like Cau Giay (5.45%, ~236 p/ha) and Hoang Mai (7.32%, ~134 p/ha) exemplify more balanced growth, with moderate urban expansion and manageable population densities. The data underscores the contrasting urban dynamics, highlighting the need for tailored urban planning strategies that address congestion and infrastructure strain in central districts while capitalizing on the growth potential of suburban and peripheral regions to foster balanced and sustainable urban development.

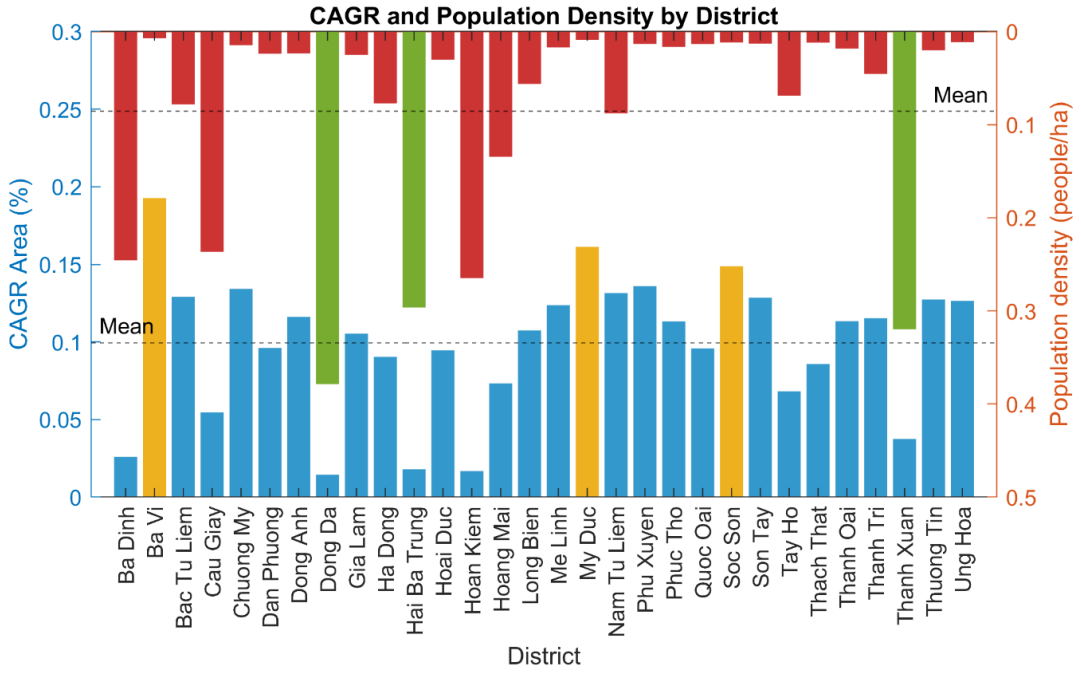

Figure 10. *CAGR of build-up area and population density by district in Hanoi*

Impact on the green ecosystem

Our analysis highlights that Hanoi has undergone rapid urban expansion, with suburban districts experiencing significant urbanization. This transformation has positively impacted the economy, improved living standards, and provided better infrastructure to support the growing population. However, alongside economic progress, the question arises of whether Hanoi is achieving sustainable development. Beyond economic growth, sustainability requires careful consideration of environmental factors such as air quality, soil health, and water resources. The green ecosystem, which includes forests, grasslands, urban green spaces (parks, tree-lined streets), and vegetation-covered landscapes, plays a crucial role as the city's "lungs." A decline in green spaces can directly impact air quality and public health, making urban greenery an essential component of a livable and resilient city.

Recognizing this, our study focuses on assessing the changes in Hanoi's vegetation cover over more than two decades of urbanization. By integrating the built-up area map developed in this study with a vegetation cover map derived from NDVI using Landsat imagery, we have identified the spatial distribution and extent of vegetation changes from

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2000 to 2023. The results, presented in *Fig. 11*, illustrate the fluctuations in the green ecosystem across both urban and suburban districts, providing a clear perspective on how Hanoi's vegetation has evolved in response to rapid urban development.

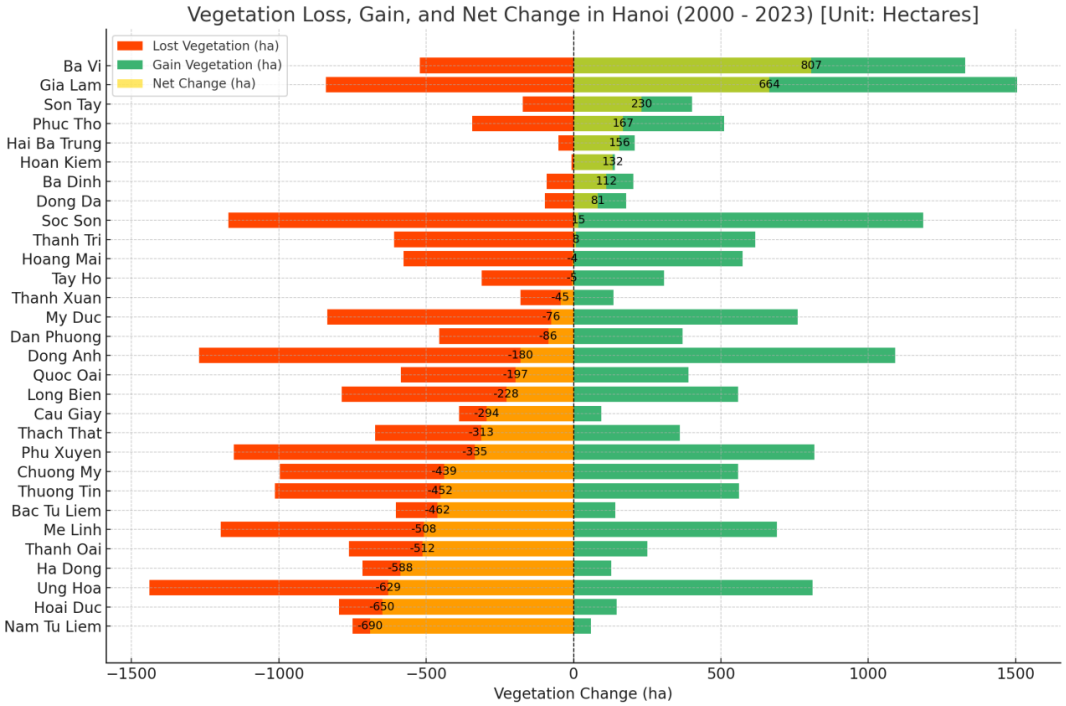

Figure 11. *Vegetation loss, gain, and net change in Hanoi from 2000 to 2023*

The findings reveal critical spatial patterns, with Hanoi losing a total of 19,400 ha of vegetation, while recovering only 15,081 ha, resulting in a net decline of 4,319 ha. One of the most prominent spatial patterns is the loss of vegetation in urban districts, particularly in Thanh Xuan (–44 ha), Cau Giay (–294 ha), Tay Ho (–5 ha), and Hoang Mai (–3.6 ha). These areas, central to Hanoi's infrastructure expansion, highlight the pressures of urban sprawl and urbanization, where green spaces are increasingly replaced by residential and commercial developments. This trend is especially concerning, as these districts are not only facing increased population density but also environmental degradation. In contrast, core urban area such as Hai Ba Trung, Hoan Kiem, and Ba Dinh saw modest vegetation gains (e.g., +156 ha, +132 ha, and +112 ha, respectively). These gains are likely attributed to urban greening initiatives, such as small-scale parks, street trees, and rooftop gardens. However, the limited availability of land in these areas presents a significant challenge for expanding these efforts. As infrastructure development continues, the space for new green projects is further constrained, contributing to worsening air quality, the urban heat island effect, and a lack of public green spaces. Suburban districts such as Ung Hoa (–1,439 ha), Hoai Duc (–650 ha), and Nam Tu Liem (–690 ha) experienced the most severe vegetation loss, primarily due to large-scale land conversion for industrial and residential development. The rapid development in these areas presents a critical risk to regional ecological balance, as the loss of agricultural and forested land—previously providing vital ecosystem services such as flood regulation and carbon sequestration—demands stricter land-use policies and

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sustainable development strategies to curb unchecked urban sprawl. Meanwhile, some suburban areas, like Ba Vi (+807 ha), Gia Lam (+664 ha), and Son Tay (+230 ha), saw notable vegetation recovery. This recovery is likely the result of natural regeneration and conservation efforts in less urbanized parts of the city. These districts present opportunities for future reforestation and sustainable land-use management, which could restore lost ecosystems and create green buffers around urbanized areas.

These spatial patterns highlight a critical gap between the urban core, where green space is increasingly scarce, and suburban areas, where land conversion is widespread. The broader relevance of this study lies in its potential to inform policy decisions aimed at creating sustainable and resilient cities**.** As Hanoi continues to grow, the city faces the dual challenge of managing urban expansion while preserving vegetation. To address this, urban planning must prioritize integrating green infrastructure in both densely built urban districts and suburban zones. Strict land-use regulations in suburban areas, coupled with investments in green infrastructure within urban areas, are crucial for ensuring a balanced and sustainable urban environment.

Limitation

These findings highlight the importance of data integration in improving classification accuracy, particularly in complex urban environments. While Landsat performs well due to its spectral resolution, integrating radar data like Sentinel-1 helps address issues like cloud cover interference, leading to more reliable results. Nevertheless, this study has several limitations that should be acknowledged. The use of predefined thresholds, such as NDBI > -0.02 and VV > -5 dB, may limit the applicability of the findings to other regions. These thresholds are often region-specific and may not account for local variations in vegetation or land cover. While the approach works well for Hanoi, it could lead to misclassifications, especially in barren or vegetated urban areas. Future research could refine thresholds using machine learning algorithms, allowing for more accurate, context-specific classifications. The spatial resolution of Landsat (30m) and Sentinel-1 (10m) may miss fine-scale urban features or rapid development changes. Smaller green spaces, such as pocket parks and rooftop gardens, may not be captured at these resolutions. Incorporating higher-resolution imagery (e.g., WorldView, Pleiades) or LiDAR data could improve detection of small-scale green spaces. Another limitation is the exclusion of socioeconomic factors like population density, economic activities, and income distribution, which influence urbanization and green space availability. Future studies should integrate these factors to better understand how they interact with urban vegetation patterns, leading to more equitable urban planning. Validation challenges, such as the availability of up-to-date ground-truth data, and the influence of seasonal variations on optical indices, may affect accuracy. Addressing these limitations with refined thresholds, additional data sources, and enhanced validation techniques could improve the study's robustness and applicability.

Conclusions

This study successfully integrated Landsat and Sentinel-1 imagery to classify urban land in Hanoi with high accuracy, achieving an overall accuracy of 93% and a Kappa coefficient of 0.81. The integration of SAR and optical data improved classification accuracy and provided comprehensive insights into urban dynamics. The results revealed an uneven spatial distribution of urban expansion between 2000 and 2023, characterized

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by significant growth from the city center into surrounding districts, particularly in the north, northeast, and northwest. During this period, Hanoi's urban land area increased by 30,697.8 hectares, with the most rapid growth occurring between 2000 and 2010, driven by land-use changes, population growth, and infrastructure development. The analysis highlighted stark contrasts in urbanization patterns. Central districts such as Dong Da, Hai Ba Trung, and Thanh Xuan exhibited high population densities but limited land expansion due to spatial saturation. In contrast, suburban districts like Hoang Mai and Long Bien, along with peripheral districts such as Ba Vi and Soc Son, experienced significant land expansion, emphasizing the increasing importance of suburban and peri-urban areas in Hanoi's future development. This urban expansion has significantly impacted the green ecosystem, resulting in a net vegetation loss of 4,319 hectares over 23 years. The most affected districts include Ung Hoa (-1,439 ha), Hoai Duc (-650 ha), Nam Tu Liem (-690 ha), Ha Dong (-588 ha), and Thanh Oai (-512 ha), where large-scale conversion of tree and agricultural lands into industrial and residential zones has driven significant vegetation loss. Meanwhile, some districts such as Ba Vi (+807 ha), Gia Lam (+664 ha), Son Tay (+230 ha), and Soc Son (+15 ha) have achieved notable vegetation recovery. The integration of optical and radar data proved to be a robust method for monitoring urbanization, effectively addressing challenges in classifying complex landscapes. This study demonstrates the potential of Google Earth Engine (GEE) and remote sensing techniques as scalable tools for tracking urban growth in rapidly developing cities. The findings provide valuable insights for urban planners and policymakers, offering a scientific basis for strategies to enhance Hanoi's livability and sustainability.

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