


Overtourism triggered built-up expansion over a decade in Canggu, Bali

Nyoman Sunarta³, I Nyoman Sukma Arida¹, Ni Made Trigunasih²,
Kothleitner Michele⁴, Moh Saifulloh^{1,2*} 

¹ Spatial Data Infrastructure Development Center, Udayana University, Denpasar, Indonesia

² Marine Science Study Program, Faculty of Marine Sciences and Fisheries, Udayana University, Badung, Indonesia

³ Doctoral Program of Tourism Sciences, Faculty of Tourism, Udayana University, Denpasar, Indonesia

⁴ ZHAW Zürcher Hochschule für Angewandte Wissenschaften, Einsiedlerstrasse, Wädenswil, Switzerland

* Corresponding authors's e-mail: m.saifulloh@unud.ac.id

ABSTRACT

The conducted research aimed to quantify urban expansion implicated by the overtourism phenomenon in Canggu, Bali, a crucial issue for local and international citizens. Other researchers have not explored this area extensively, despite its recent popularity and complex environmental problems. However, the conducted examination solely focused on the expansion of built-up land in a time series spanning the past decade. To rapidly map urban growth, archived Landsat imagery were processed and the index-based built-up index (IBI) was computed. Year-specific thresholds were applied to classify each annual composite into built-up and non-built-up (vegetated/other) surfaces. Built-up expansion was then quantified for 2014–2024 and mapped at the village scale to show both extent and change. Built-up area increased by 317.97 ha (22.31%) over 2014–2024, with a sharp 177.84 ha (12.48%) rise concentrated in 2022–2024. Kerobokan Kelod (+2.95%), Tibubeneng (+2.14%), and Canggu (+1.85%) recorded the largest gains; Pererenan, Cemagi, and Beraban each added up to 0.82%. Over the same period, international tourist arrivals grew by an average of 71.22% per month, aligning with the acceleration of built-up expansion. Causality is not claimed; however, the timing and spatial concentration near tourism corridors indicate strong tourism-related pressure on land conversion. Uncertainty arises from the IBI threshold used to separate built-up from non-built-up surfaces. Bare land can share spectral values with impervious surfaces and create mixed pixels. IBI was binarized using -0.10 in 2016 and 2020 and -0.08 in other years, so area estimates near these cutoffs are sensitive. A brief threshold-sensitivity test and validation with higher-resolution imagery will improve accuracy. Despite this limitation, the Landsat results show concentrated, tourism-linked built-up expansion around Canggu that coincides with the internationally publicized overtourism surge. These village-scale metrics provide clear evidence for local government to control land conversion, protect blue-green infrastructure, and refine spatial-planning regulations.

Keywords: overtourism, built-up land expansion, urban tourism, coastal tourism, land use change, Canggu tourism, urban agglomeration, urban sprawl.

INTRODUCTION

Bali is one of the most popular travel destinations in the world because of its stunning natural surroundings, rich cultural heritage, and friendly locals

(Chin et al., 2017). Every year, the island welcomes millions of tourists from both domestic and foreign countries, and it makes a significant economic contribution to Indonesia (Law et al., 2016). Facilities and supporting infrastructure for tourism have rapidly grown to meet this demand. However, the rate of expansion has exerted pressure on environmental management and spatial planning, particularly in coastal areas that serve as the foundation for the growth of the tourism industry.

In Bali, overtourism has emerged as a major issue (Dodds and Butler, 2019). It refers to visitor numbers that are higher than what a destination can sustainably handle (Milano et al., 2019). Both Canggu and the neighboring Tanah Lot area exhibit the problem (Utama et al., 2024). Within ten years, the landscapes that were formerly primarily composed of green space and agriculture have changed into popular tourist destinations. The area's natural beauty, laid-back vibe, and easy accessibility are the reasons for the activity shift from Kuta to Canggu; however, the area's rapid development has resulted in ongoing traffic, declining air quality, increased waste and greenhouse gas emissions (Sunarta et al., 2022; Sunarta and Saifulloh, 2022a, 2022b; Grekousis et al., 2024). These stresses are exacerbated by the growth of built-up land, which also calls into question the long-term viability of Bali's tourism industry.

The land conversion of Canggu coast reflects the dynamics of urbanization typical of quickly developing areas (Suamba et al., 2022). Competition for land is heightened by population growth and the growing need for social, economic, as well as tourism services. Strong accessibility draws investment and concentrates administrative as well as economic activities, which speeds up conversion. New construction can boost employment and growth, but poor management destroys ecosystems, reduces urban green space, and causes spatial conflict.

A reliable method for monitoring these changes over long periods of time and over wide regions is remote sensing. Cost-effective analysis of land cover dynamics is made possible by multi-temporal satellite imagery, and the Landsat program provides a lengthy, continuous archive that goes back to 1972. The current sensors that provide spatial and temporal resolutions appropriate for in-depth change detection include Landsat 8 OLI/TIRS and Landsat 9 OLI-2/TIRS-2 (Hemati et al., 2021, Wulder et al., 2019).

The index-based built-up index (IBI) was used in this study to identify and assess the growth of built-up areas in Canggu and nearby coastal villages. In order to suppress the backgrounds of water and vegetation and enhance the built-up signal, Xu (2008) developed the IBI, which combines NDBI, SAVI, and MNDWI. According to reports, the accuracy of the Landsat 7 and Landsat 8 applications was 88.86% and 82.52%, respectively (Estoque and Murayama,

2015). In Tehran, comparisons revealed that the overall accuracy of the IBI was 87.66%, while the Urban Index, NDBI, and Normalized Difference Impervious Surface Index were 81.67%, 81.91%, and 52.20%, respectively (Ezimand et al., 2018). Other studies in Chbar Ampov District, Phnom Penh, confirm strong results with overall accuracy of 95–98% and Kappa values of 0.85–0.88 (Mohiuddin et al., 2023). They also note that IBI yields positive values over built-up areas while filtering water and vegetation, improving extraction precision (Kaur and Pandey, 2022).

The issue of overtourism in Bali has not been widely examined by previous researchers. Recent research publications, especially case studied in Canggu shows that residents experience typical disruptions of overtourism, including an influx of long-stay foreign visitors, noise pollution, traffic congestion, rapid gentrification, and inter-community conflict. Still, people who live there tend to make sense of these things (Suyandnya et al., 2025). Another study on how tourists feel about tourism infrastructure found a modest positive link between infrastructure density and perceived overcrowding. This means that infrastructure can make visitors unhappy (Antonio and Alamsyah, 2024). A subsequent study examining travelers' opinions of overtourism reveals that destination sentiment averages 70% positive, with certain sites falling below this average, indicating less fulfilling visitor experiences. A strong correlation between tourist numbers and the physical environment indicates that environmental pressure increases as visitor numbers grow (Khairina and Irawan, 2025).

Many recent studies focus only on the tourist perspective, so the information presented in this paper is novel and adds complexity by examining impacts through built-up land expansion. This research aimed to detect built-up land from Landsat satellite imagery, then analyze the expansion of built-up land over a decade (2014–2024). The authors provided the first village-scale, reproducible dataset and maps that quantify where and how quickly built-up land expanded during the recent overtourism surge in Canggu-Bali, supplying decision-ready information for spatial planning and growth control. It was hypothesized that built-up area increased significantly over 2014–2024, which is in line with the phenomenon of overtourism in this tourist area. The resulting indicators and maps

support local government in controlling land conversion and in formulating or refining regional spatial planning regulations that protect blue-green infrastructure while accommodating tourism demand.

METHODS

Research site

The study concentrated on Bali's southern coastal corridor, which runs from Canggu to the Tanah Lot tourist destination. Between 8°36'00" and 8°40'00" S and 115°4'00" and 115°11'00" E, the study area spans 5,968.98 hectares (Figure1). Twelve administrative villages spread over three subdistricts in two regencies are included. Mengwi Sub-district (Pererenan, Tumbak Bayuh, Munggu, Cemagi) and North Kuta Sub-district (Kerobokan, Kerobokan Kelod, Tibubeneng, Canggu) in

Badung Regency were investigated. Kediri Sub-district (Beraban, Belalang, Pangkung Tibah, and Bengkel) in Tabanan Regency was visited.

This corridor was chosen because, with Petitenget Beach, Canggu Beach, and Tanah Lot as its anchors, it is a significant hub for the growth of tourism. The region is ideal for spatial analysis of tourism-driven urbanization because of the rapid expansion of amenities and attractions like Atlas Beach Club and Bali Beach Glamping, which have increased land conversion. The necessity of keeping an eye on land-use change and its effects on the environment is highlighted by the recent transition from vegetated and agricultural land to built-up uses.

Data sources and preprocessing

Landsat 8 imagery (USGS Landsat 8 Collection 2 Tier 1 TOA Reflectance) from the Google Earth Engine archive was used. The radiometric

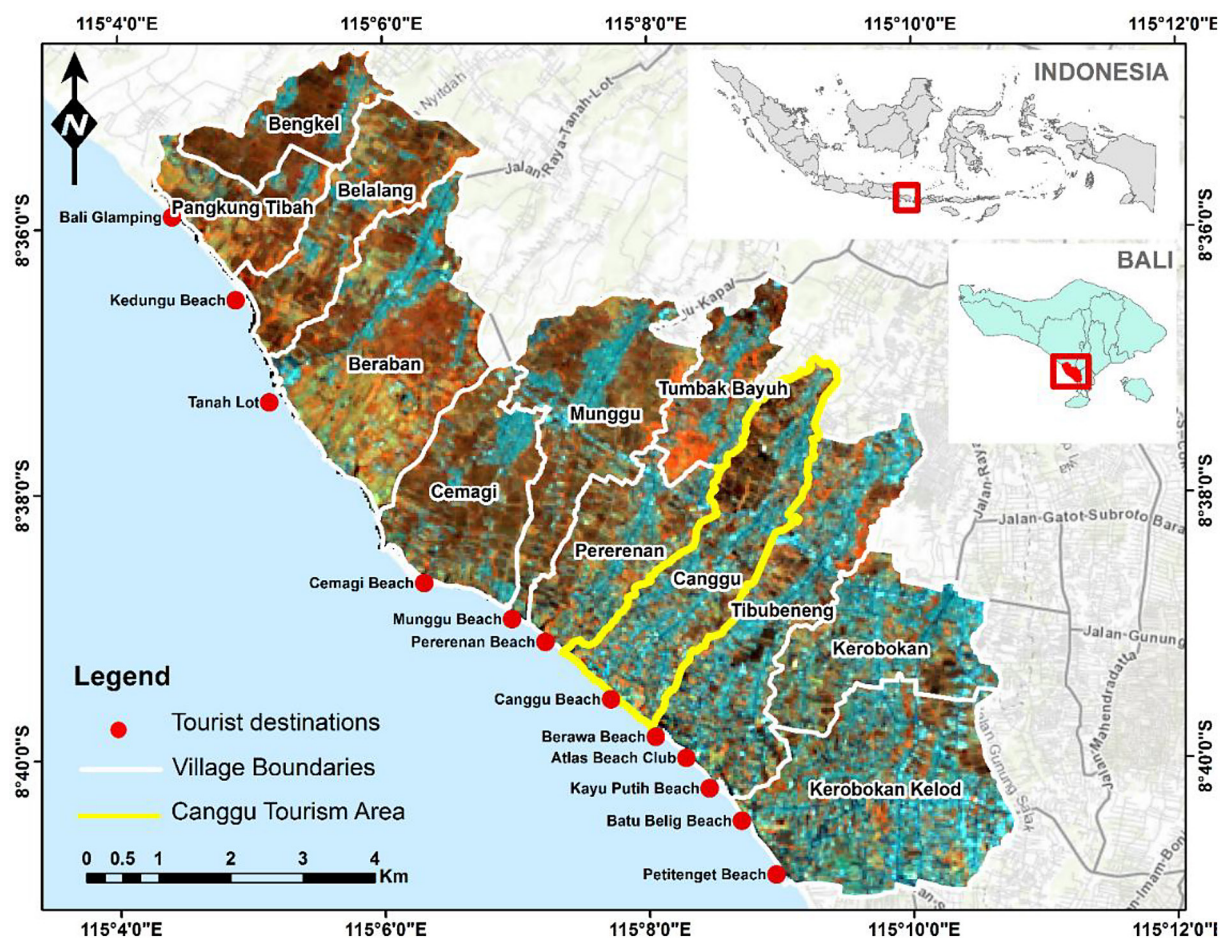


Figure 1. Area study in the Canggu tourist area, village boundaries (white) and coastal tourist destinations (red), with the approved Canggu tourist area (yellow). Visualization with Landsat basemap with RGB (NIR-SWIR1-SWIR2) where the bold colors indicate built-up areas

and geometric quality of Tier 1 data, which facilitates land-change analysis, led to their selection (USGS, 2021). For every year from 2014 to 2024, the time frame runs from March to December. In order to validate the choice of IBI threshold and to assist in the interpretation of built-up change, historical Google Earth imagery was also studied.

Preprocessing was done to guarantee temporal comparability and maximize usable observations. The QA_PIXEL band was used to apply cloud and cloud-shadow masking. Those pixels were filtered to keep only clear-sky observations after a bitwiseAnd operator identified cloud and shadow bits. By lowering noise, this step enhanced the caliber of calculations that followed. In accordance with Chander et al. (2009), top-of-atmosphere (TOA) Reflectance from Landsat 8 Collection 2 Tier 1 for radiometric calibration were used in order to standardize reflectance over time. Reliable multi-temporal comparisons are supported by this adjustment, which takes sensor and illumination variations into account.

Calculation of the index-based built-up index (IBI)

An extremely efficient algorithm called the IBI was created to precisely identify and evaluate built-up areas using satellite imagery. In order to distinguish urbanized areas from other types of land cover, this index combines several spectral indices. The following bands of Landsat 8 OLI data were used in this study: green (Band 3: 0.53–0.59 μm), red (Band 4: 0.64–0.67 μm), near-infrared (NIR, Band 5: 0.85–0.88 μm), and shortwave infrared (SWIR1, Band 6: 1.57–1.65 μm). Three important spectral indices, i.e. NDBI, SAVI, and MNDWI are integrated by IBI.

a) Normalized difference built-up index (NDBI)

According to Zhao et al. (2003), NDBI is a spectral index created especially to identify urbanized or built-up areas. It separates urban features from other types of land cover by using the reflectance difference between the NIR and SWIR1 bands. Equation 1 is used to calculate NDBI:

$$NDBI = \frac{SWIR\ 1 - NIR}{SWIR\ 1 + NIR} \quad (1)$$

In comparison to the NIR band, built-up areas typically exhibit higher reflectance in the SWIR1 band. As a result, urban or developed areas are

usually indicated by positive NDBI values, whereas non-built-up features like vegetation or water are represented by negative or nearly zero values. Because of its ease of use and efficiency in identifying populated areas through multispectral satellite imagery, this index is frequently utilized in urban studies.

b) Soil-adjusted vegetation index (SAVI)

A modified form of the normalized difference vegetation index (NDVI), the SAVI is intended to enhance vegetation detection in regions with high soil exposure and little vegetation cover (Huete, 1988). Equation 2 displays the mathematical formula.

$$SAVI = \frac{NIR - Red \times 1 + L}{NIR + Red + L} \quad (2)$$

By lessening the impact of bare soil reflectance on the vegetation signal, the constant L, which is usually set to values between 0 and 1 (usually 0.5), makes up for soil brightness. SAVI is more dependable for assessing vegetation dynamics in complex landscapes because of this modification, which guarantees that it works well in areas with little vegetation cover or mixed with exposed soil, such as urban or semi-arid regions.

c) Modified normalized difference water index (MNDWI)

A spectral index called the MNDWI was created to enhance the identification of water features in satellite imagery. It successfully separates water features from other types of land cover by utilizing the difference in reflectance between the green and shortwave infrared (SWIR1) bands (Xu, 2006). Equation 3 displays the mathematical formula.

$$MNDWI = \frac{Green - SWIR\ 1}{Green + SWIR\ 1} \quad (3)$$

Positive MNDWI values are the result of the high reflectance of water bodies in the Green band and low reflectance in the SWIR1 band. On the other hand, land features like vegetation and soil usually produce values that are negative or very close to zero. By substituting the near-infrared (NIR) band with SWIR1, which lessens soil interference, the MNDWI provides improved accuracy over its predecessor, NDWI. Because of this, MNDWI works especially well in urban and semi-urban areas, where bare soil and built-up

structures can make it more difficult to detect water. Because of its increased accuracy, MNDWI is a useful tool for land-use classification and hydrological studies.

d) Index-based built-up index

These three indices were combined to calculate IBI using the Equation 4:

$$IBI = \frac{NDBI - \frac{SAVI + MNDWI}{2}}{NDBI + \frac{SAVI + MNDWI}{2}} \quad (4)$$

While other land features, like vegetation and water bodies, have values near zero or negative, built-up areas are given positive values by IBI. In satellite imagery, this distinction makes it easier to identify built-up land. By combining these indices, the IBI algorithm can reduce background noise, such as pixels from vegetation and water, and extract built-up land with greater accuracy. Prior research has confirmed that this algorithm performs exceptionally well in detecting urban areas under a range of environmental and geographic circumstances. Because of its dependability as well as high temporal and spatial resolution of Landsat 8, IBI is a perfect tool for examining changes in land use in the areas that are rapidly urbanizing, like the tourist destinations of Canggu and Tanah Lot.

Satellite image interpretation

After computing the IBI, we converted each raster to a binary map using year-specific thresholds. The 2016 and 2020 scenes used a threshold of -0.10 ; all other years used -0.08 . The thresholding strategy followed the Otsu method (Otsu, 1979), which underpins the IBI procedure described by Xu (2008). Although Xu reported an effective threshold near 0.013 in his case study, the values were adjusted to local conditions after visual validation against high-resolution Google Earth imagery.

For an annual IBI image, let its histogram have L bins with normalized probabilities p_k ($\sum_{k=1}^L p_k = 1$). Define the cumulative probability $\omega(t) = \sum_{k=1}^t p_k$, the cumulative first moment $\mu(t) = \sum_{k=1}^t k p_k$, and the global mean $\mu_T = \sum_{k=1}^L k p_k$. The between-class variance for a threshold at bin t calculated by Equation 5, and the optimal Otsu threshold index by Equation 6.

$$\sigma_b^2(t) = \frac{[\mu_T \omega(t) - \mu(t)]^2}{\omega(t) [1 - \omega(t)]} \quad (5)$$

$$t^* = \arg \max_{t \in \{1, \dots, L-1\}} \sigma_b^2(t) \quad (6)$$

Let T^* be the IBI value at the center of bin t^* . The binary classification is then (Equation 7)

$$B(x) = \begin{cases} 1, & IBI(x) \geq T^* \text{ (built-up)} \\ 0, & IBI(x) < T^* \text{ (non-built-up)} \end{cases} \quad (7)$$

where: p_k is the probability of the k -th IBI histogram bin; $\omega(t)$ is the cumulative probability up to bin t ; $\mu(t)$ is the cumulative first moment; μ_T is the global mean of the histogram; $\sigma_b^2(t)$ is the between-class variance; t^* is the maximizing threshold bin; T^* is the corresponding IBI threshold value; and $B(x)$ is the binary built-up label at pixel x .

Published work shows that IBI thresholds vary by season, landscape, and sensor characteristics. Reported examples include -0.070 (Es-toque and Murayama, 2015), -0.083 (Bouhen-nache et al., 2019), 0.26 for 2013 and 0.20 for 2016 (Sekertekin et al., 2018), and -0.336 (Xi et al., 2019). More recent analyses also note year-to-year variation linked to regional factors (Kebede et al., 2022). These differences reflect how vegetation cover, land-use composition, and atmospheric conditions shape reflectance; for example, rainy-season vegetation can resemble bare soil, complicating separation from built-up surfaces. In contrast, simpler land-use mosaics (e.g., water bodies, urban forests, and dense built-up cores) tend to yield more stable thresholds.

Following thresholding, the rasters were reclassified to built-up = 1 and non-built-up = 0 and quantified area by village using the Zonal Histogram tools in ArcGIS 10.8. This produced a consistent spatial dataset of built-up extent for each administrative unit and provided the basis for assessing decadal land-conversion dynamics in the Canggu coastal tourism of Bali.

Quantifying built-up expansion

To report built-up area expansion consistently, the portion of end-year built-up land that was newly converted since the baseline year was quantified. This expresses expansion as a percentage of the final built-up area (Equation 8).

$$E_{t_1 \rightarrow t_2} = \frac{A_{\text{built}}(t_2) - A_{\text{built}}(t_1)}{A_{\text{built}}(t_2)} \times 100\% \quad (8)$$

where: $E_{t_1 \rightarrow t_2}$ is built-up expansion between years t_1, t_2 (%); $A_{\text{built}}(t)$ is built-up area at year t (ha), obtained from the binary IBI raster (count of built-up pixels \times pixel area); t_1 is baseline year; t_2 is later year.

RESULTS AND DISCUSSION

Index-based built-up index

Built-up land has clearly expanded throughout the study area, according to the Landsat 8 time-series analysis. Built-up surfaces are represented by red zones in Figure 2, which show a noticeable spread from 2014 to 2024. Additionally, mean IBI values increase over time, rising from -0.19 in 2014, -0.22 in 2016, -0.18 in 2018, -0.21 in 2020, -0.20 in 2022, and -0.17 in

2024 (Figure 2). The 2024 highest mean shows a stronger built-up signal and is consistent with the mapped expansion. The vegetation dynamics surrounding tourist zones, where agricultural and vacant parcels displayed regrowth and increased canopy density, are reflected in the lowest mean in 2016. As agricultural fields momentarily restored vegetation cover along the Pererenan and Pangkung Tibah coasts in 2020, the annual mean decreased in comparison to 2018 and 2022 (Figure 3). Built-up areas exhibited stable spectral behavior that permitted consistent separation from other land covers in spite of these transient fluctuations (As-syakur et al., 2012; Rasul et al., 2018).

Extensive conversion along the main tourism corridor is confirmed by a pixel-by-pixel comparison between 2014 and 2024 (Figure 3). A thorough replacement of agricultural land by built-up surfaces can be seen when tracking values from the southern region, close to Como Beach Club, northward along Padang Lingjong Road and the nearby Pantai Batu Bolong Road. The flanks of

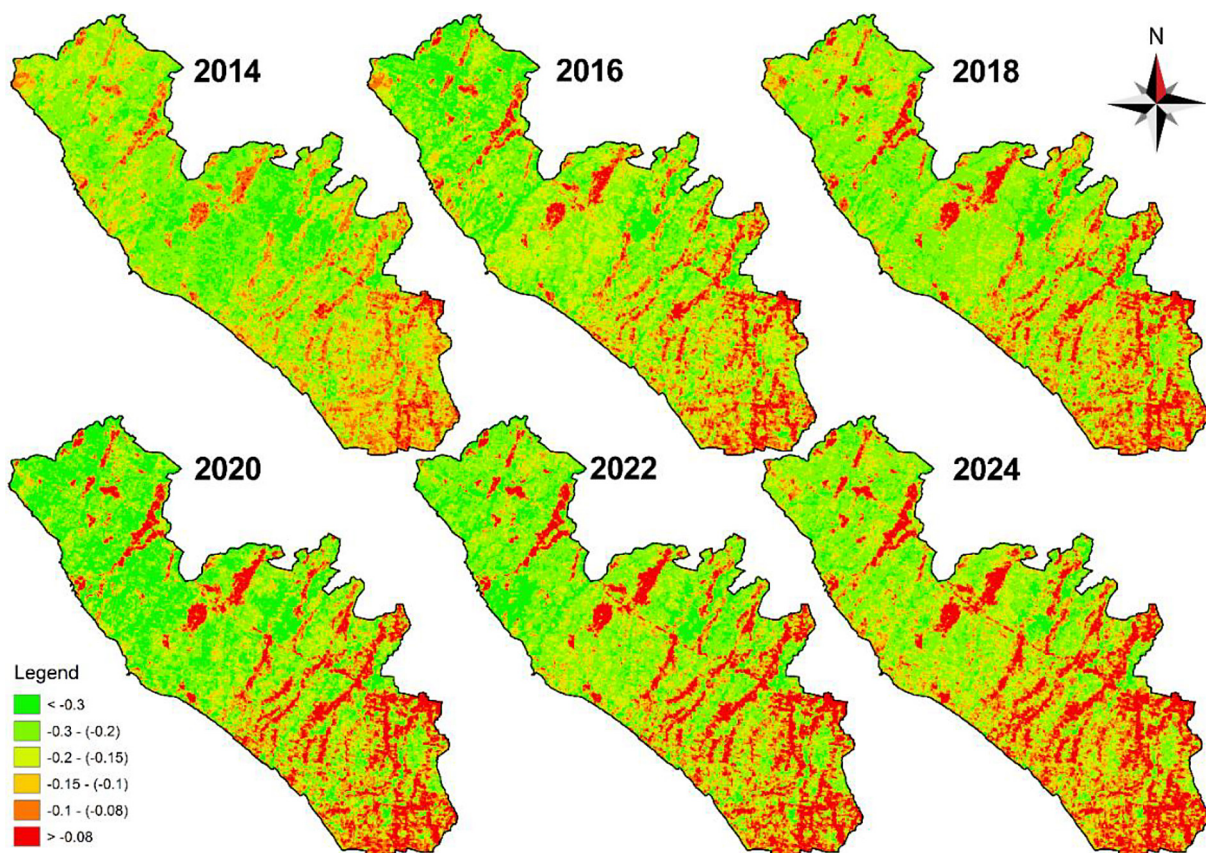


Figure 2. Multi-temporal index-based built-up index (IBI) maps (2014–2024) for the Canggu tourism areas, green indicates low IBI (< -0.30), and yellow–red indicates increasing IBI and higher likelihood of built-up surfaces (red > -0.08)

these roads, which run north to Canggu Village, become areas of rapid change. These trends show how the demand for tourism infrastructure is driving rapid urbanization, underscoring the necessity of ongoing observation and evidence-based spatial planning to control growth while preserving remaining green space.

Built-up expansion

The IBI raster was reclassified into two classes: built-up and non-built-up. Water bodies, shrubs, plantations, urban forests, rice fields, and other vegetated land are all considered to be part of the non-built-up class. According to earlier research, construction sites with bare soil frequently display spectra resembling those of impervious surfaces and were probably mapped as built-up (Kaur and Pandey, 2022).

The Canggu-Tanah Lot corridor exhibits a consistent increase in the amount of built-up area between 2014 and 2024. According to Table 1, the amount of built-up land was 1,107.27 hectares in 2014, 1,160.19 hectares in 2016, 1,191.69 hectares in 2018, 1,207.71 hectares in 2020, 1,247.40 hectares in 2022, and 1,425.24 hectares in 2024. The annual growth is consistent with the fast urbanization of the region brought on by tourism and the expansion of auxiliary infrastructure.

With a total increase of 22.31% over the course of ten years, this expansion shows a substantial change in the land use of the area. The largest change, which accounted for more than half of the total change over the course of the study, happened during the 2022–2024 period,

when built-up land increased by 12.48% (Figure 4). This quick growth coincides with the spike in post-pandemic travel and the construction of infrastructure to meet the rising demand. Different rates of expansion are revealed when the data is broken down into intervals. Built-up land grew 4.56% between 2014 and 2016, then 2.64% between 2016 and 2018 and 1.33% between 2018 and 2020. Prior to the dramatic increase in the last two years of the study, a moderate acceleration of 3.18% growth was noted between 2020 and 2022.

This development boom coincides with the post-pandemic surge in travel. The main driver of land-use change, particularly along Bali's southern coast, was the swift recovery in foreign arrivals (Antara and Sumarniasih, 2024; Wirata and Ermawati, 2024; Wisnumurti, 2023). The number of arrivals increased from 1,310 in February 2022 to 454,801 in February 2024, and from 246,504 in July 2022 to 625,665 in July 2024 (Central Bureau of Statistics, 2024). The recovery strength and tenacity were highlighted by the average monthly growth of 71.22% from February to October.

The demand for lodging, entertainment, and other tourism-related services increased as the number of visitors increased, hastening the conversion of vegetated and agricultural land into urban areas. According to the results of the remote sensing, the built-up areas in Canggu and the surrounding areas have significantly expanded, extending northward toward Tanah Lot. These trends monitor the growth of supporting infrastructure and the escalation of tourism-related activities.

The boom increased social and environmental pressures while also bringing about economic

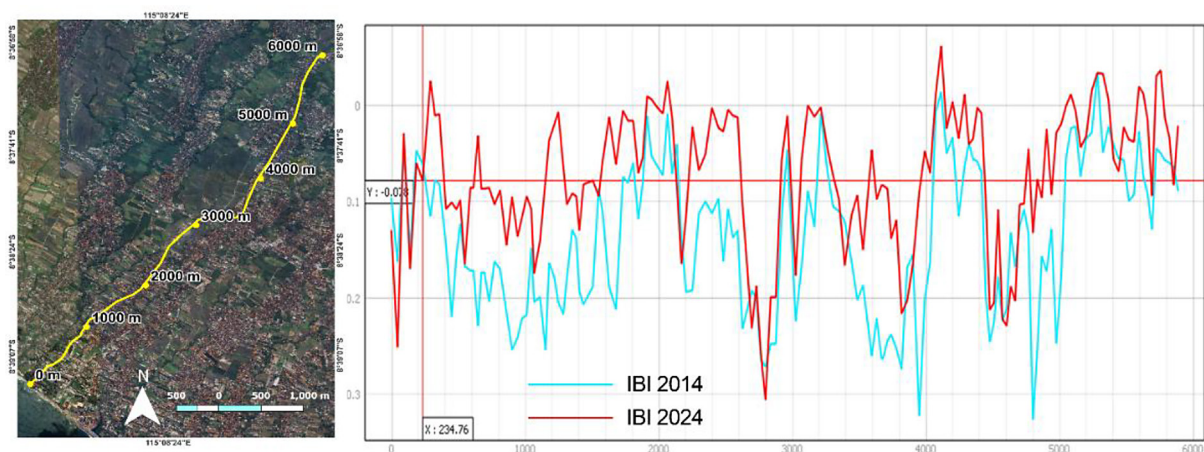
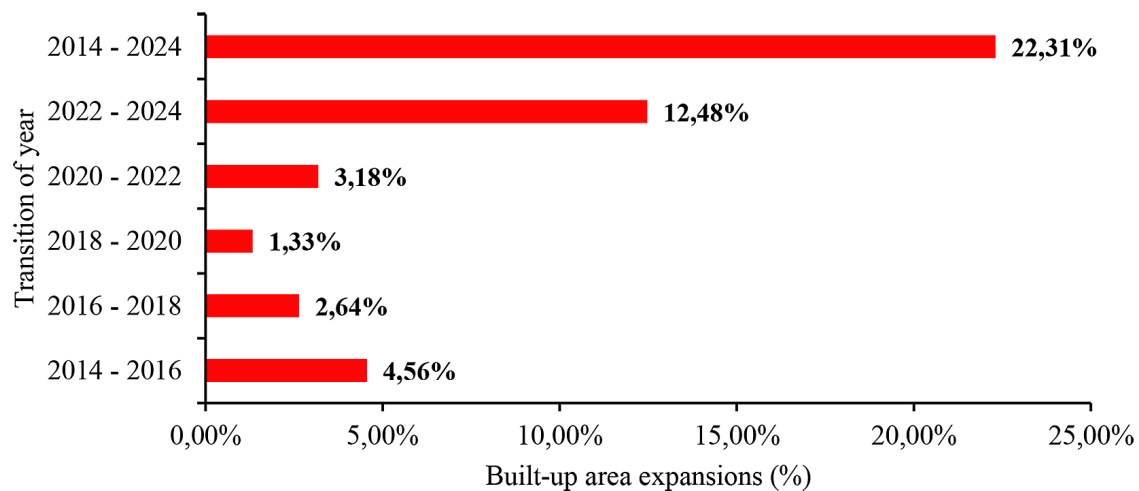


Figure 3. Pixel value profile graph of the index-based built-up index (IBI) comparing 2014 and 2024 in the Canggu central tourism activities

Table 1. Statistical summary of built-up and non-built-up area coverage (2014–2024)

Years	Built-up areas		Non-Built-up areas	
	Area (pixel)	Area (ha)	Area (pixel)	Area (ha)
2014	12303	1107.27	54019	4861.71
2016	12891	1160.19	53431	4808.79
2018	13241	1191.69	53081	4777.29
2020	13419	1207.71	52903	4761.27
2022	13860	1247.40	52462	4721.58
2024	15836	1425.24	50486	4543.74

**Figure 4.** Percentage of built-up land expansion for each biannual transition (2014–2024)

gains. The local and international media have extensively covered the visible signs of overtourism, which include congestion, increased waste, deteriorated air quality, and vegetation loss (Kompas, 2024; Responsible Travel, 2024; Baloch et al., 2023). Continuous monitoring and spatial planning that supports growth while preserving green space and coastal ecosystems are necessary, according to the evidence (Figure 5).

Land use changes

The map shows a clear coastal gradient in urbanization. Yellow marks long-established built-up areas; these form a continuous core in the southeast around Kerobokan Kelod and Kerobokan. Moving northwest through Tibubeneng and Canggu, dense red pixels appear around Berawa, Kayu Putih, and Canggu Beaches, indicating recent conversion of agricultural or open land. This band of new construction extends past Pererenan and Munggu toward Cemagi and Tanah Lot, where red patches cluster near beach nodes and tourism facilities. Farther northwest, red concentrations

near Kedungu and Pangkung Tibah mark emerging expansion fronts along the urban edge. Inland, red spurs cut into the teal background (unchanged non-built-up) in Tumbak Bayuh, Pererenan, and Munggu, tracing lot-by-lot infill along roads and village centers. Although sizeable teal areas remain between settlements, their fragmentation signals an ongoing loss of non-built land. Analysis of the 2014–2024 period confirms these patterns (Figure 6).

The highest conversion rates from non-built-up to built-up occur in Kerobokan Kelod (2.95%), Tibubeneng (2.14%), Canggu (1.85%), and Kerobokan (1.39%). All exceed the study-area average and reflect strong demand for tourism-related construction. Kerobokan and Kerobokan Kelod act as gateways to the southern tourism belt, concentrating villas, restaurants, as well as commercial services that serve growing domestic and international flows. As development pushed outward, Tibubeneng positioned between Canggu and Kerobokan converted land rapidly and now functions as a transition zone with high-end

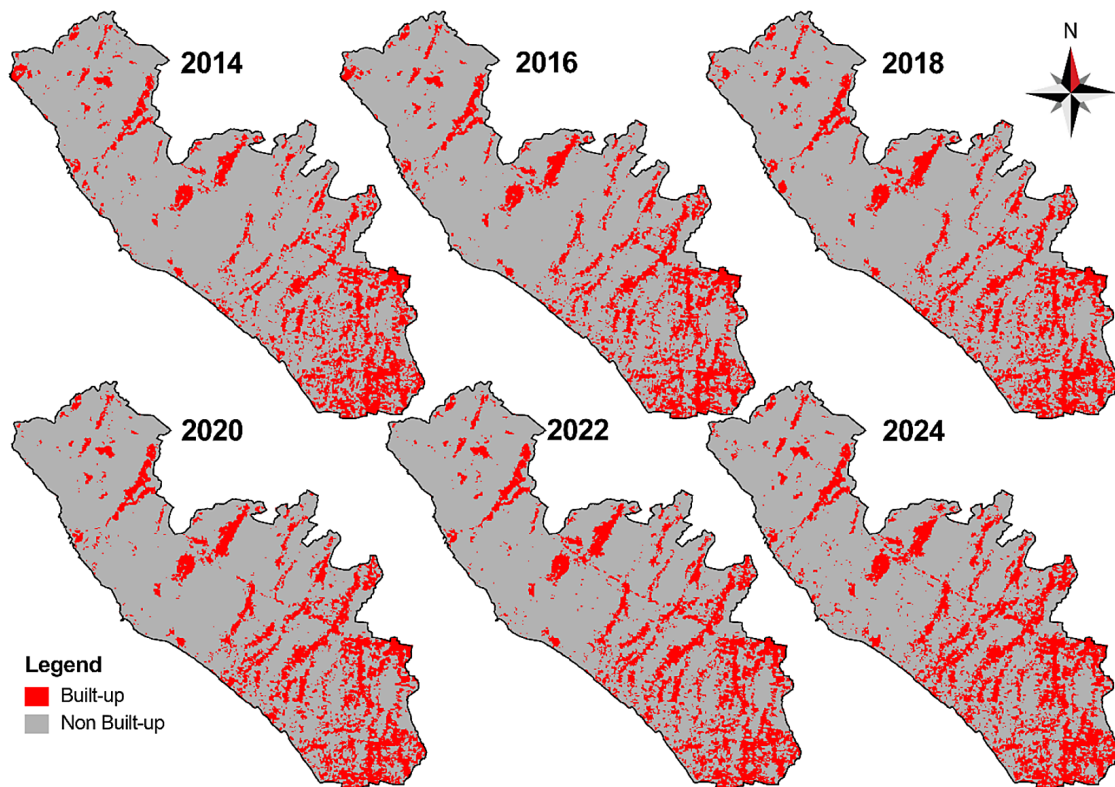


Figure 5. Spatial distribution of built-up area expansion (red zones) during the 2014–2024 period

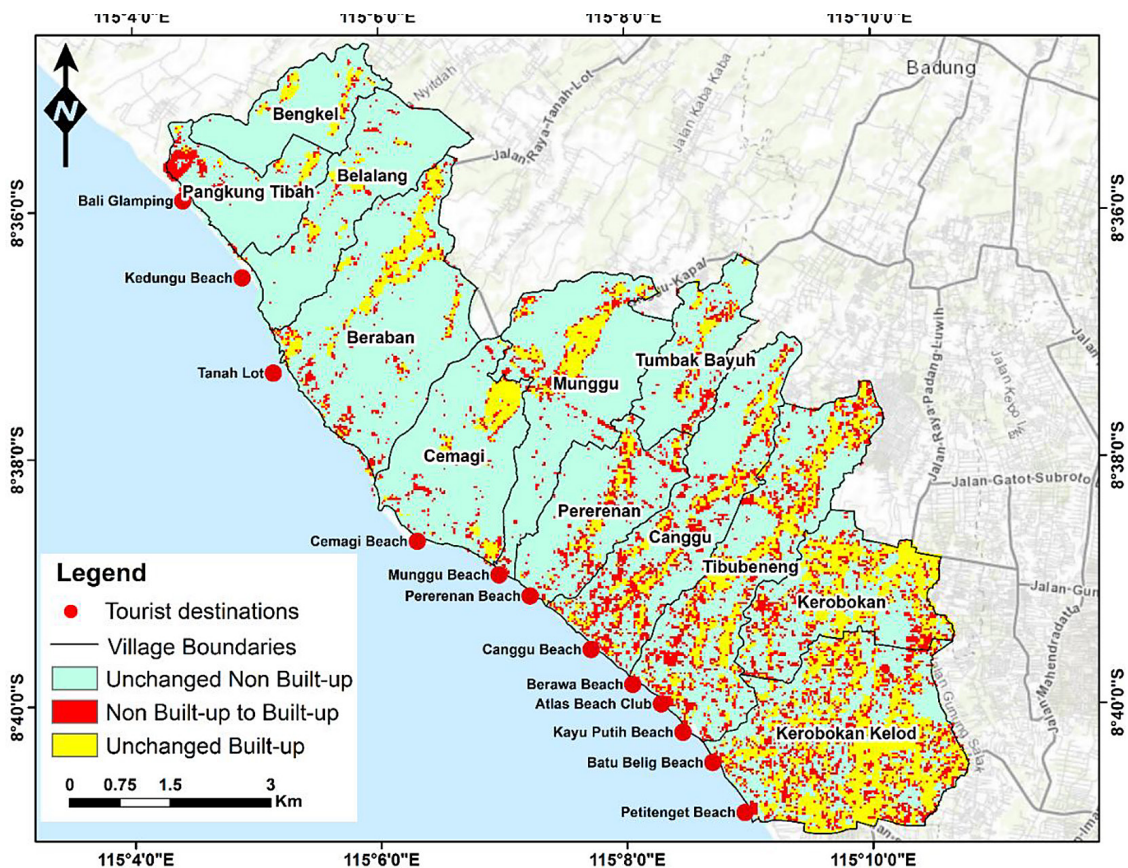


Figure 6. Land conversion map of the Canggu tourism areas, with emphasis on red-shaded zones representing the expansion of built-up areas along coastal tourism destinations between 2014 and 2024

lodging and entertainment. This shift, however, increases pressure on local ecosystems as well as water and waste services.

Urbanization has continued to spread west from Canggu toward Tanah Lot. Although rates in Pererenan, Cemagi, and Beraban are lower 0.80–0.82%, they still indicate steady expansion into amenity-rich coastal landscapes. Cemagi and Beraban attract investment in luxury accommodation, while Pererenan is emerging as a quieter alternative to the Canggu beachfront. Even villages with comparatively low pressure (Pangkung Tibah, Belalang, and Bengkel) show measurable conversion of 0.13–0.43% (Figure 7). Together, these results show that as tourism infrastructure and urban services extend along the coast and inland corridors, no locality in the study area remains unaffected by land-use transformation.

The mapped changes show a two-stage dynamic overall. Development initially focused on core nodes, like Kerobokan, Kerobokan Kelod, and Tibubeneng. As those nodes became

saturated, the focus shifted to nearby villages, resulting in corridor-wide sprawl from Canggu to Tanah Lot. There are significant planning and sustainability ramifications (Warastuthi et al., 2024). High accessibility areas are subject to disproportionate pressure, and major conversion can worsen environmental quality by decreasing carbon reserves, increasing the risk of flooding, and reducing green space (Andyana et al., 2023; Diara et al., 2024; Sudarma et al., 2024).

Built-up expansion and overtourism

Built-up land expanded sharply from the Canggu tourist area to the Tanah Lot destination along Bali's southern coast. The obtained time-series results show an average built-up area of 1,182.85 ha (4.84%) per year. There was a clear surge of 12.48% during 2022–2024, coinciding with the transition from the COVID-19 pandemic to the post-pandemic period. Because literature on overtourism in Bali, and Canggu in particular, is limited, this interpretation was

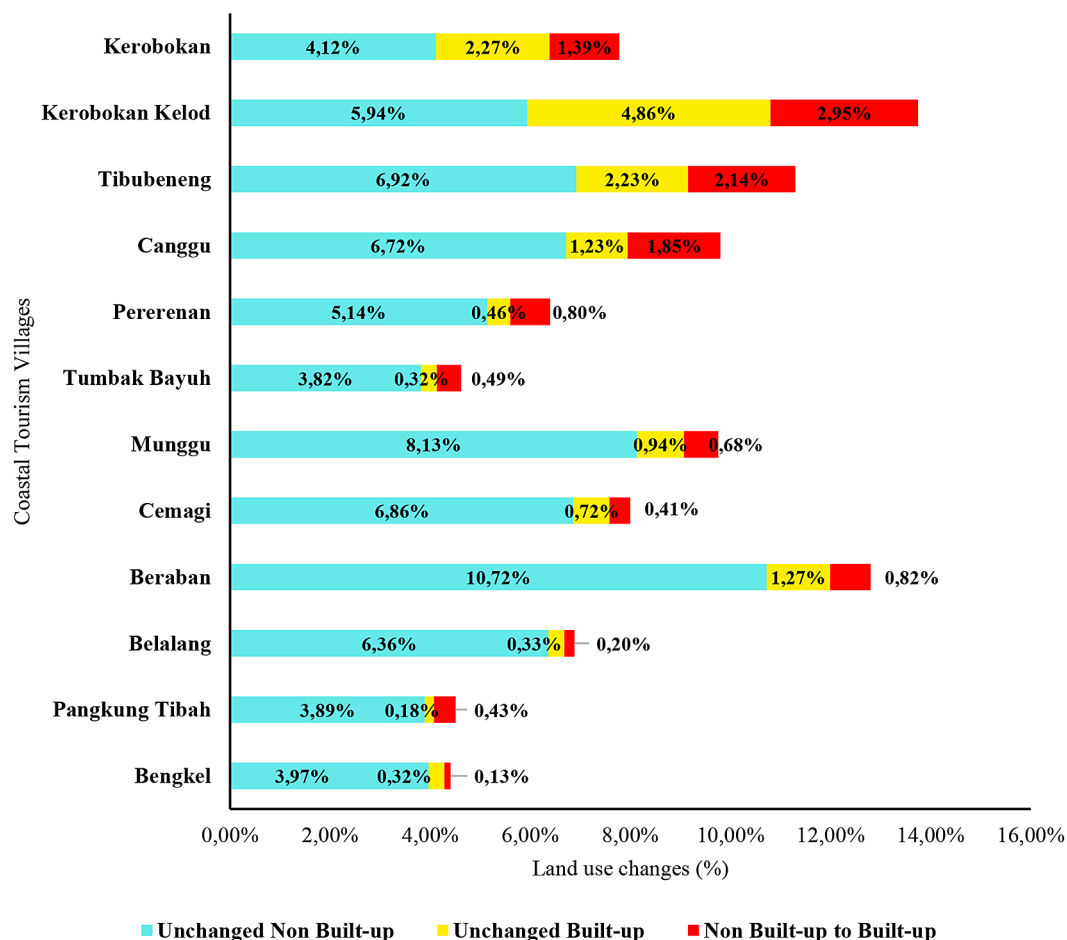


Figure 7. Percentage of land use changes in coastal villages of south Bali tourism area



Figure 8. Photographic views illustrating the transformation of rice field landscapes in Canggu: (a) and (b) depict former agricultural areas now dominated by hotels, villas, and various tourism-related facilities; (c) and (d) show the rapid expansion of built-up infrastructure and tourism amenities in the vicinity of Canggu tourism areas

supported with international media reports. These reports indicate that after the pandemic Bali received 6.33 million international tourists in 2024 and is targeting 6.5 million in 2025; however, only about one-third were recorded as paying the tourism levy, indicating weak local policy enforcement (de Guzman, 2025).

CNA describes “Concrete Canggu,” where low land prices, unregulated growth, and the absence of a coherent master plan have created daily congestion and visible environmental pressure (Paulo and Pardomuan, 2024). SCMP details the on-the-ground reality: the famous Canggu shortcut routinely becomes a car park, with traffic jams and piles of rubbish (Smith, 2024). ABC News (Foreign Correspondent) documents a property boom that has turned rice paddies into “Instagrammable” villas and large-scale projects aimed at foreign residents and digital nomads (see Figure 8a). Local activists describe this change as “from heaven to hell,” with an estimated 1,000 ha of farmland lost each year (Birtles and Waterhouse, 2024).

The Guardian complements this with declassified 1965 spy-satellite imagery compared with 2024 views, visually showing how the coastline from Seminyak to Canggu has shifted from quiet villages to dense rows of resorts and villas; the article links these changes to overtourism,

land-use pressure, and weak early levy collection (Neilson, 2025) see Figure 8c and Figure 8d. Reuters also reports the moratorium as part of a broader national plan to reform tourism, noting about 200,000 foreign residents and issues ranging from crime as well as job competition to waste, as well as 2.9 million foreign visits in the first half of 2024 (Nangoy, 2024). International news outlets also point out that waste and pollution are common signs of too many tourists. Reuters shows how urgent the situation is by showing pictures of beaches full of plastic (Widianto, 2024). Some travel sites go even further and have “No List” features that make people think twice about going to places like Bali, which have too many visitors and a “plastic apocalypse” (Fodor’s Travel, 2024; Vlamis, 2024).

The obtained findings provide the inaugural empirical trajectory that correlates tourism dynamics during prosperous years with spatial urban expansion. The fact that 2022–2024 made the most contribution to the decade’s growth supports the idea that overtourism is linked to land conversion, mobility saturation, waste burdens, and environmental dangers downstream. These numbers give us a way to measure how Bali is changing from a tourist model based on volume to one based on quality.

CONCLUSION

This study bridged a critical evidence gap on overtourism in the Canggu coastal tourism areas by providing corridor-wide, decade-scale, Landsat-based evidence of built-up land conversion using the index-based built-up index. The first village-scale, reproducible dataset and maps that locate as well as characterize the pace and direction of expansion, offering decision-ready information for spatial planning and growth control, were delivered. The findings support the hypothesis that built-up area increased substantially over the study period in ways consistent with the overtourism dynamic in this coastal tourism zone.

Acknowledgments

This work was supported by the DIPA PNPB Universitas Udayana for Fiscal Year 2025 under the Research Implementation Assignment Agreement Letter No. B/229.195/UN14.4.A/PT.01.03/2025, dated April 28, 2025, and by the Kemdiktisaintek Grant from the Directorate of Research and Community Service for Fiscal Year 2025 under Contract No. 121/C3/DT.05.00/PL/2025, dated May 28, 2025.

REFERENCES

1. Andyana, I. W. S., As-Syakur, A. R., Sunarta, I. N., Suyarto, R., Diara, I. W., Susila, K. D., Saifulloh, M., Kusmiyarti, T. B., Wiyanti, W. (2023). Urban tourism expansion monitoring by remote sensing and random forest. *IOP Conference Series: Earth and Environmental Science*, 1180(1). <https://doi.org/10.1088/1755-1315/1180/1/012046>
2. Antara, M., Sumarniasih, M. S. (2024). Structure analysis and growth trends the economy of Bali Province-Indonesia post COVID-19 pandemic. *Asian Journal of Agricultural Extension, Economics & Sociology*, 42(5), 82–98.
3. Antonio, R. S., Alamsyah, A. (2024, December). Analyzing Overtourism Dynamics in Bali: A Data-Driven Approach Using Geospatial Analysis and Text Classification. In: *2024 Beyond Technology Summit on Informatics International Conference (BTS-I2C)* 544–549. IEEE. <https://doi.org/10.1109/BTS-I2C63534.2024.10941993>
4. As-syakur, A. R., Adnyana, I. W. S., Arthana, I. W., Nuarsa, I. W. (2012). Enhanced built-UP and bareness index (EBBI) for mapping built-UP and bare land in an urban area. *Remote Sensing*, 4(10). <https://doi.org/10.3390/rs4102957>
5. Badan Pusat Statistik. (2024). Central Bureau of Statistics Bali. BPS, 1101001. <https://bali.bps.go.id/id>
6. Baloch, Q. B., Shah, S. N., Iqbal, N., Sheeraz, M., Asadullah, M., Mahar, S., Khan, A. U. (2023). Impact of tourism development upon environmental sustainability: a suggested framework for sustainable ecotourism. *Environmental Science and Pollution Research*, 30(3). <https://doi.org/10.1007/s11356-022-22496-w>
7. Birtles, B., Waterhouse, P. (2024, September 11). Inside the real estate gold rush carving up Bali. ABC News. <https://www.abc.net.au/news/2024-09-12/inside-the-building-boom-swallowing-bali/104301044> ABC
8. Birtles, B., Waterhouse, P. (2024, September 11). Inside the real estate gold rush carving up Bali. ABC News. <https://www.abc.net.au/news/2024-09-12/inside-the-building-boom-swallowing-bali/104301044>
9. Bouhennache, R., Bouden, T., Taleb-Ahmed, A., Cheddad, A. (2019). A new spectral index for the extraction of built-up land features from Landsat 8 satellite imagery. *Geocarto International*, 34(14). <https://doi.org/10.1080/10106049.2018.1497094>
10. Chander, G., Markham, B. L., Helder, D. L. (2009). Summary of current radiometric calibration coefficients for Landsat MSS, TM, ETM+, and EO-1 ALI sensors. *Remote Sensing of Environment*, 113(5). <https://doi.org/10.1016/j.rse.2009.01.007>
11. Chin, W. L., Haddock-Fraser, J., Hampton, M. P. (2017). Destination competitiveness: evidence from Bali. *Current Issues in Tourism*, 20(12). <https://doi.org/10.1080/13683500.2015.1111315>
12. de Guzman, C. (2025, March 28). Can Bali ever solve its overtourism conundrum? TIME. <https://time.com/7272442/bali-overtourism-tourist-tax-behavior-rules-foreign-visitors-economy-indonesia/>
13. Diara, I. W., Susila, K. D., Wiyanti, W., Sunarta, I. N., Kusmiyarti, T. B., Saifulloh, M. (2024). Exploring the influence of various land use land cover on land surface temperature of coastal tourism areas in Bali Using Landsat 9. *Environmental Research, Engineering and Management*, 80(2), 118–132.
14. Dodds, R., Butler, R. (2019). The phenomena of overtourism: a review. *International Journal of Tourism Cities* 5(4). <https://doi.org/10.1108/IJTC-06-2019-0090>
15. Estoque, R. C., Murayama, Y. (2015). Classification and change detection of built-up lands from Landsat-7 ETM+ and Landsat-8 OLI/TIRS imageries: A comparative assessment of various spectral indices. *Ecological Indicators*, 56. <https://doi.org/10.1016/j.ecolind.2015.03.037>
16. Ezimand, K., Kakroodi, A. A., Kiavarz, M. (2018).

- The development of spectral indices for detecting built-up land areas and their relationship with land-surface temperature. *International Journal of Remote Sensing*, 39(23). <https://doi.org/10.1080/01431161.2018.1488282>
17. Fodor's Travel. (2024, November 13). *Fodor's No List 2025: 15 destinations to reconsider*. <https://www.fodors.com/news/news/fodors-no-list-2025>
 18. Grekousis, G., Sunarta, I. N., Stratoulis, D. (2024). Tracing vulnerable communities to ambient air pollution exposure: A geodemographic and remote sensing approach. *Environmental Research*, 258, 119491.
 19. Hemati, M., Hasanlou, M., Mahdianpari, M., Mohammadimanesh, F. (2021). A systematic review of landsat data for change detection applications: 50 years of monitoring the earth. In *Remote Sensing* 13(15). <https://doi.org/10.3390/rs13152869>
 20. Huete, A. R. (1988). A soil-adjusted vegetation index (SAVI). *Remote Sensing of Environment*, 25(3). [https://doi.org/10.1016/0034-4257\(88\)90106-X](https://doi.org/10.1016/0034-4257(88)90106-X)
 21. Hughes, R. A. (2024, September 13). 'We must avoid tourists becoming public enemies': Ban on new hotels as overtourism threatens Bali. Euronews. <https://www.euronews.com/travel/2024/09/13/we-must-avoid-tourists-becoming-public-enemies-ban-on-new-hotels-as-overtourism-threatens- euronews>
 22. Kaur, R., Pandey, P. (2022). A review on spectral indices for built-up area extraction using remote sensing technology. *Arabian Journal of Geosciences*, 15(5). <https://doi.org/10.1007/s12517-022-09688-x>
 23. Kebede, T. A., Hailu, B. T., Suryabhagavan, K. V. (2022). Evaluation of spectral built-up indices for impervious surface extraction using Sentinel-2A MSI imageries: A case of Addis Ababa city, Ethiopia. *Environmental Challenges*, 8. <https://doi.org/10.1016/j.envc.2022.100568>
 24. Khairina, D., Irawan, H. (2025, February). Detecting Early Signs of Overtourism in Bali: Sentiment and Multiclass Analysis Using BERT and LSTM. In *2025 International Conference on Advancement in Data Science, E-learning and Information System (ICADEIS)* 1–7. IEEE. <https://doi.org/10.1109/ICADEIS65852.2025.10933341>
 25. Kompas.id. (2024, January 3). Bali holds the title of overtourism. Kompas.id. retrieved from <https://www.kompas.id/baca/english/2024/01/03/en-bali-menyandang-predikat-overtourism>
 26. Law, A., De Lacy, T., Lipman, G., Jiang, M. (2016). Transitioning to a green economy: The case of tourism in Bali, Indonesia. *Journal of Cleaner Production*, 111. <https://doi.org/10.1016/j.jclepro.2014.12.070>
 27. Milano, C., Novelli, M., Cheer, J. M. (2019). Overtourism and Tourismphobia: A journey through four decades of tourism development, planning and local concerns. In *Tourism Planning and Development*. <https://doi.org/10.1080/21568316.2019.1599604>
 28. Mohiuddin, G., Mund, J. P., Rahaman, K. J. (2023). Detection of Urban Expansion using the Indices-Based Built-Up Index Derived from Landsat Imagery in Google Earth Engine. *GI Forum*, 11(2). https://doi.org/10.1553/giscience2023_02_s18
 29. Nangoy, F. (2024, August 30). *Indonesia to reform tourism on tropical island Bali, senior minister says*. Reuters. <https://www.reuters.com/world/asia-pacific/indonesia-reform-tourism-tropical-island-bali-senior-minister-says-2024-08-30/> Reuters
 30. Neilson, M. (2025, February 24). *Rice paddies to mega resorts: Declassified spy satellite images reveal Bali's transformation*. The Guardian. <https://www.theguardian.com/world/2025/feb/25/bali-transformation-tourism-declassified-spy-satellite-reports-nusantara-atlas> The Guardian
 31. Otsu, N. (1979). Threshold selection method from gray-level histograms. *IEEE Trans Syst Man Cybern*, SMC-9(1). <https://doi.org/10.1109/tsmc.1979.4310076>
 32. Paulo, D. A., Pardomuan, L. (2024, April 14). *Not quite the Bali it used to be? This is what overtourism is doing to the island*. CNA. <https://www.channelnewsasia.com/cna-insider/overtourism-bali-paradise-lost-canggu-world-heritage-site-culture-4260606> CNA
 33. Rasul, A., Balzter, H., Ibrahim, G. R. F., Hameed, H. M., Wheeler, J., Adamu, B., Ibrahim, S., Najmaddin, P. M. (2018). Applying built-up and bare-soil indices from Landsat 8 to cities in dry climates. *Land*, 7(3). <https://doi.org/10.3390/land7030081>
 34. Responsible Travel. (2024). *Bali overtourism. Responsible Travel*. Retrieved December 31, 2024, retrieved from <https://www.responsibletravel.com/holidays/bali/travel-guide/overtourism>
 35. Reuters. (2024, September 10). *Bali considering a ban on new hotels amid overtourism struggles*. CNN. <https://edition.cnn.com/2024/09/10/travel/bali-considering-ban-new-hotels-intl-hnk>
 36. Sekertekin, A., Abdikan, S., Marangoz, A. M. (2018). The acquisition of impervious surface area from LANDSAT 8 satellite sensor data using urban indices: a comparative analysis. *Environmental Monitoring and Assessment*, 190(7). <https://doi.org/10.1007/s10661-018-6767-3>
 37. Smith, D. (2024, July 31). *Why Bali's traffic congestion gets worse every year, and how it is affecting tourism*. South China Morning Post. <https://www.scmp.com/lifestyle/travel-leisure/article/3272268/why-balis-traffic-congestion-gets-worse-every-year-and-how-it-affecting-tourism> South China Morning Post

38. Suamba, I. B. S., Wiryasa, N. M. A., Dwijendra, N. K. A., Putra, I. D. G. A. D. (2022). Characteristics and deviation patterns of agricultural land use in tourism area of Canggu, Bali, Indonesia. *Caspian Journal of Environmental Sciences*, 20(2). <https://doi.org/10.22124/cjes.2022.5591>
39. Sudarma, I., Saifulloh, M., Diara, I. W., As-Syakur, A. (2024). Carbon stocks dynamics of urban green space ecosystems using time-series vegetation indices. *Ecological Engineering & Environmental Technology (EET)*, 25(9).
40. Sunarta, I. N., Saifulloh, M. (2022a). Coastal tourism: impact for built-up area growth and correlation to vegetation and water indices derived from Sentinel-2 remote sensing imagery. *Geojournal of Tourism and Geosites*, 41(2). <https://doi.org/10.30892/gtg.41223-857>
41. Sunarta, I. N., Saifulloh, M. (2022b). Spatial variation of NO₂ levels during the Covid-19 pandemic in the Bali tourism area. *Geographia Technica*, 17(1). https://doi.org/10.21163/GT_2022.171.11
42. Sunarta, I. N., Suyarto, R., Saifulloh, M., Wiyanti, W., Susila, K. D., Kusumadewi, L. G. L. (2022). Surface urban heat island (SUHI) phenomenon in Bali and Lombok tourism areas based on remote sensing. *Journal of Southwest Jiaotong University*, 57(4). <https://doi.org/10.35741/issn.0258-2724.57.4.44>
43. Suyadnya, I. W., Cahyadi, R., Tirtayani, L. A., Nuryani, A. F. (2025). Overtourism sensitivity and tourism development in Canggu, Bali. *Cogent Social Sciences*, 11(1). <https://doi.org/10.1080/23311886.2025.2521364>
44. USGS. (2021). *Landsat Collection 2, level 2 Science Products*. Science for a Changing World (USGS), November.
45. Utama, I., Suardhana, I. N., Sutarya, I. G., Krisma-wintari, N. P. D. (2024). Assessing the impacts of overtourism in Bali: Environmental, socio-cultural, and economic perspectives on sustainable tourism. *Tour. Spectr. Div. Dyn*, 1(2), 81–92.
46. Vlamis, K. (2024, November 28). *15 travel destinations so overrun with tourists that you may not want to visit, according to travel guide Fodor's*. Business Insider. <https://www.businessinsider.com/travel-destinations-avoid-overtourism-crowds-tourists-fodors-2024-11>
47. Walden, M., Salim, N. (2024, September 3). *Bali authorities want to build a train line by 2027. Can it fix the island's traffic?* ABC News. <https://www.abc.net.au/news/2024-09-04/bali-subway-project-tourist-rail-by-2027-traffic/104235836> ABC
48. Warastuthi, M. R., Mahendra, M. S., Paturusi, S. A., Putra, I. (2024). Spatio-temporal changes in green open spaces in tourism areas of Bali, Indonesia and their implications on climate change. *Environment and Ecology Research*, 12(2), 203–213.
49. Widiyanto, S. (2024, September 9). Bali to ban building of some hotels to tackle over-development. Reuters. <https://www.reuters.com/world/asia-pacific/indonesias-bali-wants-ban-building-hotels-villas-media-say-2024-09-09/> Reuters
50. Wirata, G., & Ermawati, N. L. P. T. (2024). Bali Provincial government's efforts in tourism sector recovery during the Covid-19 pandemic. *Global International Journal of Innovative Research*, 2(6), 1187–1200.
51. Wisnumurti, A. A. G. O. (2023). Tourism recovery policy post corona virus disease outbreak 2019 (COVID-19) in Bali Province. *Kasetsart Journal of Social Sciences*, 44(2), 573–584.
52. Wulder, M. A., Loveland, T. R., Roy, D. P., Crawford, C. J., Masek, J. G., Woodcock, C. E., Allen, R. G., Anderson, M. C., Belward, A. S., Cohen, W. B., Dwyer, J., Erb, A., Gao, F., Griffiths, P., Helder, D., Hermosilla, T., Hipple, J. D., Hostert, P., Hughes, M. J., ... Zhu, Z. (2019). Current status of Landsat program, science, and applications. *Remote Sensing of Environment*, 225. <https://doi.org/10.1016/j.rse.2019.02.015>
53. XI, Y., Thinh, N. X., LI, C. (2019). Preliminary comparative assessment of various spectral indices for built-up land derived from Landsat-8 OLI and Sentinel-2A MSI imageries. *European Journal of Remote Sensing*, 52(1). <https://doi.org/10.1080/22797254.2019.1584737>