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Carbon Stocks Dynamics of Urban Green Space Ecosystems Using Time-Series Vegetation Indices

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ABSTRACT

The quantification of carbon stocks has emerged as a critical global issue due to its vital role in ecosystem services amid increasing urbanization and the impacts of global climate change. This study assesses carbon stocks in urban green space (UGS) ecosystems using time-series remote sensing data from 2014 to 2022. Carbon stock computation was derived from vegetation indices obtained from Landsat 8 satellite sensors, specifically the red and near infrared (NIR) bands with central wavelengths of 0.665 µm and 0.705 µm, respectively. The results, based on nine years of annual data, indicate a 24% increase in carbon stocks within UGS ecosystems. However, year-to-year transitions showed significant fluctuations, with a 19% decrease in carbon stocks from 2017 to 2019, and notable increases of 25% and 40% during the 2015–2016 and 2019–2020 periods, respectively. Spatially, carbon stock fluctuations were most pronounced in agricultural ecosystems, which are vulnerable to climate change, especially during El Niño-Southern Oscillation (ENSO) and positive Indian Ocean Dipole (IOD) events that influenced vegetation dynamics, particularly in low-density areas. The most substantial contributors to carbon stocks, exhibiting relatively stable and adaptive patterns to climate change, were mangrove and urban forest ecosystems. From a state-of-the-art perspective, this research addresses a gap in the literature where previous studies focused on calculating carbon for specific periods using various model approaches. Our implementation of a new time series analysis demonstrates that carbon stocks are dynamic, as evidenced by our findings. The results underscore the importance of preserving urban forest ecosystems, which play a significant role in climate change mitigation and the reduction of urban greenhouse gas emissions.

Keywords: climate change, carbon sequestration, urban biodiversity, vegetation dynamics, remote sensing, ENSO and IOD impact, mangrove ecosystems, Denpasar City.

INTRODUCTION

Climate change, driven predominantly by anthropogenic activities, poses one of the most pressing challenges of our time. Central to this phenomenon is the global carbon stock, encompassing carbon stored in forests, soils, oceans, and the atmosphere (Slameršak et al., 2024). This carbon cycle is intricately linked with climate dynamics, as increased carbon emissions lead to elevated atmospheric CO_2 levels, contributing to global warming and climatic alterations (IPCC, 2022). Urban metropolitan areas, characterized by their dense populations and extensive infrastructure, are significant contributors to global carbon emissions. These urban centers not only emit large quantities of carbon dioxide through industrial activities, transportation, and energy consumption but also face unique vulnerabilities to climate change impacts. As hubs of economic activity and human settlement, they play a dual role in both exacerbating and mitigating climate change (Seto and Shobhakar, 2014).

Urbanization and the rapid expansion of built-up land are common issues in major cities worldwide, significantly impacting the environment, including increased air pollution (Liang et al., 2019; Sarker et al., 2024). Denpasar, the center of tourism, government, economy, education, and other activities in Bali Province, Indonesia (Rahayu et al., 2018), exemplifies this phenomenon. Rapid growth in this area has led to the emergence of informal settlements, particularly around commercial zones, green belts, rivers, and perceived unclaimed lands. Over time, these areas have developed into dense settlements, leading to environmental degradation (As-syakur et al., 2023; As-syakur et al., 2010).

This situation has resulted in a reduction of urban green spaces, contributing to increased greenhouse gas emissions (Liu and Russo, 2021). The dynamics of land use and land cover change have become critical topics, garnering significant attention due to various global issues (Nedd et al., 2021; Pandey et al., 2021). Recent research has found that the reduction of urban vegetation contributes to the rise and spread of urban temperatures and is correlated with carbon emissions (Fattah et al., 2021; Zhang et al., 2023). Urban green spaces in city forest ecosystems play a crucial role in sequestering greenhouse gases by converting atmospheric carbon dioxide (CO_2) into carbon (C) stored within forest ecosystem components such as trees, belowground biomass, and soil (Bherwani et al., 2024). Through photosynthesis, forests absorb CO_2 from the atmosphere and store it as forest biomass. Forest biomass contains about 80% of all terrestrial carbon above ground and about 40% of all terrestrial carbon (Lubis et al., 2023). Land conversion, deforestation, forest degradation, and reforestation can alter land cover patterns and change the composition of terrestrial biomass (Merino et al., 2023).

Our case study was conducted in the central capital region of Bali Province, using time series data from 2014 to 2022. During this period, there was significant urban expansion (Adnyana et al., 2023), a drastic increase in land surface temperature (Sunarta et al., 2022), and global climate change effect (Kurniadi et al., 2021; Sulistiyono et al., 2023). In this area, limited green areas exacerbate air pollution issues, highlighting the ineffectiveness of urban regions in mitigating greenhouse gas emissions (Sunarta and Saifulloh, 2022a). We hypothesize that these phenomena impact vegetation dynamics and carbon stocks, which have not yet been fully understood in urban ecosystem areas.

Previous studies primarily focused on developing carbon stock models through the integration of terrestrial field measurements, such as the commonly used Allometric approach, with remote sensing image sensors using data from a single period (Askar et al., 2018; Choudhury et al., 2021), However, their findings have not been fully applicable over extended periods, as weather factors are inherently variable and influence the biophysical and vegetative cover characteristics. To address this research gap, we examined the dynamics of carbon stock using time series data, providing new insights into carbon dynamics and future environmental management and mitigation efforts.

In the province of Bali, previous researchers have conducted land and environmental conservation efforts in highland areas, where land use is dominated by agriculture and forests. These studies focused on identifying soil and environmental degradation (Bhayunagiri and Saifulloh, 2022; Kartini et al., 2023; Trigunasih et al., 2023a) and disaster mitigation (Diara et al., 2022; Suyarto et al., 2023; Trigunasih et al., 2023; Trigunasih and Saifulloh, 2022). By addressing the research gap in coastal urban areas, we aim to contribute a valuable research database that will benefit academics, government agencies, and stakeholders for regional-scale environmental management.

DATA AND METHODS

Research case study

Denpasar City, the capital of Bali Province, Indonesia, is spatially located on the southern coast with an elevation ranging between 0–75 meters above sea level and predominantly flat terrain categorized as 0-8% slope. Geographically, it lies between 8°36’00”S – 8°45’00”S and 115°12’00”E – 115°15’00”E as shown in Figure 1. The total area of the city is 127.78 km², divided into four administrative districts: South Denpasar with the largest area comprising 40%, followed by East Denpasar (20%), North Denpasar (21%), and West Denpasar (19%). From 2020 to 2022, the population of this city consistently increased, with 725,314 people in 2020, 726,600 in 2021, 726,800 in 2022, and 660,980 in 2023. Besides serving as the capital, this area is also a hub for tourism activities, with the number of tourist visits increasing at an average growth rate of 12% per year (Statistik, 2024).

Urban green space ecosystem

Denpasar City boasts urban green space (UGS) with various ecosystems, including mangrove forests along the coast, urban forests in government and tourism areas, and agricultural land. The dominant species in the mangrove forests are *Soneratia alba* and *Rhizophora mucronata*, along with four other species: *Avicennia marina*, *Xylocarpus granatum*, *Bruguiera gymnoriza*, *Thespesia populnea*, and *Ceriops decandra* (Wiradana et al., 2021). In the urban forest ecosystem, common street-shading tree species include *Lagerstroemia speciosa, Samanea saman*, *Plumeria rubra*, *Callistemon viminalis*, *Cerbera manghas*, *and Polyalthia longifolia* (Krisnandika et al., 2019). The agricultural ecosystem commonly features *Oryza sativa* during the wet season and *Zea mays* and *Glycine max* during the dry season. Horticultural and fruit commodities typically found in agricultural land include *Amaranthus viridis*, *Brassica rapa*, *Citrullus lanatus*, and *Cucumis melo* (Sentana et al., 2021). All species within these UGS areas contribute to urban carbon stock values and greenhouse gas absorption, forming the basis for our time-series computation using remote sensing data.

Data used

Landsat 8, launched by NASA in 2013, is a crucial component of the Landsat program, designed to monitor Earth's surface. It is equipped with two main sensors: the Operational Land Imager (OLI) and the thermal infrared sensor (TIRS). The OLI captures data in nine spectral bands, ranging from the visible to the shortwave infrared (SWIR) spectrum, with a spatial resolution of 30 meters for most bands and 15 meters for the panchromatic band (Table 1). The TIRS, in contrast, measures thermal infrared radiation in two bands with a resolution of 100 meters (USGS, 2015).

These high-resolution, multispectral images are invaluable for measuring carbon stock. Vegetation indices such as the normalized difference vegetation index (NDVI) and the enhanced vegetation index (EVI), derived from Landsat 8's spectral data, are commonly used to assess vegetation health and density. NDVI, calculated using the red and near-infrared (NIR) bands, assists in estimating biomass by identifying areas with high photosynthetic activity (Tucker, 1979).

Additionally, the SWIR bands aid in detecting moisture content in vegetation, which is crucial for accurate biomass and carbon stock estimation. By combining data from various spectral bands, researchers can create detailed maps of forest cover, identify deforestation and degradation areas, and monitor changes over time. The thermal bands of TIRS also provide information on land

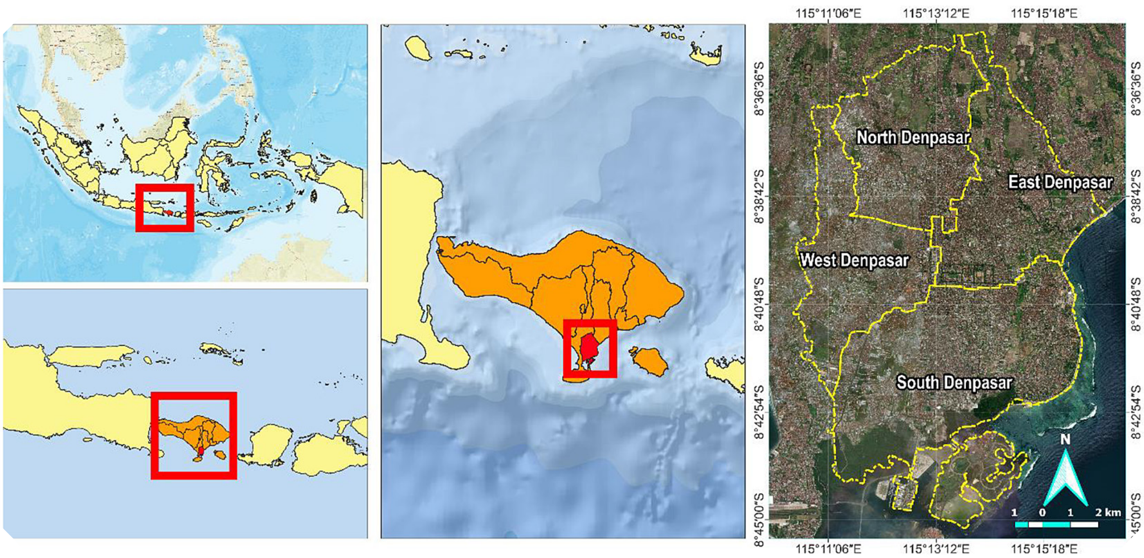

Figure 1. The research location is situated in the central part of Indonesia, within Bali Province, specifically in the city of Denpasar

surface temperature, which can be correlated with vegetation stress and productivity (Roy et al., 2014). Thus, Landsat 8's advanced imaging capabilities facilitate comprehensive monitoring and assessment of terrestrial carbon stocks, contributing to a better understanding and management of carbon sequestration and greenhouse gas emissions.

Satellite image processing

Radiometric correction

The first step is radiometric correction, aimed at removing sensor noise and correcting for differences in pixel sensitivity. This process ensures that the obtained reflectance values are consistent and accurate, which is crucial for quantitative analysis. Radiometric calibration converts the digital number (DN) values to physical values, specifically top-of-atmosphere (TOA) reflectance. This conversion is essential for standardizing the data across different scenes and dates, allowing for reliable comparison and analysis (Vermote et al., 2016). The TOA reflectance can be calculated using the following Equation 1.

$$TOA\ Reflectance = \frac{M_{reflectance} \times DN + A_{reflectance}}{sin(\theta_{sun})} \quad (1)$$

where: $M_{reflectance}$ – the multiplicative rescaling factor, $A_{reflectance}$ – the additive rescaling factor, and θ_{sun} – the solar elevation angle.

Atmospheric correction

The dark object subtraction (DOS) method for atmospheric correction is a straightforward technique used in remote sensing to mitigate atmospheric effects in satellite imagery (Chavez, 1996). It operates on the premise that very dark objects, such as deep water bodies or shadows, exhibit near-zero reflectance. The process involves identifying these dark pixels in the image and calculating their average radiance value to estimate the atmospheric contribution (Equation 2). This value is then subtracted from the radiance measured by the sensor across the entire image. Applied particularly to Landsat 8 OLI/TIRS sensor data, this method minimizes atmospheric effects, resulting in more accurate surface reflectance values and enhancing the reliability of subsequent analysis (Equation 3).

$$L_{TOA} = L_{sensor} - L_{dark} \quad (2)$$

where: L_{TOA} – the top-of-atmosphere reflectance after atmospheric correction, L_{sensor} – the radiance measured by the sensor, L_{dark} – the radiance of the dark object (assumed the near zero reflectance)

$$L = M \times Q_{cal} + A \quad (3)$$

where: L – the spectral radiance, M – the radiance multiplicative scaling factor, Q_{cal} – the quantized and calibrated standard product pixel value (digital number), A – the radiance additive scaling factor.

Calculation of vegetation indices

To determine the distribution of vegetation in the urban area of Denpasar, the NDVI was analyzed. NDVI is calculated using the NIR and Red bands proposed by (Rouse et al., 1974) as calculated in Eq. 4:

$$NDVI = \frac{NIR - Red}{NIR + Red} \quad (4)$$

Table 1. Specifications of Landsat 8 sensors

Landsat 8 Bands	Wavelength (μm)	Resolution (m)
Band 1 - Coastal aerosol	0.43–0.45	30
Band 2- Blue	0.45–0.51	30
Band 3 - Green	0.53–0.59	30
Band 4 - Red	0.64–0.67	30
Band 5 - Near Infrared (NIR)	0.85–0.88	30
Band 6 - SWIR 1	1.57–1.65	30
Band 7 - SWIR 2	2.11–2.29	30
Band 8 - Panchromatic	0.50–0.68	15
Band 9 - Cirrus	1.36–1.38	30
Band 10 – Thermal Infrared Sensor (TIRS) 1	10.6–11.19	100
Band 11 - Thermal Infrared Sensor (TIRS) 2	11.5–12.51	100

where: NIR – the reflectance value from the near-infrared band (Band 5 on Landsat 8), and *Red* is the reflectance value from the red band (Band 4 on Landsat 8).

The NIR band is highly sensitive to green biomass because plant leaves reflect a significant portion of light at this wavelength, while the Red band is situated at wavelengths where chlorophyll in plant leaves absorbs light for photosynthesis. This combination makes NDVI effective for evaluating vegetation health and density. High NDVI values indicate healthy, dense vegetation, while lower values may indicate less healthy vegetation or non-vegetated areas. Using Landsat 8 imagery, with spatial resolution (30 meters for Bands 4 and 5), provides an advantage in detecting small changes in vegetation, which is useful for urban carbon analysis and green space management.

Computation of above ground carbon

Subsequently, the NDVI results are used to calculate above ground carbon (AGC) based on a remote sensing approach proposed by (Yao et al., 2015) as calculated in Eqation 5:

$$AGC = 6{,}445.014x^{2.390} \quad (5)$$

Yao et al. (2015) developed this method based on data from 240 sampling plots. Information observed in each plot included species, the number of each species, diameter at breast height (DBH), and height for trees; for shrubs, species, the number of each species, basal diameter, canopy diameter, and height were recorded. Field data were integrated with remote sensing data from Landsat imagery to derive a carbon estimation formula. NDVI showed a good correlation ($R^2 = 0.71$) with AGC stock in urban green spaces. Other vegetation indices e.g. difference vegetation index (DVI), ratio vegetation index (RVI), soil-adjusted vegetation index (SAVI), modified soil-adjusted vegetation index (MSAVI), and renormalized difference vegetation index (RDVI) had lower correlation coefficients compared to the NDVI. NDVI is suitable for predicting carbon in urban areas with low green space canopy density (Guo et al., 2024). Therefore, this equation is used to study above ground carbon dynamics in the green spaces of Denpasar City, based on its development for urban areas with sparse vegetation and its use of the same sensor product from Landsat.

RESULTS AND DISCUSSION

Vegetation indices

The statistical values of the vegetation spectral index in the study area range from -0.99 to 0.99 (see Table 2). Figure 2 depicts the variation in the average vegetation index in Denpasar City from 2014 to 2022. In 2015, the average vegetation index in Denpasar City decreased to 0.43 compared to 2014, indicating a decline in vegetation greenness. However, in 2016, the average vegetation index increased to 0.48, indicating a significant improvement in vegetation greenness. Conversely, in 2019, the average vegetation index fell again, even lower than in 2015, highlighting a marked reduction in vegetation greenness. The spatial patterns of NDVI over a decade have shown considerable variability. NDVI values lower than 0.625 are typically associated with non-vegetated areas such as water bodies, built-up land, vacant lots, and beach sand. The most significant changes in vegetation dynamics were observed in the central to northern parts of the study area, where agricultural land use is prevalent.

Table 2. Statistical values of vegetation indices from 2014 to 2022

No	Years	Min	Max	Mean	SD
1	2014	-0.91	0.96	0.48	0.22
2	2015	-0.95	0.96	0.46	0.21
3	2016	-0.88	0.96	0.48	0.22
4	2017	-0.92	0.96	0.46	0.21
5	2018	-0.99	0.95	0.45	0.20
6	2019	-0.93	0.98	0.41	0.20
7	2020	-0.89	0.96	0.44	0.21
8	2021	-0.88	0.96	0.45	0.22
9	2022	-0.87	0.99	0.46	0.22

Agricultural land use, such as rice paddies, is notably dynamic, influenced by planting seasons, crop rotation, and cultivated agricultural commodities. The study area is predominantly planted with rice, a food commodity with highly variable vegetation dynamics depending on the planting season. During the transition from soil preparation to the next rice planting, the fields undergo flooding, and some areas temporarily become vacant land. In the generative phase of rice growth, the vegetation is lush and green, resulting in high NDVI values. Additionally, the presence of other crops like corn contributes to high spectral reflectance in the near-infrared (NIR) wavelength. Healthy plants with adequate chlorophyll content reflect light in the NIR wavelength (0.85–0.88 μm) while chlorophyll absorbs light in the Red wavelength (0.64–0.67 μm), resulting in lower reflectance (Yang, 2020). In contrast, unhealthy plants with low chlorophyll content absorb NIR wavelengths.

Overall, the coastal UGS in the southern part of the study area exhibit relatively uniform vegetation density, largely due to the presence of mangrove ecosystems. These ecosystems maintain a consistent level of vegetation cover and contribute to the overall stability of the NDVI readings in this region. NDVI derived from Landsat 8 provides a valuable tool for monitoring vegetation dynamics over time. It effectively highlights the variability and changes in vegetation cover, especially in agricultural areas, where seasonal activities and crop types significantly influence the NDVI values. The consistency in vegetation density in coastal UGS areas underscores the importance of mangrove ecosystems in maintaining ecological stability.

Urban green space mapping

UGS were delineated using a threshold approach with NDVI values greater than 0.625, validated against high-resolution Google Earth satellite images. Areas not meeting this threshold were classified as non-vegetated and excluded from the calculation of above-ground carbon (AGC) values, as detailed in subsequent sections. The extent of UGS in the study area showed dynamic changes, dependent on NDVI values. The largest UGS area was identified in 2016, covering 3,566.34 hectares (28.13%), while the smallest was in 2019, covering 2,028.69 hectares (16%).

Other researchers have reported similar findings using different satellite imagery and methodologies. For instance Marpaung et al. (2022) reported UGS areas of 3,615.14 hectares in 2016 and 3,031.45 hectares in 2021. Additionally, (Wirayuda et al., 2023) using Landsat 8 satellite data from 2022 and a supervised classification

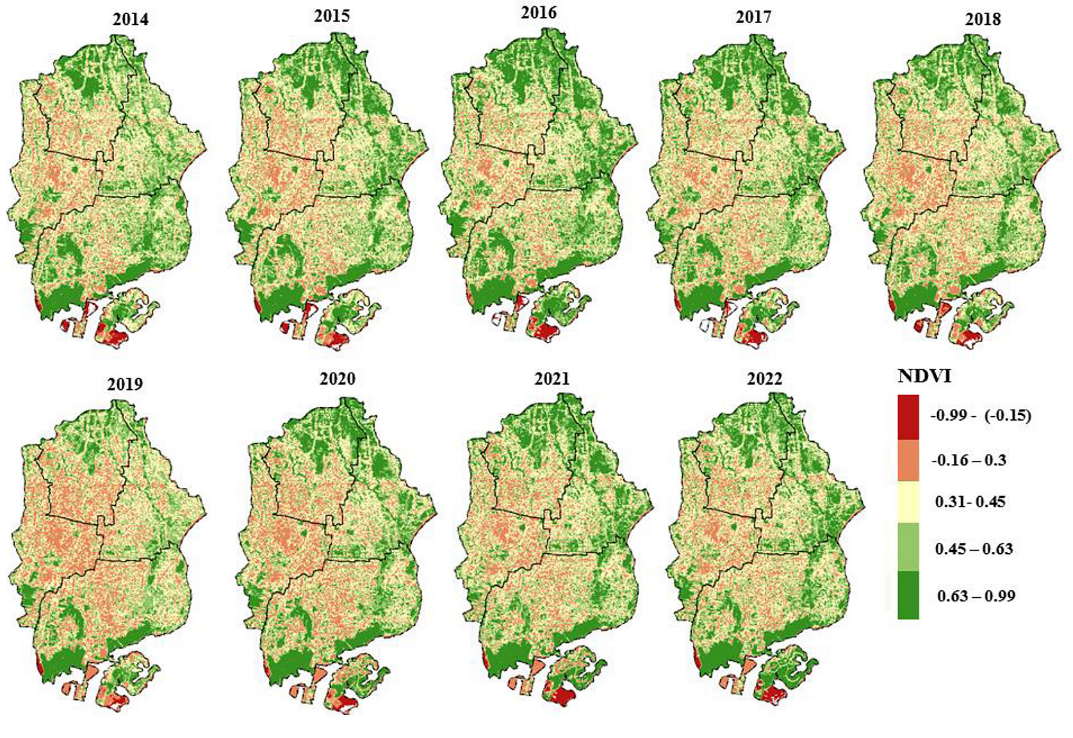

Figure 2. Spatial distribution of vegetation indices from 2014–2022

technique, identified 2,822 hectares of UGS. Over nine years of remote sensing observations, the average UGS area was found to be 23%.The largest percentage was in 2016 at 28%, and the smallest in 2019 at 16%. These findings align with the Indonesian standard for UGS proportion, which mandates that 30% of urban areas be green spaces, comprising 20% public and 10% private green spaces (Figure 3). This study primarily mapped 20% of public green spaces, as private green spaces with vegetation less than 30 meters per pixel were not captured due to the resolution limits of the satellite imagery used. (Table 3)

Table 3. Data summary on the extent of UGS in Denpasar City

Year	Pixels	Area (ha)	Area (%)
2014	28891	2,600.19	20.51
2015	32293	2,906.37	22.92
2016	39626	3,566.34	28.13
2017	34798	3,131.82	24.70
2018	28948	2,605.32	20.55
2019	22541	2,028.69	16.00
2020	31907	2,871.63	22.65
2021	33208	2,988.72	23.57
2022	35010	3,150.90	24.85

Above ground carbon

Our study focused on the carbon stock potential specifically within vegetated UGS areas. The lowest carbon stock values ranged from less than 2 tons of carbon per pixel to more than 5 tons of carbon per pixel, with each pixel representing 30 meters, in line with the spatial resolution of Landsat 8 imagery. The spatial distribution of carbon stock is shown in Figure 4, highlighting the highest carbon stock areas along the coastal regions each year. The calculation of AGC within UGS areas revealed that South Denpasar had the highest AGC potential at 51,988 tons of carbon, followed by East Denpasar (20,439 tons), North Denpasar (20,211 tons), and West Denpasar (9,674 tons), as illustrated in Figure 5. The significant carbon stock in South Denpasar is primarily due to the presence of mangrove ecosystems (Figure 6b).

Candra et al. (2016) identified eleven mangrove species in the same study area, including *Rhizophora mucronata*, *Rhizophora stylosa*, *Rhizophora apiculata*, *Avicennia marina*, *Avicennia officinalis*, *Sonneratia alba*, *Sonneratia caseolaris*, *Bruguiera gymnorrhiza*, *Bruguiera cylindrica*, *Xylocarpus granatum* and *Ceriops tagal*. The total carbon stock in these mangroves was estimated to be 35,349.87 tons, with dominant species including *Rhizophora apiculata*, *Rhizophora*

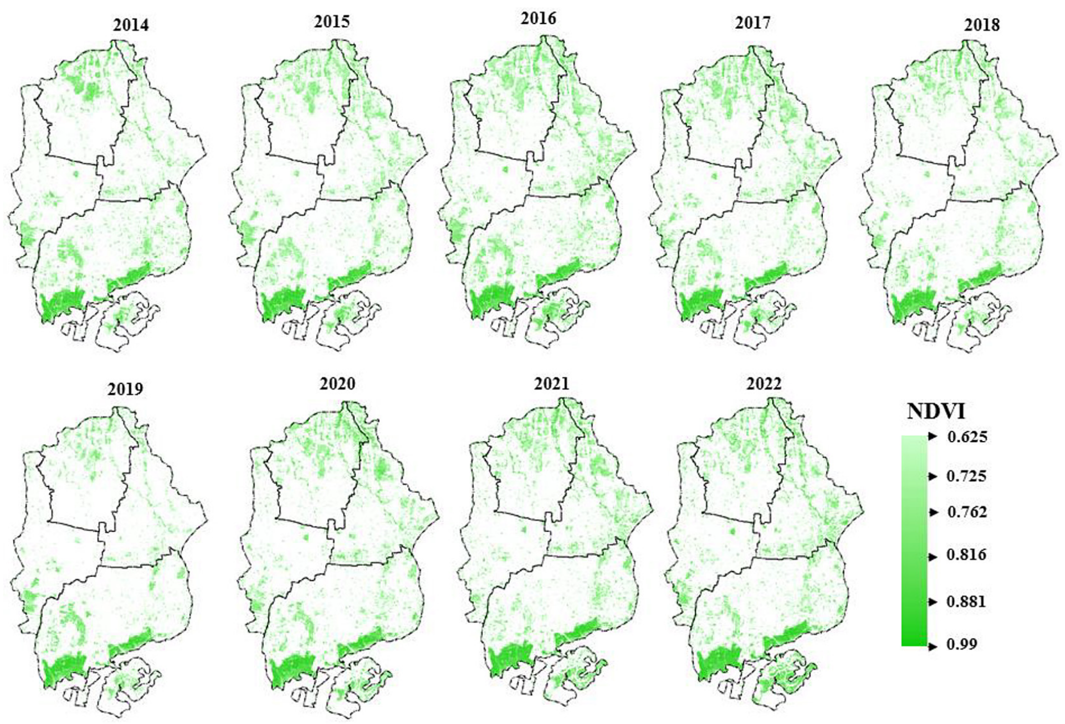

Figure 3. Spatial distribution of urban green space from 2014 to 2022

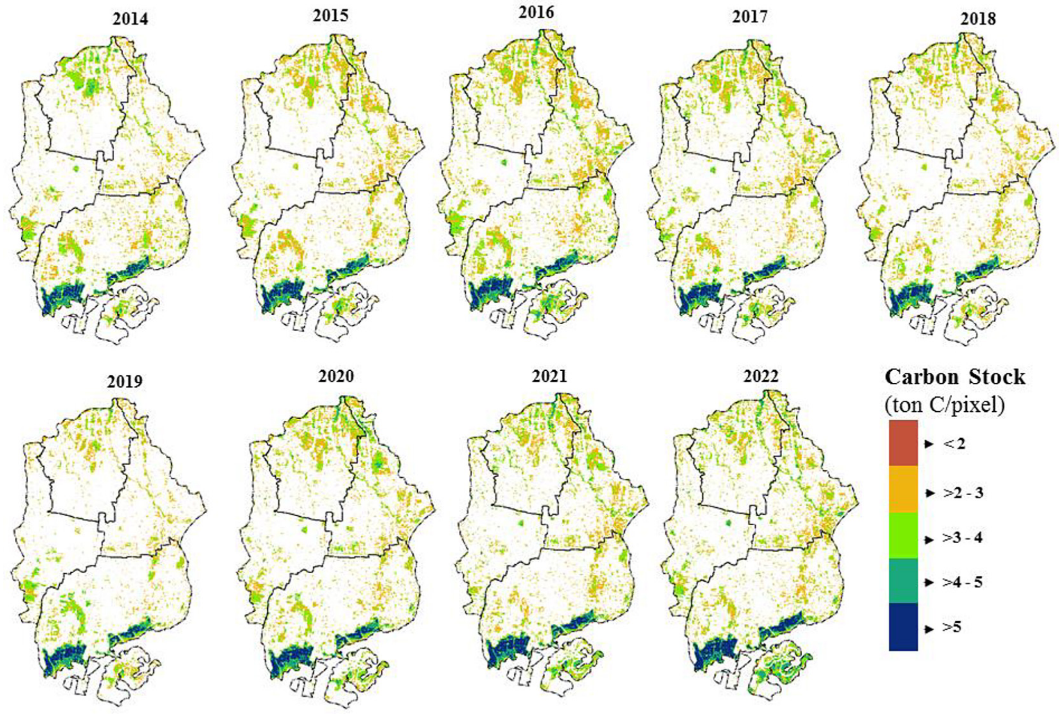

Figure 4. Time series map of carbon stocks in urban green space

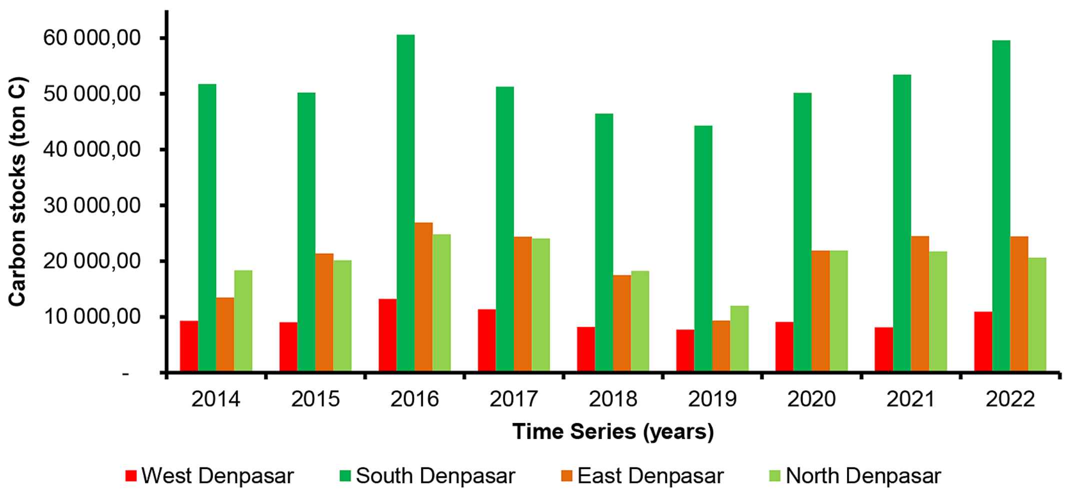

Figure 5. Graph of total carbon stocks per district from 2014 to 2022

mucronata, and *Sonneratia alba*. A recent study evaluated the carbon storage and sequestration potential of three mangrove ecosystems (*Bruguiera*, *Rhizophora*, and *Sonneratia*), finding a total capacity of 1.5 million tons of CO_2 with an annual rate of 94,573.6 tons of CO_2 per year. This research was conducted in the Mangrove Benoa Bay ecosystem, spanning the administrative regions of Denpasar City and Badung Regency (Sugiana et al., 2024). Another study, integrating field measurements with active remote sensing sensor, estimated the carbon stock potential in the Benoa Bay mangroves to be 209,027.28 tons of carbon, sequestering 767,130.11 tons of CO_2, with a CO_2 absorption rate of 3.87 tons per hectare (Mahasani et al., 2021). In the same area, other researchers found that the species *Rhizophora mucronata* was relatively dominant, and at certain observation spots, it produced a carbon stock of 175.77 tons/ha (Suardana et al., 2023).

Additionally, urban forests located at the boundary of South and East Denpasar contribute significantly to carbon sequestration, as shown in Figure 6b. A study in Jakarta, Indonesia, reported that urban

Figure 6. (a) Photo view of UGS tree canopy along urban streets (8°40'13.03"S, 115°13'48.76"E), (b) mangrove ecosystem in the southern coastal area of Denpasar (8°43'42.40"S, 115°11'33.96"E)

trees sequester approximately 184.8 metric tons of carbon per year (Aulia et al., 2023). Dominant tree species in Indonesian urban forests include *Pterocarpus indicus*, *Delonix regia*, *Polyalthia longifolia*, *Lagerstroemia speciosa*, *Mimusops elengi*, *Samanea saman*, *Tectona grandis*, *Ficus benjamina*, *Mangifera indica*, and *Tamarindus indica*, generally constituting less than 10% of UGS (Fitria et al., 2022). Preserving urban forests is crucial to prevent land-use changes, as demonstrated by a study in Changchun, China, where urban forests offset about 2.11% of carbon emissions in 2000, but this figure dropped to 0.88% in 2019 due to increased emissions from urbanization (Guo et al., 2024).

Transition of above ground carbon

Over a nine-year period, the total carbon stock within the UGS ecosystem exhibited significant variability. The highest carbon stock was recorded in 2016 at 125,588.78 tons, while the lowest was in 2019 at 73,350.48 tons, with an average of 102,311.82 tons across the period (Figure 7). The trend in carbon stock was distinctive: it increased from 2014 to 2016, gradually declined from 2016 to 2018, and then rose again from 2020 to 2022. A significant increase in carbon stock was observed between 2019 and 2020, reaching 40%. Another notable increase of 25% occurred between 2015 and 2016. Smaller increases, less than 8%, were noted during the transitions from 2014 to 2015, 2021 to 2022, and 2020 to 2021. Conversely, a decline in carbon stock was observed between 2016 and 2019, with reductions of -11.52% and -19% respectively (Figure 8). These findings suggest that factors such as vegetation density, plant health, and spatial distribution significantly influence carbon stock.

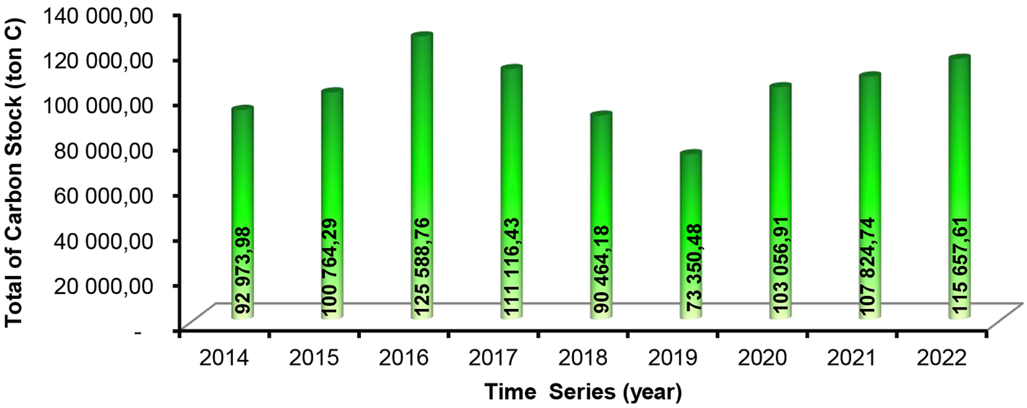

Figure 7. Graph of total carbon stocks in Denpasar City from 2014 to 2022

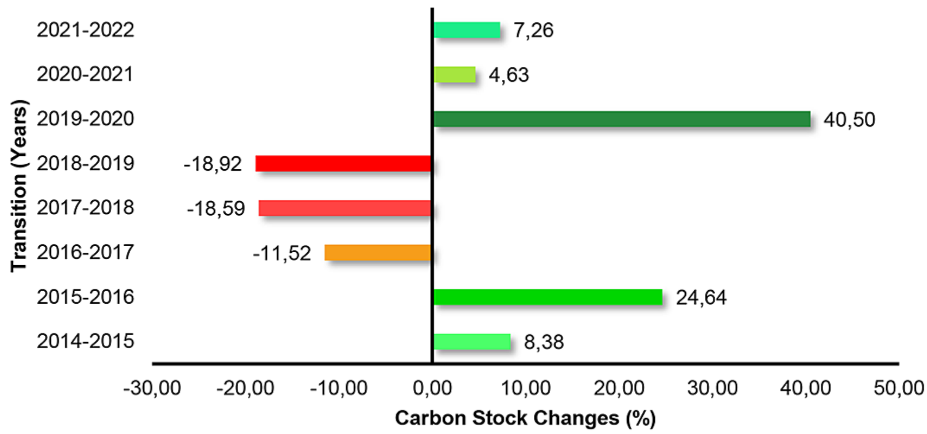

Figure 8. Transition of carbon stock changes over nine years

Climate dynamics on carbon stocks

The dynamics of carbon stocks in urban ecosystem areas are justified by the influence of extreme climate change dynamics, as shown in Figure 9, which describes the relationship between rainfall variability and land surface temperature (LST). Data from the rainfall estimates from Rain Gauge and Satellite Observations (CHIRPS) and the MODIS Land Surface Temperature and Emissivity (MOD11A1.061) indicate that the average monthly rainfall and LST patterns are highly dynamic each year. The lowest rainfall was consecutively detected in 2015 and 2019, with values of 95.83 mm/month and 96.44 mm/month, respectively. This relatively low rainfall influenced an increase in LST in both 2015 and 2019, with corresponding values of 37.52 °C and 36.68 °C. On the other hand, an increase in relatively high rainfall was observed in 2016 and 2021, at 202.20 mm/month and 200.94 mm/month, respectively, leading to a reduction in LST to 33.74 °C and 33.64 °C. Overall, the rainfall patterns in the study area align with the dynamics of carbon stocks (Figure 7) and are inversely related to temperature variability.

Climate variability, particularly in terms of rainfall and temperature, significantly influences vegetation dynamics and, consequently, carbon stocks in urban green spaces. Variability in rainfall and temperature impacts the growth, health, and distribution of vegetation, which are critical determinants of carbon sequestration. During periods of low rainfall, such as those observed in 2015 and 2019, water stress can inhibit plant growth and reduce biomass accumulation, leading

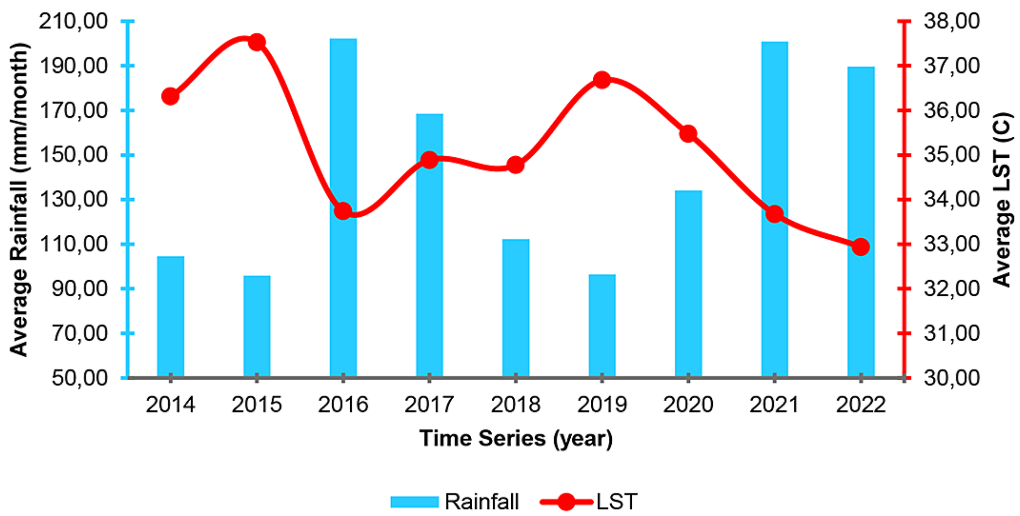

Figure 9. Dynamics of climate change in urban green spaces over nine years as indicated by average rainfall and land surface temperature (LST) data

to lower carbon sequestration rates. High temperatures further exacerbate this stress by increasing evapotranspiration rates, causing soil moisture depletion and adversely affecting plant physiological processes. This combination of low rainfall and high temperatures can lead to decreased vegetation cover and reduced carbon stocks. Conversely, higher rainfall, as seen in 2016 and 2021, can enhance plant growth by providing sufficient water for photosynthesis and other metabolic activities. Adequate rainfall promotes healthy vegetation growth, leading to increased biomass accumulation and higher carbon sequestration. The observed reduction in LST during these years indicates a cooling effect, likely due to enhanced transpiration from lush vegetation, which also helps moderate local microclimates.

The interplay between rainfall and temperature variability is crucial in understanding the dynamics of carbon stocks in urban green spaces. Vegetation acts as a carbon sink, absorbing CO_2 from the atmosphere and storing it in biomass and soil. Therefore, changes in climatic factors directly impact the carbon sequestration potential of urban ecosystems. During favorable climatic conditions (adequate rainfall and moderate temperatures), urban green spaces can significantly contribute to carbon sequestration, helping mitigate urban greenhouse gas emissions and contributing to climate change mitigation efforts.

However, extreme climate events, such as prolonged droughts or heatwaves, can disrupt these processes, leading to fluctuations in carbon stocks. Urban planning and management strategies should consider these climatic influences to enhance the resilience of urban green spaces and their capacity to sequester carbon. Sustainable practices, such as increasing vegetation diversity, optimizing water use, and protecting existing green spaces, can help buffer against adverse climatic impacts and support stable carbon sequestration over time.

Urban ecosystems management for climate change mitigation

Agricultural ecosystems, including rice fields, play an important role in storing and sequestering carbon, in addition to the widely described contributions of mangrove and urban forest ecosystems. Paddy fields are frequently studied for their soil organic carbon (SOC). According to Liu et al. (2021), the global average SOC stock in paddy fields is estimated at 108 Mg ha^{-1} for the 0–100 cm soil layer, with the top 1 meter of paddy soil worldwide containing 18 Pg of organic carbon. This amount represents approximately 1.2% of the global SOC total or about 14.2% of the total SOC in agricultural land globally. Without the return of straw or the application of manure, SOC in paddy fields would continue to decline. Fresh straw and decayed straw manure can increase soil SOC by 9–11% (Ku et al., 2019). Incorporating straw into the soil also reduces carbon emissions by more than 50% and decreases NH_3 and N_2O emissions by 13% and 11%, respectively (Moreno-Ramón et al., 2024). Additionally, soil management with manure or biochar can promote SOC accumulation and enhance carbon sequestration by 0.22% (Yin et al., 2020). Multiple cropping systems can increase carbon sequestration compared to monoculture farming, contributing to global warming mitigation and sustainable food systems (Komatsuzaki and Syuaib, 2010; Wang et al., 2023).

Although paddy fields significantly contribute to carbon stock, they are vulnerable to climate change and land-use changes, particularly conversion to residential areas (Firdaus et al., 2020; Sunarta and Saifulloh, 2022b). In Denpasar, urban area expansion increased by 1.736 hectares, while paddy field area decreased by 1.695 hectares between 2002 and 2013, with annual residential area growth of 133.5 hectares and paddy field reduction of 130 hectares (Supardan et al., 2018). Climate phenomena like the El Niño-Southern Oscillation (ENSO) and IOD also impact to vegetation dynamics (Adnyana et al., 2024) and carbon stock stability. ENSO causes temperature anomalies exceeding +0.5 °C, leading to prolonged droughts and decreased paddy production, while La Niña causes extended heavy rainfall, resulting in flooding and submerged paddy fields (Ismail and Chan, 2020). The study area frequently experiences flooding during prolonged heavy rainfall (Trigunasih and Saifulloh, 2022; Widantara and Mutaqin, 2024).

Climate change and anthropogenic factors contribute to the instability of carbon stock in Denpasar's UGS. Previous studies highlighted that the very strong El Niño events in 2015 and 2016, followed by La Niña, rejuvenated previously drought-affected areas, increasing carbon stock by 25%. Additionally, the positive IOD in 2019 caused a 19% decrease in carbon stock, which sharply increased by 40% from 2019 to 2020, coinciding with a moderate La Niña event in 2020 (Dimyati et al., 2024). Climate change can degrade vegetation and increase soil temperatures, leading to urban heat islands (UHI), emphasizing the importance of early mitigation efforts (Mas'uddin et al., 2023). Preserving urban forest and mangrove ecosystems is crucial due to their resilience to extreme climate dynamics.

Effective environmental management practices are essential for mitigating the impacts of climate change on urban green spaces and agricultural ecosystems. Strategies such as sustainable agriculture, urban planning, and the conservation of existing green spaces can significantly enhance carbon sequestration and resilience to climate variability. Urban planning should prioritize the preservation and expansion of green spaces, including urban forests and mangroves, which are highly effective at sequestering carbon and providing resilience against climate extremes. Implementing green infrastructure, such as green roofs, urban parks, and community gardens, can help reduce urban heat islands and enhance local biodiversity. Developing and promoting climate-resilient agricultural and urban management practices is crucial. This includes using drought-resistant plant varieties, efficient water management systems, and adaptive land-use planning to cope with the impacts of extreme weather events such as ENSO and IOD. Engaging local communities in sustainable practices and raising awareness about the importance of carbon sequestration and climate resilience can lead to more effective implementation of environmental management strategies. Community-based initiatives, such as urban gardening and conservation projects, can foster a sense of stewardship and collective action.

Limitations and outlook

This study has several limitations, primarily related to the methodological approaches used to estimate the proportion of green space and calculate carbon stock. While the NDVI is widely used for estimating carbon stock, its sensitivity to vegetation greenness and density thresholds poses challenges for accurately mapping UGS. Future research should consider incorporating supervised machine learning techniques for land-use classification in remote sensing data to address these limitations and improve accuracy.

The current calculation methods are not fully optimized, especially for densely vegetated areas like mangrove ecosystems. NDVI may not accurately capture carbon stocks in high-density vegetation. Comprehensive methods, such as combining multiple vegetation indices or utilizing advanced remote sensing techniques, should be employed in future research to ensure more representative carbon stock estimates for each ecosystem type. Additionally, our study generalized vegetation density and greenness levels, potentially equating healthy green grass with urban forests and underestimating carbon stocks for urban forests with sparse canopies and unhealthy foliage.

For more precise carbon stock estimation, higher spatial resolution satellite imagery is recommended. Future studies should utilize high-resolution satellite images, such as those from PlanetScope and WorldView, to overcome the limitations associated with lower resolution data. These high-resolution images will provide more detailed and accurate models of carbon stock estimation, serving as a robust basis for urban environmental management and spatial planning.

CONCLUSIONS

This study highlights the effectiveness of using remote sensing data, particularly vegetation indices from Landsat 8, to map and quantify carbon stocks in UGS ecosystems over an extended period. Analyzing time-series data from 2014 to 2022 provided significant insights into the spatial and temporal dynamics of carbon stocks. The findings revealed a 24% overall increase in carbon stocks, though year-to-year fluctuations were notable. Carbon stocks decreased by 19% between 2017 and 2019 but saw substantial increases of 25% and 40% during the 2015–2016 and 2019–2020 periods, respectively. Different UGS ecosystems, such as mangroves and urban forests, responded variably to climate change, with mangroves showing more stable and adaptive patterns.

Despite these promising results, the study acknowledged limitations. The sensitivity of the NDVI to vegetation greenness and density poses challenges in accurately mapping UGS and estimating carbon stocks, particularly in dense mangrove areas. This limitation suggests that NDVI may underestimate carbon stock variability in high-density vegetation. To improve accuracy, future research should use supervised machine learning techniques for land-use classification in remote sensing data and combine multiple vegetation indices or advanced methods for comprehensive carbon stock assessments. The current study's generalization of vegetation density may have underestimated carbon stocks in some areas. High-resolution satellite imagery from platforms like PlanetScope and WorldView is recommended for precise carbon stock estimation. These images offer detailed and accurate models, enhancing urban environmental management and spatial planning. This approach will provide a reliable basis for climate change mitigation and reduce urban greenhouse gas emissions, promoting effective environmental management.

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REFERENCES

1. Adnyana, I.W.S., As-syakur, A.R., Suyarto, R., Sunarta, I.N., Nuarsa, I.W., Diara, I.W., Saifulloh, M., Wiyanti. 2024. Geospatial technology for climate change: Influence of ENSO and IOD on soil erosion. In Technological Approaches for Climate Smart Agriculture, 249–275. Springer.
2. 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
3. Askar, Nuthammachot, N., Phairuang, W., Wicaksono, P., Sayektiningsih, T. 2018. Estimating aboveground biomass on private forest using sentinel-2 imagery. Journal of Sensors, 2018. https://doi.org/10.1155/2018/6745629
4. As-syakur, A.R., Setiawati, M.D., Mukaromah, L., Osawa, T., Adnyana, I.W.S., Sunarta, I.N. 2023. Growing urban tourism activities while increasing vegetation ecosystem service under land use changes pressure: A case study of Sanur, Bali, Indonesia. In Springer Geography. https://doi.org/10.1007/978-3-031-24767-5_29
5. As-syakur, A., Osawa, T., Adnyana, I.W.S. 2010. Medium spatial resolution satellite imagery to estimate gross: primary production in an urban area. Remote Sensing, 2(6). https://doi.org/10.3390/rs2061496
6. Aulia, R., Kaswanto, Arifin, H.S., Mosyaftiani, A., Syasita, N., Wahyu, A., Wiyoga, H. 2023. Assessing the benefits and management of urban forest in supporting low carbon city in Jakarta, Indonesia. Biodiversitas, 24(11). https://doi.org/10.13057/biodiv/d241136
7. Bhayunagiri, I.B.P., Saifulloh, M. 2022. Mapping of subak area boundaries and soil fertility for agricultural land conservation. Geographia Technica, 17(2). https://doi.org/10.21163/GT_2022.172.17
8. Bherwani, H., Banerji, T., Menon, R. 2024. Role and value of urban forests in carbon sequestration: review and assessment in Indian context. Environment, Development and Sustainability, 26(1). https://doi.org/10.1007/s10668-022-02725-5
9. Candra, E.D., Hartono, Wicaksono, P. 2016. Above ground carbon stock estimates of mangrove forest using Worldview-2 imagery in Teluk Benoa, Bali. IOP Conference Series: Earth and Environmental Science, 47(1). https://doi.org/10.1088/1755-1315/47/1/012014
10. Chavez, P.S. 1996. Image-based atmospheric corrections - Revisited and improved. In Photogrammetric Engineering and Remote Sensing, 62(9).
11. Choudhury, M.A.M., Marcheggiani, E., Galli, A., Modica, G., Somers, B. 2021. Mapping the urban atmospheric carbon stock by lidar and worldview-3 data. Forests, 12(6). https://doi.org/10.3390/f12060692
12. Diara, I.W., Suyarto, R., Saifulloh, M. 2022. Spatial distribution of landslide susceptibility in new road construction Mengwitani-Singaraja, Bali-Indonesia: Based On Geospatial Data. International Journal of GEOMATE, 23(96). https://doi.org/10.21660/2022.96.3320
13. Dimyati, M., Rustanto, A., Ash Shidiq, I.P., Indratmoko, S., Siswanto, Dimyati, R.D., Nurlambang, T., Zubair, A., Fakhruddin, A., Siddiq, A., Adhanto, D.H., Maulidina, K., Auni, R. 2024. Spatiotemporal relation of satellite-based meteorological to agricultural drought in the downstream Citarum watershed, Indonesia. Environmental and Sustainability Indicators, 22. https://doi.org/10.1016/j.indic.2024.100339
14. Fattah, M.A., Morshed, S.R., Morshed, S.Y. 2021. Impacts of land use-based carbon emission pattern on surface temperature dynamics: Experience from the urban and suburban areas of Khulna, Bangladesh. Remote Sensing Applications: Society and Environment, 22. https://doi.org/10.1016/j.rsase.2021.100508
15. Firdaus, R.B.R., Leong Tan, M., Rahmat, S.R., Senevi Gunaratne, M. 2020. Paddy, rice and food security in Malaysia: A review of climate change impacts. In Cogent Social Sciences, 6(1). https://

doi.org/10.1080/23311886.2020.1818373

16. Fitria, M., Cheong, E.J., Solikhin, A., Firdaus, M.I., Ward, D.B. 2022. Indonesian urban forest policies, practice and bioenergy potential of urban forest tree species. Arboricultural Journal, 44(2). https://doi.org/10.1080/03071375.2021.2014706
17. Guo, Y., Ren, Z., Wang, C., Zhang, P., Ma, Z., Hong, S., Hong, W., He, X. 2024. Spatiotemporal patterns of urban forest carbon sequestration capacity: Implications for urban CO2 emission mitigation during China's rapid urbanization. Science of the Total Environment, 912. https://doi.org/10.1016/j.scitotenv.2023.168781
18. IPCC. 2022. Global Warming of 1.5 °C. In Global Warming of 1.5 °C. https://doi.org/10.1017/9781009157940
19. Ismail, N.W., Chan, S.M. 2020. Impacts of the El Niño-Southern Oscillation (ENSO) on paddy production in Southeast Asia. Climate and Development, 12(7). https://doi.org/10.1080/17565529.2019.1673141
20. Kartini, N.L., Saifulloh, M., Trigunasih, N.M., Narka, I.W. 2023. Assessment of soil degradation based on soil properties and spatial analysis in dryland farming. Journal of Ecological Engineering, 24(4). https://doi.org/10.12911/22998993/161080
21. Komatsuzaki, M., Syuaib, M.F. 2010. Comparison of the farming system and carbon sequestration between conventional and organic rice production in West Java, Indonesia. Sustainability, 2(3). https://doi.org/10.3390/su2030833
22. Krisnandika, A.A.K., Kohdrata, N., Semarajaya, C.G.A. 2019. Identifikasi tanaman penyerap Pb di tiga ruas jalan Kota Denpasar. Jurnal Arsitektur Lansekap. https://doi.org/10.24843/jal.2019.v05.i02.p10
23. Ku, H.H., Ryu, J.H., Bae, H.S., Jeong, C., Lee, S.E. 2019. Modeling a long-term effect of rice straw incorporation on SOC content and grain yield in rice field. Archives of Agronomy and Soil Science, 65(14). https://doi.org/10.1080/03650340.2019.1583330
24. Kurniadi, A., Weller, E., Min, S.K., Seong, M.G. 2021. Independent ENSO and IOD impacts on rainfall extremes over Indonesia. International Journal of Climatology, 41(6). https://doi.org/10.1002/joc.7040
25. Liang, L., Wang, Z., Li, J. 2019. The effect of urbanization on environmental pollution in rapidly developing urban agglomerations. Journal of Cleaner Production, 237, 1–15. https://doi.org/10.1016/j.jclepro.2019.117649
26. Liu, O.Y., Russo, A. 2021. Assessing the contribution of urban green spaces in green infrastructure strategy planning for urban ecosystem conditions and services. Sustainable Cities and Society, 68. https://doi.org/10.1016/j.scs.2021.102772
27. Liu, Y., Ge, T., van Groenigen, K.J., Yang, Y., Wang, P., Cheng, K., Zhu, Z., Wang, J., Li, Y., Guggenberger, G., Sardans, J., Penuelas, J., Wu, J., Kuzyakov, Y. 2021. Rice paddy soils are a quantitatively important carbon store according to a global synthesis. Communications Earth and Environment, 2(1). https://doi.org/10.1038/s43247-021-00229-0
28. Lubis, M.I., Lee, J.S.H., Rahmat, U.M., Tarmizi, Ramadiyanta, E., Melvern, D., Suryometaram, S., Trihangga, A., Isa, M., Yansyah, D., Abdullah, R., Ardiantiono, Marthy, W., Jones, K.R., Andayani, N., Linkie, M. 2023. Planning for megafauna recovery in the tropical rainforests of Sumatra. Frontiers in Ecology and Evolution, 11. https://doi.org/10.3389/fevo.2023.1174708
29. Mahasani, I.G.A.I., Osawa, T., Adnyana, I.W.S., Suardana, A.A.M.A.P., Chonnaniyah. 2021. Carbon stock estimation and mapping of mangrove forest using ALOS-2 PALSAR-2 in Benoa Bay Bali, Indonesia. IOP Conference Series: Earth and Environmental Science, 944(1). https://doi.org/10.1088/1755-1315/944/1/012044
30. Marpaung, N., Nuarsa, I.W., Diara, I.W. 2022. Using sentinel 2A imagery to analyze the capability of green open space in absorbing carbon dioxide emissions in Denpasar City. 2(3), 110–118. [Indonesia]
31. Mas'uddin, Karlinasari, L., Pertiwi, S., Erizal. 2023. Urban heat island index change detection based on land surface temperature, Normalized difference vegetation index, normalized difference built-up index: A case study. Journal of Ecological Engineering, 24(11). https://doi.org/10.12911/22998993/171371
32. Merino, A., Omil, B., Piñeiro, V., Barros, N., Souza-Alonso, P., Campo, J. 2023. Soil C dynamics after deforestation and subsequent conversion of arable cropland to grassland in humid temperate areas. Science of the Total Environment, 901. https://doi.org/10.1016/j.scitotenv.2023.165793
33. Moreno-Ramón, H., Ulzurrum, J., Lidon, A., Sanjuán, N. 2024. Assessing the environmental impacts of rice in an anthropized Mediterranean wetland: Towards carbon farming. Sustainable Production and Consumption, 45. https://doi.org/10.1016/j.spc.2024.01.019
34. Nedd, R., Light, K., Owens, M., James, N., Johnson, E., Anandhi, A. 2021. A synthesis of land use/land cover studies: Definitions, classification systems, meta-studies, challenges and knowledge gaps on a global landscape. In Land, 10(9). https://doi.org/10.3390/land10090994
35. Pandey, P.C., Koutsias, N., Petropoulos, G.P., Srivastava, P.K., Ben Dor, E. 2021. Land use/land cover in view of earth observation: data sources, input dimensions, and classifiers—a review of the state of the art. In Geocarto International, 36(9). https://doi.org/10.1080/10106049.2019.1629647
36. Rahayu, H., Haigh, R., Amaratunga, D. 2018. Strategic challenges in development planning for

Denpasar City and the coastal urban agglomeration of Sarbagita. Procedia Engineering, 212, 1347–1354. https://doi.org/10.1016/j.proeng.2018.01.174

37. Rouse, J.W., Hass, R.H., Schell, J.A., Deering, D.W., Harlan, J.C. 1974. Monitoring the vernal advancement and retrogradation (green wave effect) of natural vegetation. Final Report, RSC 1978-4, Texas A & M University, College Station, Texas.
38. Roy, D.P., Wulder, M.A., Loveland, T.R., C.E., W., Allen, R.G., Anderson, M.C., Helder, D., Irons, J.R., Johnson, D.M., Kennedy, R., Scambos, T.A., Schaaf, C.B., Schott, J.R., Sheng, Y., Vermote, E.F., Belward, A.S., Bindschadler, R., Cohen, W.B., Gao, F., Hipple, J.D., Zhu, Z. 2014. Landsat-8: Science and product vision for terrestrial global change research. Remote Sensing of Environment, 145. https://doi.org/10.1016/j.rse.2014.02.001
39. Sarker, T., Fan, P., Messina, J. P., Mujahid, N., Aldrian, E., Chen, J. 2024. Impact of Urban built-up volume on Urban environment: A Case of Jakarta. Sustainable Cities and Society, 105, 1–11. https://doi.org/10.1016/j.scs.2024.105346
40. Sentana, I.K.A.W., Dibia, I.N., Trigunasih, N.M. 2021. Evaluation of land suitability for several horticultural crop commodities based on geographic information systems in the Subak Area, West Denpasar District. Jurnal Agroekoteknologi Tropika, 10(3). [Indonesia]
41. Seto, K., Shobhakar, D. 2014. Climate change 2014: Mitigation of climate change — Chapter 12 Human settlements, infrastructure and spatial planning. Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change, January.
42. Slameršak, A., Kallis, G., O'Neill, D.W., Hickel, J. 2024. Post-growth: A viable path to limiting global warming to 1.5 °C. In One Earth, 7(1). https://doi.org/10.1016/j.oneear.2023.11.004
43. Statistik, B.P. 2024. Denpasar municipality in figures 2024. In Statistik Indonesia 2023, 32, 1–306. https://doi.org/https://denpasarkota.bps.go.id/
44. Suardana, A.A.M.A.P., Anggraini, N., Nandika, M.R., Aziz, K., As-Syakur, A.R., Ulfa, A., Wijaya, A.D., Prasetio, W., Winarso, G., Dimyati, R.D. 2023. Estimation and mapping above-ground mangrove carbon stock using Sentinel-2 data derived vegetation indices in Benoa Bay of Bali Province, Indonesia. Forest and Society, 7(1). https://doi.org/10.24259/fs.v7i1.22062
45. Sugiana, I.P., Prartono, T., Rastina, Koropitan, A.F. 2024. Ecosystem carbon stock and annual sequestration rate from three genera-dominated mangrove zones in Benoa Bay, Bali, Indonesia. Biodiversitas, 25(1). https://doi.org/10.13057/biodiv/d250133
46. Sulistiyono, H., Yasa, I. W., Saidah, H., Negara, I.D.G.J., Setiawan, E. 2023. Impact of climate change and the El Niño – Southern oscillation on extreme rainfall. Environment and Ecology Research, 11(2). https://doi.org/10.13189/eer.2023.110205
47. Sunarta, I.N., Saifulloh, M. 2022a. Spatial variation of NO_2 levels during the Covid-19 pandemic in the Bali tourism area. Geographia Technica, 17(1). https://doi.org/10.21163/GT_2022.171.11
48. Sunarta, I.N., Saifulloh, M. 2022b. 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
49. 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
50. Supardan, N., Panularsih, M., Darmawan, M. 2018. Landuse change identification using SPOT 6 for food security analysis of Denpasar City, Bali Province, Indonesia. IOP Conference Series: Earth and Environmental Science, 149(1). https://doi.org/10.1088/1755-1315/149/1/012036
51. Suyarto, R., Wiyanti, Saifulloh, M., Fatahillah, A. W., Diara, I.W., Susila, K.D., Kusmiyarti, T.B. 2023. Hydrological Approach for Flood Overflow Estimation in Buleleng Watershed, Bali. International Journal of Safety and Security Engineering, 13(5). https://doi.org/10.18280/ijsse.130512
52. Trigunasih, N.M., Saifulloh, M. 2022. The investigating water infiltration conditions caused by annual urban flooding using integrated remote sensing and Geographic Information Systems. Journal of Environmental Management and Tourism, 13(5). https://doi.org/10.14505/jemt.v13.5(61).22
53. Trigunasih, N.M., Saifulloh, M. 2023. Investigation of soil erosion in agro-tourism area: Guideline for Environmental conservation planning. Geographia Technica, 18(1). https://doi.org/10.21163/GT_2023.181.02
54. Trigunasih, N.M., Narka, I.W., Saifulloh, M. 2023a. Measurement of soil chemical properties for mapping soil fertility status. International Journal of Design and Nature and Ecodynamics, 18(6). https://doi.org/10.18280/ijdne.180611
55. Trigunasih, N.M., Narka, I.W., Saifulloh, M. 2023b. Mapping eruption affected area using Sentinel-2A imagery and machine learning techniques. Journal of Degraded and Mining Lands Management, 11(1). https://doi.org/10.15243/jdmlm.2023.111.5073
56. Tucker, C.J. 1979. Red and photographic infrared linear combinations for monitoring vegetation. Remote Sensing of Environment, 8(2). https://doi.org/10.1016/0034-4257(79)90013-0
57. USGS. 2015. Landsat 8 (L8) Data Users Handbook.

Earth Resources Observation and Science (EROS) Center, 8(June).

58. Vermote, E., Justice, C., Claverie, M., Franch, B. 2016. Preliminary analysis of the performance of the Landsat 8/OLI land surface reflectance product. Remote Sensing of Environment, 185. https://doi.org/10.1016/j.rse.2016.04.008
59. Wang, S., Sun, N., Liang, S., Zhang, S., Meersmans, J., Colinet, G., Xu, M., Wu, L. 2023. SOC sequestration affected by fertilization in rice-based cropping systems over the last four decades. Frontiers in Environmental Science, 11. https://doi.org/10.3389/fenvs.2023.1152439
60. Widantara, K.W., Mutaqin, B.W. 2024. Multi-hazard assessment in the coastal tourism city of Denpasar, Bali, Indonesia. Natural Hazards. https://doi.org/10.1007/s11069-024-06506-3
61. Wiradana, P., KetutSundra, I., Budi Kurniawan, S., Rozaimah Sheikh Abdullah, S., Amin Alamsjah, M., FauzulImron, M. 2021. Monitoring of diversity, characteristics, threatening rate and potency of mangrove vegetation in Denpasar, Bali, Indonesia. Plant Archives, 21(Suppliment-1). https://doi.org/10.51470/plantarchives.2021.v21.s1.090
62. Wirayuda, I.K.A.K., Widayani, P., Sekaranom, A.B. 2023. Urban green space analysis and its effect on the surface urban heat island phenomenon in Denpasar City, Bali. Forest and Society, 7(1). https://doi.org/10.24259/fs.v7i1.24526
63. Yang, C. 2020. Remote sensing and precision agriculture technologies for crop disease detection and management with a practical application example. In Engineering, 6(5). https://doi.org/10.1016/j.eng.2019.10.015
64. Yao, Z.Y., Liu, J.J., Zhao, X.W., Long, D.F., Wang, L. 2015. Spatial dynamics of aboveground carbon stock in urban green space: a case study of Xi'an, China. Journal of Arid Land, 7(3). https://doi.org/10.1007/s40333-014-0082-9
65. Yin, S., Zhang, X., Lyu, J., Zhi, Y., Chen, F., Wang, L., Liu, C., Zhou, S. 2020. Carbon sequestration and emissions mitigation in paddy fields based on the DNDC model: A review. In Artificial Intelligence in Agriculture, 4. https://doi.org/10.1016/j.aiia.2020.07.002
66. Zhang, M., Kafy, A. Al, Xiao, P., Han, S., Zou, S., Saha, M., Zhang, C., Tan, S. 2023. Impact of urban expansion on land surface temperature and carbon emissions using machine learning algorithms in Wuhan, China. Urban Climate, 47. https://doi.org/10.1016/j.uclim.2022.101347