GeoJournal of Tourism and Geosites
ISSN 2065-1198, E-ISSN 2065-0817

Year XV, vol. 41, no. 2, 2022, p.509-516
DOI 10.30892/gtg.41223-857

# COASTAL TOURISM: IMPACT FOR BUILT-UP AREA GROWTH AND CORRELATION TO VEGETATION AND WATER INDICES DERIVED FROM SENTINEL-2 REMOTE SENSING IMAGERY

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**Citation:** Sunarta, I.N., & Saifulloh, M. (2022). 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), 509–516. https://doi.org/10.30892/gtg.41223-857

**Abstract:** Indonesia is an archipelagic country that has diverse tourism potential, one of which is the island of Bali. The island of Bali is famous for its tourism potential to the World Level, especially the potential for natural and cultural tourism that is not found in other countries. Tourist visits to the island of Bali, from various countries, always increase every year. The increase in the number of tourists has triggered the tourism industry business players to build tourism facilities such as hotels, restaurants, shopping centers, and other facilities, thereby causing an increase built-up area in the coastal tourism area. This study aims to analyze the spatial pattern of built-up land through the transformation of the built-up land index (NDBI) and correlate it with the vegetation index (NDVI, SAVI) and the water index (NDWI). Data analysis using Remote Sensing method using a cloud-based computing platform, namely Google Earth Engine (GEE), on Satellite Imagery Sentinel 2, acquisition on 2016 and 2021. The results of this study indicate that there is an increase in the pattern of built-up area in the Southern coastal area, Tourism Area. The increase in built-up area causes a decrease in the level of vegetation density and increase the level of wetness of the soil surface.

**Key words:** Tourism Area, Bali Island, Built-up area, Google Earth Engine (GEE)

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## INTRODUCTION

Indonesia is an archipelagic country that has very beautiful natural potential, one of which is the island of Bali. Bali is the best tourism destination in the world (Ginaya et al., 2019; Hansun and Kristanda, 2019; Irawan et al., 2019; Zuraidah, 2019). Currently, the southern coast of Bali is developing rapidly, one of which is the existence of the Pandawa Beach tourist attraction (Swabawa et al., 2021), as well as other tourism such as Kuta beach (Carlos et al., 2020). In addition to natural tourist attractions in coastal areas, there are cultural tours (Handaru, 2020) and other destinations.

The existence of various tourism destinations, invites many foreign and domestic tourists visiting the island of Bali. The number of tourists visiting the island of Bali from year to year always increases (Subadra et al., 2019) . The increasing number of tourists has triggered tourism players and investors to develop tourism industry businesses such as hotels, restaurants, supermarkets, souvenir centers and other tourism industries. Thus, many absorb workers who come from the island of Bali and from outside the island. This condition causes high urbanization in tourism areas which indirectly triggers an increase in built-up land for the residence of employees in the tourism sector. High building density in coastal areas can cause aesthetic pollution, reduced vegetated land cover (Sunarta et al., 2021; Widyarini and Sunarta, 2019), increased temperature (Rizvi et al., 2021), carbon emissions (Wang and Wang, 2021), water scarcity (Sunarta and Arida, 2014). So that the green area, in coastal tourism areas need to be maintained (Dinh and Pham, 2021).

To determine the development of built-up land in tourism areas, one of them is by using remote sensing data Sentinel 2. The use of Sentinel 2 Satellite Imagery to monitor built-up land has been carried out by (Gbetkom et al., 2019). An analysis of the built-up land has previously been carried out in Denpasar City using Landsat ETM+ satellite imagery (As-syakur et al., 2012). The researcher tried to do the research again but using remote sensing data with higher resolution and linking it with the vegetation index and water index. Utilization of Sentinel-2A Imagery, which is a European optical imaging satellite launched in 2015. The Sentinel-2A satellite was launched as part of the Copernicus European Space Agency (ESA) program (Phiri et al., 2020). The reason the researcher uses this image is that Sentinel 2-A Image can be accessed for free on the European Space Agency (ESA) website. In addition, its spectral resolution produces 13 channels that include visible, near-infrared, and shortwave infrared sensors as well as a fairly high spatial resolution of 10 meters in the red, blue, green, and near-infrared bands. The building index used is the NDBI (Normalized Difference Built-up Index), the water index used is the Normalized Difference Water Index (NDWI), and the vegetation index NDVI (Normalized Difference Vegetation Index) and SAVI (Soil Adjusted Vegetation Index). The reason for choosing NDVI is because the best transformation to detect buildings is NDBI, although the highest value is bare land as a comparison, the development of built-up land is carried out by analyzing other indices so that the impact

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of building development on the development of buildings is known vegetation density and the level of wetness of the soil surface. The acquisition and analysis of remote sensing data are carried out using cloud-based computing, namely Google Earth Engine (GEE). The emergence of GEE makes it easier for researchers in the field of remote sensing to carry out data acquisition, data analysis, and data visualization (Tamiminia et al., 2020), so this is the reason researchers use the GEE platform in conducting research related to monitoring the built-up area in coastal tourism. The purpose of this study was to determine the spatial pattern, the increase in the built-up area and its effect on the vegetated area, and the level of soil surface wetness represented by the water index. The results of this study later can also be used as local government policies to formulate policies related to controlling development in tourism areas and building green tourism area.

## MATERIALS AND METHODS

This research was conducted in a tourism area on, south coast of Bali Island. Figure 1a shows the research location on a small scale, Figure 1b shows the regional scale of the spatial distribution of tourism areas, while Figure 1c. The research location is between 115°17’30” E to 8°37, 00” S. There are 7 tourist areas on the southern coast of Bali Island, such as the Regional Tourism Strategic Area (KSPD) Kuta, KSPD Lebih, KSPD Nusa Dua KSPD, KSPD Pulau Serangan, KSPD Sanur, KSPD Tanah Lot, and KSPD Tuban (Figure 1).

### Tools and Material

This study uses a tool in the form of cloud computing, namely Google Earth Engine (GEE) which is used for data acquisition and index processing (NDVI, NDBI, SAVI, NDWI). ArcGIS 10.8 application for extracting pixel values of each image index and map layout and other applications to support the writing of this paper. The materials used are Sentinel Image 2 Level 1-C sensing date 2016 to 2021, a map of the spatial plan of the Province of Bali, and a map of administrative boundaries from the Geospatial Information Agency (BIG).

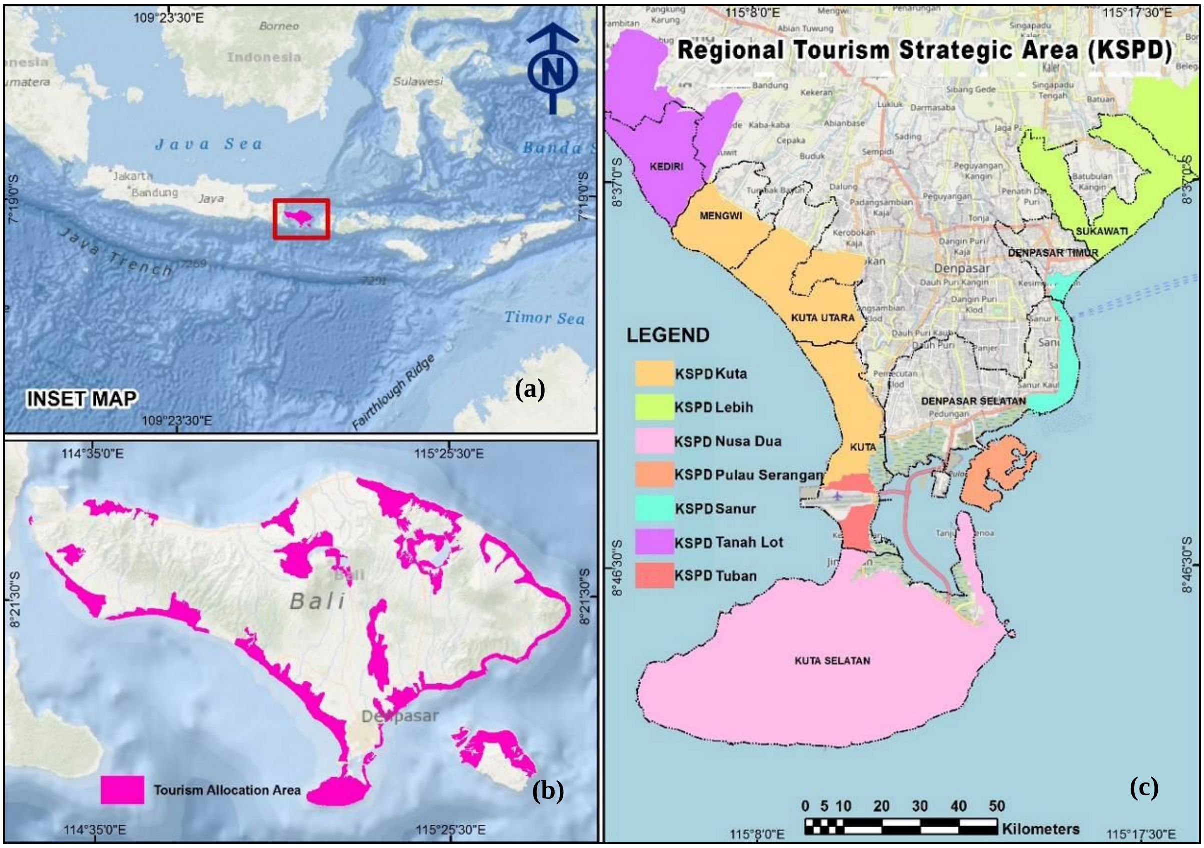


Figure 1. Bali Island Position from Small Scale (a), Tourism Allocation Area (b), Regional Tourism Srategic Area (KSPD) in South Coastal Area (c). (Source: Bali Province Spatial Plan 2009-2029 (Public Works and Spatial Planning Department, Bali Province and layout map by authors)

### Method - Data Acquisition

To monitor the built-up land and its influence on other factors, it is carried out using Sentinel 2A Remote Sensing data. Sentinel-2 is a European optical imager launched in 2015. Sentinel-2 is the first satellite to be launched as part of the European Space Agency (ESA) Copernicus program. This satellite carries a variety of high-resolution multispectral imagers with 13 spectral bands (Table 1). This satellite will carry out terrestrial observations to support services such as forest monitoring, land cover change detection, and natural disaster management. The image is filtered on May 1, 2016-30 July 2016 and as a comparison for the image on May 1, 2021-30 July 2021. Data acquisition on GEE can be seen in Figure 2. Automatically the GEE application will filter based on the script that has been ordered on the dashboard. Furthermore, data processing is carried out on the same cloud computing-based application. The Earth Engine (EE) Code Editor at code.earthengine.google.com is a web-based IDE for the Earth Engine JavaScript API. Code Editor features are designed to make developing complex geospatial workflows fast and easy. The Code Editor has the following elements (Figure 2). Utilization of GEE in sentinel 2 image analysis in addition to monitoring the built area (Celik, 2018), also to conduct an classification of land use land cover (LULC) (Soe Thwal et al., 2019; Xu, 2021; Zeng et al., 2020). This research flow chart is presented in Figure 3a.

Table 1. Characteristic of Sentinel 2 Image
(Source : European of Space Agency (ESA), 2015)

| Band | Wavelength (μm) | Spatial Resolution (m) |
|---|---|---|
| Band 1 – Coastal Aerosol | 0.443 | 60 |
| Band 2 – Blue | 0.490 | 10 |
| Band 3 – Green | 0.560 | 10 |
| Band 4 – Red | 0.665 | 10 |
| Band 5 – Vegetation Red Edge | 0.705 | 20 |
| Band 6 – Vegetation Red Edge | 0.740 | 20 |
| Band 7 – Vegetation Red Edge | 0.783 | 20 |
| Band 8 – NIR | 0.842 | 10 |
| Band 8A – Vegetation Red Edge | 0.865 | 20 |
| Band 9 – Water Vapour | 0.945 | 60 |
| Band 10 – SWIR – Cirrus | 1.375 | 60 |
| Band 11 – SWIR | 1.610 | 20 |
| Band 12 – SWIR | 2.190 | 20 |

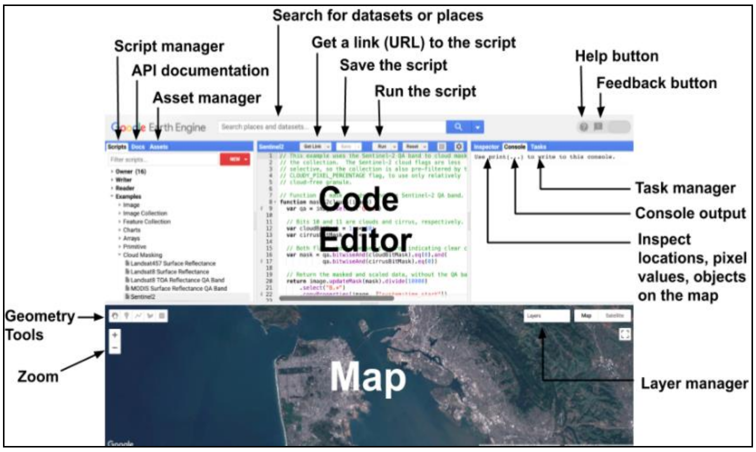


Figure 2. Diagram of components of the Earth Engine Code Editor at code.earthengine.google.com (Source : https://developers.google.com/)

## Data Analysis

NDVI (Normalized Difference Vegetation Index) is an image calculation that is used to determine the very good level of greenery as the beginning of the division of vegetation areas. NDVI can show parameters related to vegetation, including green foliage biomass, green foliage area which is an estimated value for vegetation division. NDVI value calculation requires Band 8 (NIR) and Band 4 (Red). NDVI calculation formula presented in Eq. 1.

$$NDVI = \frac{NIR - Red}{NIR + Red} \quad (1)$$

The NDVI value range is between -1 to +1. Values greater than 0.1 usually indicate an increase in the degree of greenery and intensity of vegetation. Values between 0 and 0.1 are generally characteristic of rock and bare land, and values less than 0 may indicate clouds of ice, clouds of water vapor, and snow. Surface vegetation has an NDVI value range of 0.1 for savanna (grasslands) to 0.8 for tropical rainforest areas.

The NDBI index will focus on highlighting urban areas or built-up areas where there is usually a higher bounce in the Shortwave Infrared (SWIR) area. NDBI value calculation requires Band 8 (NIR) and Band 11 (SWIR). NDBI calculation formula presented in Eq. 2.

$$NDBI = \frac{SWIR - NIR}{SWIR + NIR} \quad (2)$$

NDWI has been used to achieve the goal of separating water and non-water features. Mcfeeters (1996) developed the NDWI formula using the green and near-infrared (NIR) bands. NDWI value calculation requires Band 3 (Green) and Band 8 (NIR). In this study, using the development of Mcfeeters with the NDWI formula as follows Eq. 3.

$$NDWI = \frac{Green - NIR}{Green + NIR} \quad (3)$$

Table 2. Correlation coefficient (Source: Singh, 2018: 57)

| Description | Value |
|---|---|
| Very Weak | 0.00-0.19 |
| Weak | 0.20-0.39 |
| Moderate | 0.40-0.59 |
| Strong | 0.60-0.79 |
| Very Strong | 0.80-1.00 |

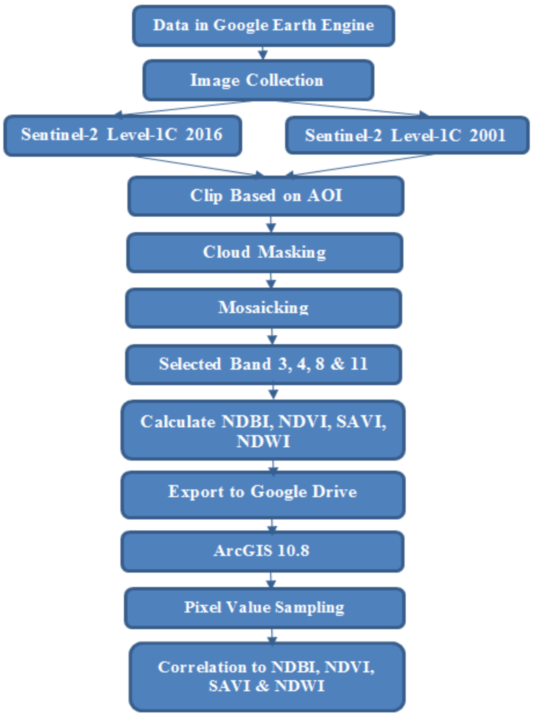


Figure 3a. Research flow chart

This soil vegetation index is adjusted and similar to NDVI , but suppresses the effect of ground pixels and uses a background canopy adjustment factor (L), which is a function of vegetation density and often requires prior knowledge of the amount of vegetation. Huete (1996) showed the optimal value of L = 0 .5 to account for first-order soil background variation. This index is best used in areas with relatively sparse vegetation where the soil is visible through the canopy. SAVI calculation formula presented in Eq. 4.

$$SAVI = \frac{1.5 * (NIR - Red)}{(NIR + Red + 0.5} \quad (4)$$

$$r = \frac{n\Sigma xy - (\Sigma x)(\Sigma y)}{\sqrt{\{n\Sigma x^2 - (\Sigma x)^2\}\{n\Sigma y^2 - (\Sigma y)^2\}}} \quad (5)$$

To find out the relationship between land changes built with other indices conducted correlation tests on Sentinel-2 Imagery. The regression used in this research is simple linear regression. Regression analysis is a statistical calculation used to determine whether satellite image data can be used to describe conditions that exist in the field. The relationship between the regression correlation is expressed in the correlation coefficient (r) and the coefficient of determination (R squared) to calculate the correlation coefficient value, the equation is used (Equation 5). Information on the strength of correlation is presented in Table 2.

## RESULTS AND DISCUSSION

### Google Earth Engine

Google Earth Engine makes it easy to perform remote sensing data acquisition, data processing, and visualization (Amani et al., 2020; Jahromi et al., 2021; Philipp et al., 2021; Tamiminia et al., 2020; Wang et al., 2020) . The results of data analysis through the GEE platform are presented in Figure 1. The script that is built simultaneously represents the NDBI, NDVI, SAVI, NDWI images, and the composite band of Sentinel 2 A images. Figure 1 shows the analysis results of one of the building indexes, namely NDVI 2016. The highest pixel value is shown in red while the lowest pixel value is shown in green. The results of image extraction that have been processed through GEE show pixel values that vary between 2016 and 2021. The 2016 NDBI has a threshold value of -0.818 to 0.531 with an average of -0.139. Meanwhile, the NDBI in 2021 has a threshold value of -0.777 to 0.549 with an average of -0.086. The differences in the minimum, mean and maximum values for the NDVI, SAVI, NDWI index are presented in Table 3. The Maximum value of each index shows an increase from 2016 to 2021. Graphs the pixel values of NDBI, NDVI, and SAVI images presented in Figure 4.

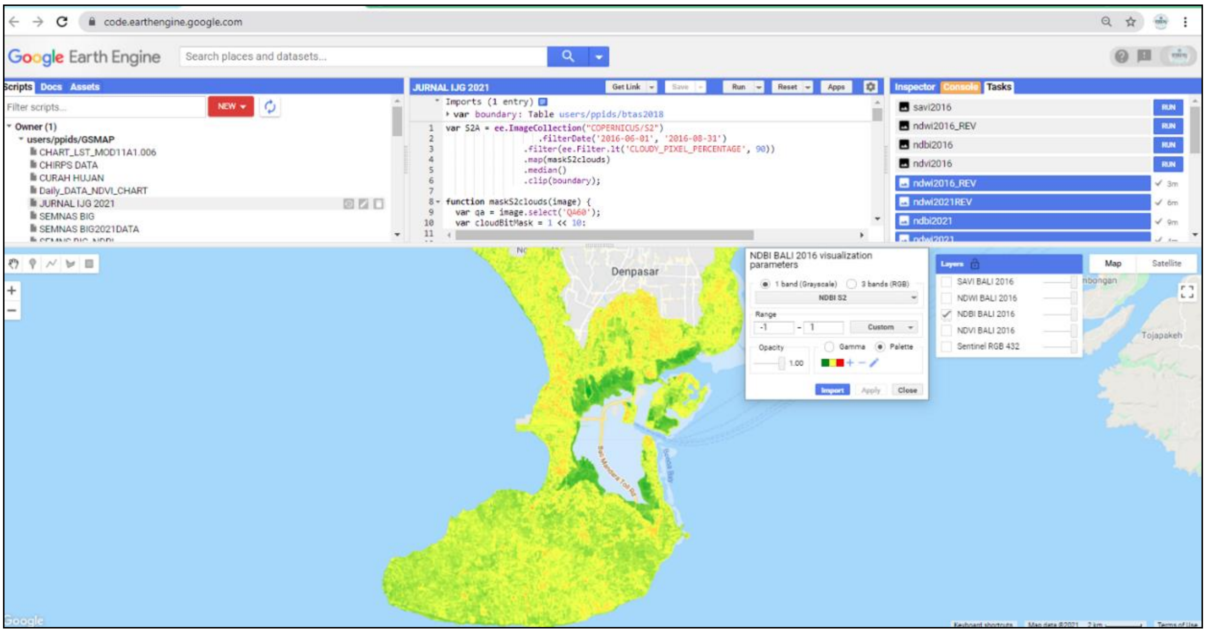


Figure 3. Dashboard Google Earth Engine. On the dashboard, displaying the results of each indices for 2016 and 2021

Tabel 3. Value of NDBI, NDVI, SAVI and NDWI values in 2016 and 2021 (Source: Primary data analyst, 2021)

| No | Index | Pixel Value | | |
|---|---|---|---|---|
| | | Minimum | Mean | Maximum |
| 1 | NDBI 2016 | -0.818 | -0.139 | 0.531 |
| 2 | NDBI 2021 | -0.777 | -0.086 | 0.549 |
| 3 | NDVI 2016 | -0.675 | 0.481 | 0.814 |
| 4 | NDVI 2021 | -0.528 | 0.389 | 0.815 |
| 5 | SAVI 2016 | -1.013 | 0.623 | 1.220 |
| 6 | SAVI 2021 | -0.791 | 0.584 | 1.222 |
| 7 | NDWI 2016 | -0.678 | -0.345 | 0.686 |
| 8 | NDWI 2021 | -0.678 | -0.329 | 0.697 |

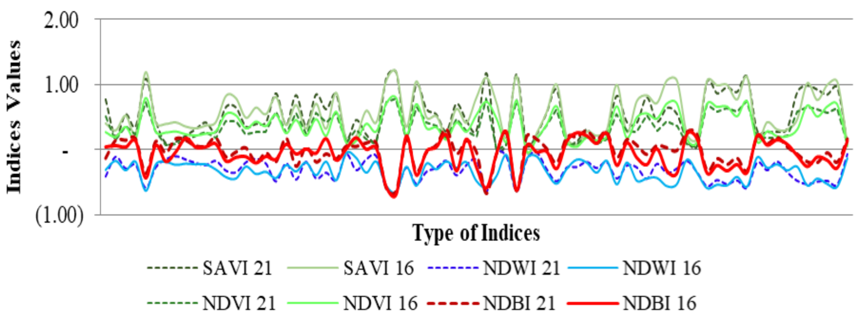


Figure 4. Graphs the Pixel Value NDBI, NDVI, SAVI, NDWI.
The graph is the result of sampling the pixel values of each vegetation index (Figure 5)

### Spatial Distribution Map of NDBI, NDVI, SAVI and NDWI

The NDBI map is visualized with a yellow to red color gradation (Figure 5a). The yellow color indicates the lowest value of the NDBI image, while the red color indicates the highest value of the NDBI image. Visually, more red zones are found in the 2021 NDBI images than in 2016. Such as located in the regional tourist area (KSPD) in Kuta District, KSPD Nusa Dua in South Kuta District and KSPD Kuta in Kuta District. Areas in red indicate high levels of building density. Meanwhile, the yellow area indicates a high density of vegetation, such as the Mangrove Forest which is located in the coastal area of South Denpasar District and Kuta District. The NDVI map is visualized with gradations of green, yellow to red colors (Figure 5b). The red color indicates the lowest value of the NDVI image, while the green color indicates the highest value of the NDVI image. Visually, more green zones are found in the 2016 NDVI image than in 2021. For example, it is located in the Tanah Lot Regional Tourist Area (KSPD) in Kediri District, and the KSPD Lebih in Sukawati

District. The green area indicates a high level of vegetation density. While the yellow area indicates a high level of building density, such as those located in the KSP Tuban and Kuta, Kuta District. The red color indicates the highest pixel value, which is in the body of water in KSPD Pulau Serangan, South Denpasar District. SAVI (Soil Adjusted Vegetation Index) is an algorithm developed from NDVI by suppressing the influence of the soil background on the brightness of the canopy.

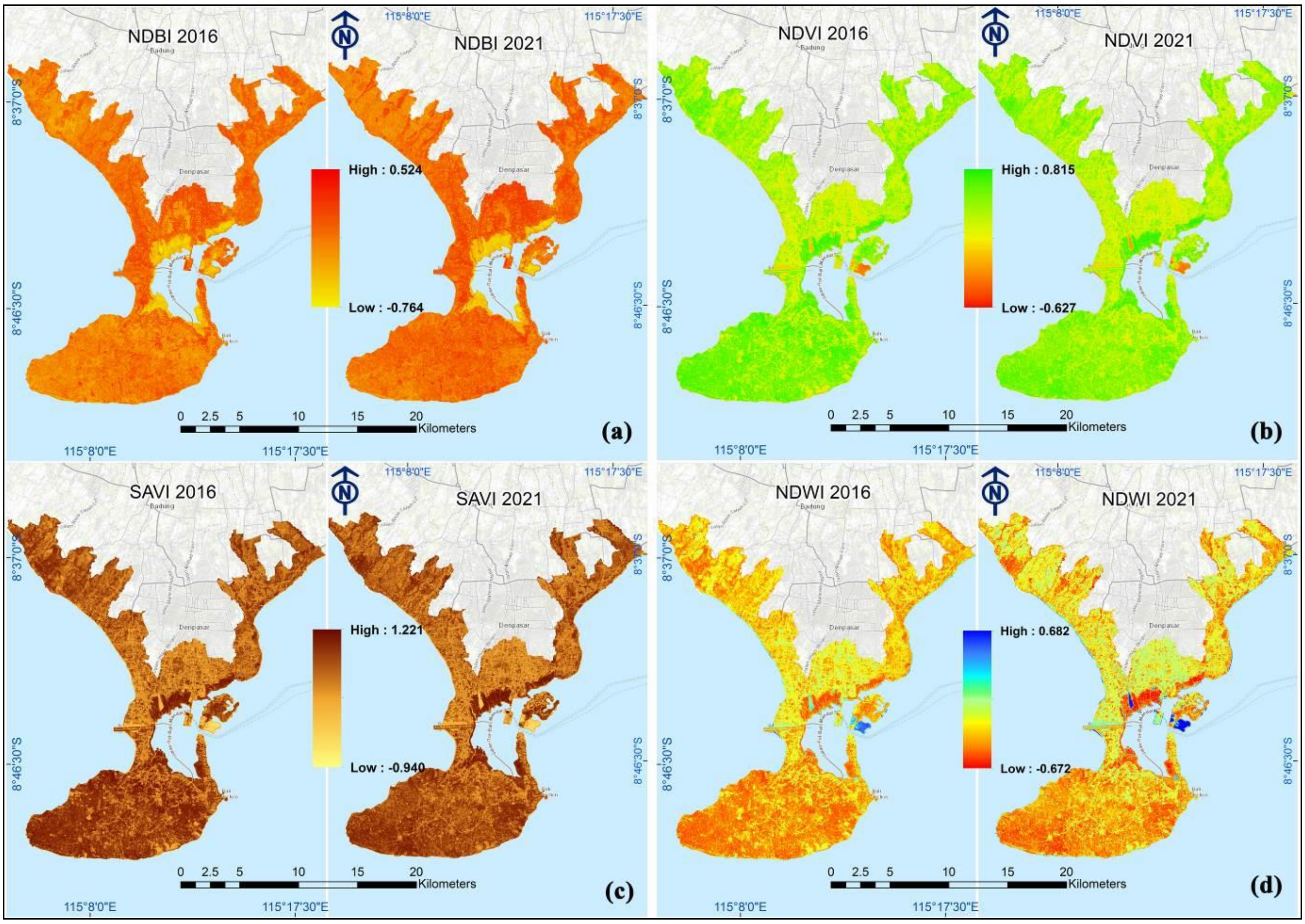

Figure 5. Spatial Pattern of NDBI (a), NDVI (b), SAVI (c), and NDWI (d). There is a change in spatial patterns. The more the awakened area (red zone) (a), and the decrease in the area of deviation (b), (c) and increase the value of the water indices (d). (Source: Authors)

The SAVI map is visualized with gradations of yellow, to brown (Figure 5c). The yellow color indicates the lowest value of the SAVI image, while the brown color indicates the highest value of the SAVI image. Visually, more brown zones are found in the 2016 NDVI image than in 2021. For example, it is located in the Nusa Dua Regional Tourist Area (KSPD) in the South Kuta District, which has a contrasting contrast of brown color sharpness between 2016 and 2021. The NDWI map is visualized with blue, yellow to red gradations (Figure 5d). The red color indicates the lowest value of the NDWI image, while the blue color indicates the highest value of the NDWI image. NDWI represents the level of wetness of the earth's surface detected from remote sensing images. A high value indicates a high level of wetness on the earth's surface, which in this study is a body of water in the KSPD Pulau Serangan, South Kuta District. The NDBI and NDWI values show a relatively similar pattern, but opposite the SAVI values with NDVI. For example, when NDVI and SAVI show a value of 1, NDBI and NDWI show a value of -0.50 (Figure 4). This condition occurs because the transformation of the highest NDVI and SAVI values (close to 1) is in high vegetation density land cover. In the Building Density Index (NDBI) a pixel value close to 1 indicates a high level of building density, while NDWI indicates a high level of wetness on the earth's surface.

**Correlation between NDBI with (NDVI, SAVI, and NDWI)**

The correlation line between NDBI and (NDVI, SAVI and NDWI) shown on Figure 6. The essence of this research is to monitor changes in building density in the coastal tourist area of Bali Island. Spatially, the building density in 2021 is higher than in 2016. This study does not examine the best index to detect building density, but the researcher only uses NDBI to determine the pattern of building density and correlates it with vegetation cover as indicated by NDVI and SAVI and the level of surface wetness. Earth due to massive development, especially in the tourism area. The correlation value between NDBI and NDVI in 2016 ($r= 0.894$), while in 2021 ($r= 0.859$). The correlation between NDBI and SAVI in 2016 ($r=0.894$), while the correlation between the two in 2021 ($r=0.859$). The correlation between NDBI and NDWI in 2016 ($r= 0.845$), while in 2021 ($r= 0.811$). The correlation between NDBI and other indices, indicates a very strong relationship. Image visualization with a combination of bands (B8, B4, B3) makes it easier to visually interpret the built-up area and the vegetated land (Figure 7). The combination of color infrared bands is meant to emphasize healthy and unhealthy vegetation (Al-Doski et al., 2020; Beisel et al., 2018; Bindu et al., 2020; Franke et al., 2012; Kala et al., 2018; Saheed et al., 2020; Sawaiker and Gaonkar, 2020; Shahukhal and Semke, 2016). By using the near-infrared band (B8), it is very good at reflecting chlorophyll (Ali et al., 2020; Ansper and Alikas, 2019; Bramich et al., 2021; Clevers and Gitelson, 2013; Clevers et al., 2017; Darvishzadeh et al., 2019; Delloye et al., 2018; Govindaraj and Saravanakumar, 2019). This is why in color infrared images, denser vegetation is colored red, as in Mangrove Forests. Meanwhile, the Nusa Dua Regional Tourism Area is partly white and brown which indicates the existence of built-up land. The condition of the built-up land visually experiences growth from 2016 to 2021.

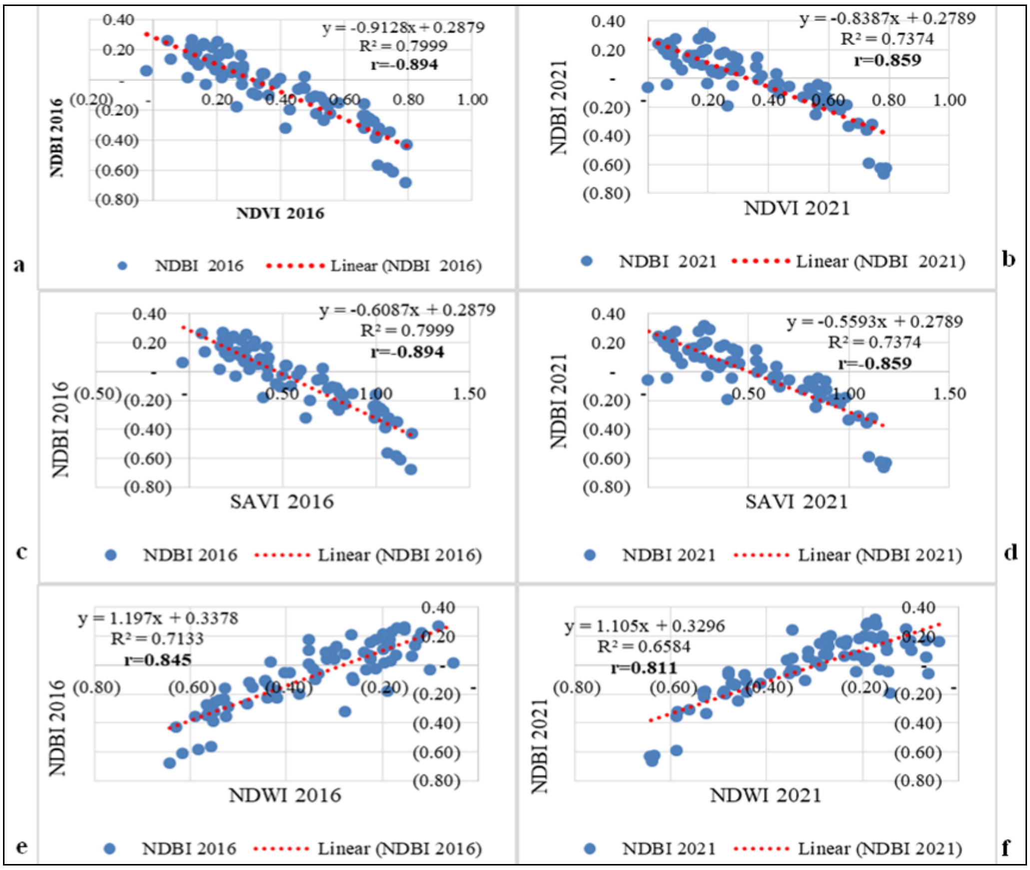


Figure 6. Correlation between NDBI and NDVI in 2016 (a), NDBI and NDVI 2021 (b), NDBI and SAVI 2016 (c), NDBI and SAVI 2021 (d), NDBI and NDWI 2016 (e) and, NDBI and NDWI 2021 (f). The correlation between NDBI and NDVI (a), SAVI (b) has a negative correlation, and is positively correlated with NDWI (c)

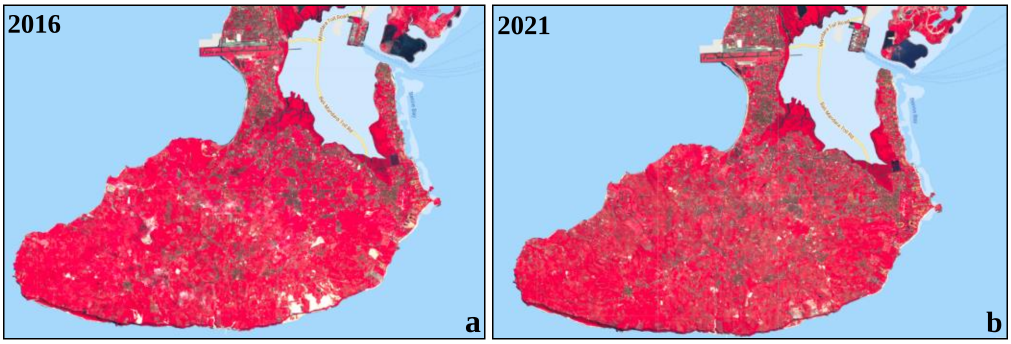


Figure 7. Map using Color Infrared Band Combination RGB ( B8, B4 and B3), Conditions in 2016 (a), and 2021 (b). Using infrared color it appears more clear, that the area of land is built and the empty land is indicated by brown. The map is located in KSP Kuta Selatan (Source: Authors)

The tourist area of the coastal part of the island of Bali is experiencing the development of built-up land from 2016 to 2021. The development of built-up land causes a decrease in vegetation density (Koko et al., 2021) and causes drougt land (Vinh et al., 2020), indicated by a high level of land wetness. So that in areas with tall buildings, it is easily inundated with water during the rainy season. On the other hand, the decrease in vegetation density, also affects the increase in surface temperature (Goldblatt et al., 2021) so that the atmosphere of the tourism area becomes heat. The density of industrial and transportation activities in tourism areas has an impact on air pollution, such as nitrogen dioxide ($NO_2$), which can be harmful to human health and tourists (Sunarta and Saifulloh, 2022). Based on this research, it is recommended that the construction of tourism facilities in the form of hotels, restaurants, shopping places, and other tourism supporting facilities be carried out so that development is carried out in the northern part of the region which has a high vegetation density. However, development must be based on regional spatial planning (Saputra and Santosa, 2020), so as not to violate the law. In areas that have already been developed, it is recommended to carry out greening around the building in order to create an atmosphere of a green tourism area (Vdovenko et al., 2021).

## CONCLUSION

There is a change in spatial patterns, the built-up area in the coastal tourism area. The built-up area having growth from 2016 to 2021, such as in the Kuta Selatan, Kuta and Nusa Dua regional tourism strategic area. The correlation between the built up area indices and the vegetation indices shows a negative correlation. This shows that the higher the value of the built-up area indices, the lower the value of the vegetated land indices.

The correlation between the built-up area indices and the water indices shows a positive correlation, this shows the high value of the built-up area indices, which is directly proportional to the high value of the water indices. The correlation is an increase in built-up areas, a decrease in vegetation density, and an increase in the level of wetness of the soil surface. Based on this research, it is recommended that the construction of tourism facilities be accompanied by the addition of vegetation through greening around the buildings in the coastal tourism area.

**Acknowledgement**

The authors thank the Dean of the Faculty of Geography, Gadjah Mada University and the Dean of the Faculty of Tourism, Udayana University. Because research in the field of tourism and remote sensing can be carried out well. The researcher also thanks the Head of the Center for Spatial Data Infrastructure Development at Udayana University who has facilitated the equipment to perform Image Processing, so that this scientific work can be completed in a timely manner.

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Article history: Received: 09.10.11.2021 Revised: 11.03.2022 Accepted: 18.04.2022 Available online: 12.05.2022