IDENTIFYING LAND USE AND LAND COVER (LULC) CHANGE FROM 2000 TO 2025 DRIVEN BY TOURISM GROWTH: A STUDY CASE IN BALI

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ABSTRACT:

Bali has been open to tourism since the beginning of the 20th century and is known as the first tourist destination in Indonesia. The Denpasar, Badung, Gianyar, and Tabanan (Sarbagita) areas experience the most rapid growth of tourism activity in Bali. This rapid tourism growth has caused land use and land cover (LULC) to change drastically. This study mapped the land-use change in Bali from 2000 to 2025. The land change modeller (LCM) tool in ArcGIS was employed to conduct this analysis. The images were classified into agricultural land, open area, mangrove, vegetation/forest, and built-up area. Some Landsat images in 2000 and 2015 were exploited in predicting the land use and land cover (LULC) change in 2019 and 2025. To measure the accuracy of prediction, Landsat 8 OLI images for 2019 were classified and tested to verify the LULC model for 2019. The Multi-Layer Perceptron (MLP) neural network was trained with two influencing factors: elevation and road network. The result showed that the built-up growth direction expanded from the Denpasar area to the neighbouring areas, and land was converted from agriculture, open area and vegetation/forest to built-up for all observation years. The built-up was predicted growing up to 43 % from 2015 to 2025. This model could support decision-makers in issuing a policy for monitoring LULC since the Kappa coefficients were more than 80% for all models.

1. INTRODUCTION

1.1 General instructions

Globally, tourism generates 9% of global GDP, and 1 in 11 sectors creates job opportunities UNWTO (UNWTO, 2014). Tourism in Bali is the first sector contributing to Gross Domestic Production (GDP). Furthermore, more than 50% of the Bali population is related to the tourism sector (Antara and Sumarniasih, 2018). Hence, people from neighboring provinces move to Bali to seek jobs. It causes urbanization, especially in Denpasar City and its neighboring cities (Rimba et al., 2019) since urban growth is primarily triggered by the development of the tourism sector, which produces spaces that are exclusively dedicated to tourism purposes (Qian et al., 2012).

Urbanization is an agent for development, and tourism urbanization creates employment opportunities and increases the income of the community. At the same time, it is an agent for causing land use land cover (LULC) change since tourism consumes the natural landscape alongside the coastline, making them land for fancy accommodations, especially along the coastline (Mullins, 1995).

Land use and land cover (LULC) change are distinguished as the most prominent component in global environmental change. It is influenced dominantly by anthropogenic activities. The LULC change benefits city service improvement through urbanization and population growth (Liu et al., 2011); however, it also has a negative impact. For example, urban structure and anthropogenic activities release heat, causing a microclimate that advances new risk, for example, heat stress (Stone et al., 2010). Urbanization is a significant motorist of LULC change and has been a concern in both developed and developing countries, as well as in Indonesia. Bali is recognized as the primary tourist target in Indonesia and pointer Denpasar City, the capital city of Bali Province, as the highest populated city in Bali. The tourism area influences a wide area, for example, agriculture land, nature areas, and beaches, and affects the neighbouring areas.

Bali island, which has been open since the beginning of the 20th century, has been exploited as the center of tourism activity in Indonesia. As mentioned in the previous research, 54% of land-use has changed over 16 years in Bali (Rimba et al., 2019). However, there few empirical studies in the literature which predict the growth of Bali island's spatial pattern in the future. This study combined remote sensing and GIS method in predicting LULC growth in the center of tourism activities in the Bali province.

Remote-sensing technology integrated with the Geographic Information System (GIS) has been widely utilized and is acknowledged as a remarkable and efficient tool in analysing LULC change. Remote-sensing images support profitable multi-resolution, multi-spectral, and multi-temporal data, and provide valuable information for monitoring earth surface time by time. Monitoring the previous and predicting

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LULC in the future will be beneficial to urban planning and management, especially in the tourism area, which is proliferating.

Cellular Automata (CA) Markov, Markov chain, GEOMOD, etc., have done LULC modelling (Hernández-Guzmán et al., 2019; Islam et al., 2018). However, their performances vary depending on various factors, for example, resolutions. The Land Change Model (LCM) is a new technique and it is widely used in analysing and predicting LULC. This method allows the user to add dominant drivers in change by integrating biological, physical, and socio-economic drivers that influence the LULC change. It contains a customary sensible tool designed to solve the complexity of land-use change and management (Gontier et al., 2010). (Gontier et al., 2010). A few studies have been done by utilizing LCM in water management (Ansari and Golabi, 2019; Hernández-Guzmán et al., 2019), and agriculture (Abd EL-kawy et al., 2019), but there is no study related to tourism especially in Bali Province-Indonesia.

This study utilized the LCM to predict the LULC change over 25 years in the tourism area to show the LULC change from 2000 to 2025 in the tourism area. It is important to investigate the LULC change in order to propose inputs to decision-makers in issuing policies to control the urban growth in the Sarbagita area; this can reduce undesirable socio-economic and other effects.

2. DATA AND METHODOLOGY

2.1 Study area

Figure 1 shows the research location known as Sarbagita, a habitat of 2,325,050 people, in 2017. It covers four regencies in the south part of Bali Province, i.e., Denpasar (12,778 ha), Badung (41,862 ha), Gianyar (36,800 ha), and Tabanan regency (101,388 ha). These areas are the most developed areas in Bali Province, which were established based on Presidential Decree No. 45, 2011.

2.2 Data sets and the proposed framework

This study utilized Landsat Enhanced Thematic Mapper (ETM) and Landsat 8 Operational land Imager (OLI) data to produce LULC in 2000 and 2015, respectively. Moreover, Landsat 8 OLI was employed to verify the prediction model for 2019. Figure 2 shows the whole steps of this study. The inputs from satellite images were pre-processed and classified to generate change analysis. The maps from classified LULC were used as an input to transitional potential and generate change prediction for 2019 and 2025. All maps have to be validated by field survey and google earth image, and measured by the Kappa coefficient.
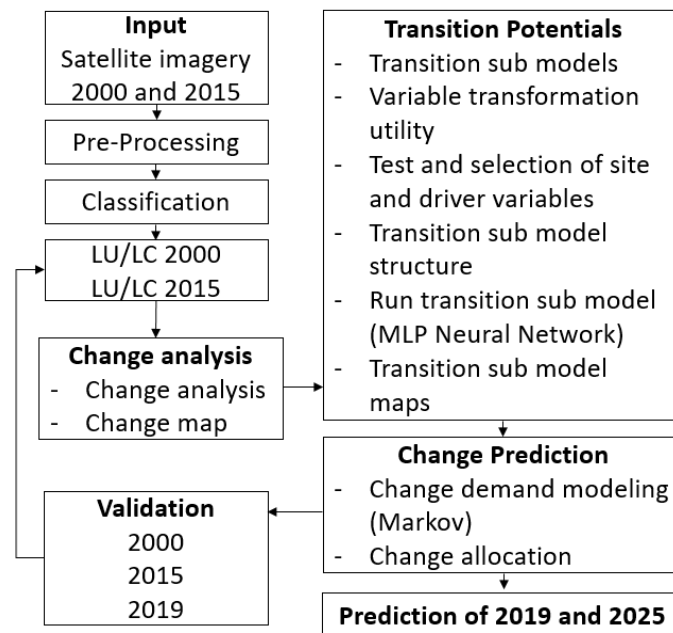

Figure 1. Study area

Figure 2. Flow chart of study

2.2.1 Pre-processing of satellite images: Six temporal Landsat images were selected as the primary input to this study from path/row 116/066 and 117/066. The image compositions were two images of Landsat ETM to generate LULC in 2000, two images of Landsat 8 OLI to produce 2015 LULC, and two Landsat 8 OLI to verify the model for 2019. However, additional images were included to compile the blank area due to the cloud. However, fewer cloud coverage images were the main priority criteria in images selection. Nevertheless, a clean image without a cloud was unfeasible to record by a visible band. Each Landsat image was re-projected to the WGS 84/UTM Zone 50S following a third-order polynomial fit and nearest neighbour resampling method

2.2.2 Image classification: Image classification was grouped into three steps: supervised classification, post-classification, and filtering. Some supervised classification methods were run to create a classified-image; however, this study employed the maximum likelihood because it showed the best classification in identifying the LULC. Local knowledge and Google Earth were the main methods in selecting training area for classification. Some training areas for each class (i.e., agriculture, open area, mangrove, vegetation/forest, and built-up) were selected to classify the images. Post-classification has done to minimize the small number of pixels of each class. It was impossible to get 100% cloud-free images. Hence, in the classification image, additional images were added to fill the cloud gap in a particular area. One of the challenging processes in image classification was different seasons of the images, probably showing various classifications.

2.2.3 Land Change Model (LCM): LCM assesses LULC changes between two different times, computes the differences, and presents the findings with several diagrams and spatial distribution. Then, it forecasts opportunity LULC maps based on drivers and potential transition by applying Multi-Layer Perceptron (MLP) neural networks (National Research Council, 2014). LCM was discovered to generate advance forecast precision because neural network analysis are capable to definite the change of different LULC types more effectively than singular possibilities achieved through the others predicting methods.

The transition matrix between dates t_0 and t_1 ($t_1 = t_0 + T$) is attained by overlapping the two LULC layers recorded t_0 and t_1. This matrix shows the number of pixels for each change, which is the origin for projecting to a future period after one or several times T (for example, date $t_1 + T$). However, it is regularly required to use a period set dissimilar from the original date T for projecting into the future. For example, the date between the two LULC layers used to standardize the model is typically multiple years, and the model runs using one year as the time step. The projections are also performed by creating a matrix to calculate the quantity of each LULC for the desired date. When the date projected forward is a multiple of the calibration period, this transition probability matrix is calculated using a simple powering (Mas et al., 2014). Equation 1 projects the trend change on an annual basis, where A is an annual matrix, t is the number of years, B is the original base transition matrix, H is the eigenvector of B, and λ is the i-th eigenvalue of B.

$$A = B^{1/t} = H \begin{pmatrix} (\lambda_1)^{1/t} & & 0 \\ & \ddots & \\ 0 & & (\lambda_n)^{1/t} \end{pmatrix} \tag{1}$$

2.2.4   Accuracy assessment: Kappa coefficient (K_{hat}) is one of the validation methods that are often used in remote sensing. It calculates the agreement between the interpretation and the original form of the land covered on the site. Equation 2 shows how to compute K_{hat}:

$$K_{hat} = \frac{OA - CA}{1 - CA} \qquad (2)$$

where   OA = Observed accuracy
            CA = Change agreement

3.   RESULT AND DISCUSSION

3.1   Remotely-sensed LULC classification accuracy

The LULC map was generated from satellite images, based on five categories: agriculture, open area, mangrove, vegetation/forest, and built-up area. They were classified by supervised classification and visual interpretation from satellite images, with secondary information from Google Earth and local knowledge. One hundred field-survey points were utilized to measure the accuracy of each LULC class; they were more focused on the built-up area. Trials and errors of image classifications were performed to obtain a satisfying accuracy. The Kappa coefficient from Equation 1 was employed to measure the accuracy of LULC. The accuracy was 81.25% and 84.12 % for 2000 and 2015, respectively.

The LULC prediction model was run two times, i.e., in 2019 and 2025. The first model predicted LULC in 2019, and this is the current year of LULC. This model was verified by using Google Earth and field visits, and the accuracy was 80.01%. The assumption was that all models have the same accuracy level. Thus, the second model was run to predict LULC in 2025. All LULC models from (i.e., 2000, 2015, 2019, and 2025 models) convinced the standard of K_{hat}.

However, in advance, the LCM model for 2025 can be verified by using the Bali land use plan map, which was issued by the local government. This step will measure the suitability LCM model and government plan.

3.2   Change analysis

The input images for changing analysis must hold identically consistent metadata (i.e., size, legend, depth, and a number of pixels, projection, etc.). By comparing two different years, i.e., 2000 and 2015, change analysis for a specific year could be produced. Transition potential was a prominent step in prediction; this step would decide whether specific class converted or not depended on the size of the threshold. In this study, the threshold for transition potential was 100 hectares; this value was the proper size from the total area and pixel size of satellite images. Another critical factor was the changing drivers. This study utilized two drivers in predicting LULC, i.e., road and slope. The road was a crucial driver because usually, the built-up area increasingly develops when it has good access and a flat slope (0-2%), flat area overgrows compared to the hilly area. The transition potential and driver were integrated to

calculate the relative operation characteristic (ROC). If the ROC and the Cramer values are lower than 0.75 and 0.15, respectively, that means the driver does not have a strong influence on the change. The MLP Neural Network was utilized to run the transition potential with an accuracy value of more than 0.75. LCM offers three methods to generate the probability map: logistic regression, multilayer perceptron (MLP) trained by backpropagation, which is a frequently used supervised neural network, and a similarity-weighted instance based machine learning tool known as SimWeight (Sangermano et al., 2010, Mas et al., 2014).

The LULC change has been discussed for a long time in Bali. The rapid tourism growth generates urbanization, which transfigures the agriculture area into tourism-related infrastructures, such as hotels, villas, restaurants, etc. The expansion of the urban area to the neighbourhood area (the urban sprawl) is happening in Bali. Since Bali was crowned as the first tourist destination in Indonesia, urban sprawl has expanded due to the tourism sector. The increased build-up of the area from 2000 to 2015 was 501%, i.e., 4,088.7 Ha to 25,589.8 Ha as shown in Fig.3. Tourism influenced broad areas, including beaches and natural parks (Boavida-Portugal et al., 2016). However, in the Bali area, the majority are changing from agriculture, and another LULC was converted to built-up as well.

Tourism brings advantages and disadvantages to the community. Rural and urban communities have embraced tourism and its stimulus effect on economic growth. However, tourism activity drives a massive LULC, which creates physical and social problems. Insufficient land capacity to support the urban area initiated other environmental problems, for example, worse garbage management, water shortages, and job conversion to the tourism sector.

Interviews with farmers were conducted during the field visit; the reasons for land conversion were due to economic factors and a lack of policies; this finding is in line with previous studies (Budiasa et al., 2015; Mohan et al., 2018; Rimba et al., 2019). Since tourism is the primary sector in Bali, the farmers left their fields and moved to the city for tourism-related jobs (e.g., hotel or restaurant staff, guide, driver, etc.), or even to be construction workers to build hotels, villas, roads, etc. As a result, the young generation prefers working in the tourism sector rather than in farming (Rimba et al., 2019b) which has led to abandoned farmland and massive land conversion. Furthermore, water shortages due to climate change exacerbated the farmer's situation and put more pressure on them to convert their land. Moreover, the demand for land and prices for housing are higher than in agriculture.

The continuous trends of the high demand for land to construct houses or develop tourism-related activities will continue into 2025, as shown in Fig. 3 and 4. The conversion of farmland seems to be the main change. According to the LCM tool, built-up area will increase by approximately 43 % (35,363.16 Ha) from 2015 to 2025. This trend appears alarming to the natural resources of the Sarbagita area and requires quick action from policymakers to control the LULC change, especially in the area of agriculture. However, the tourism sector in Bali has developed as per Balinese culture, according to Bali Provincial Regulation No. 2, 2012.
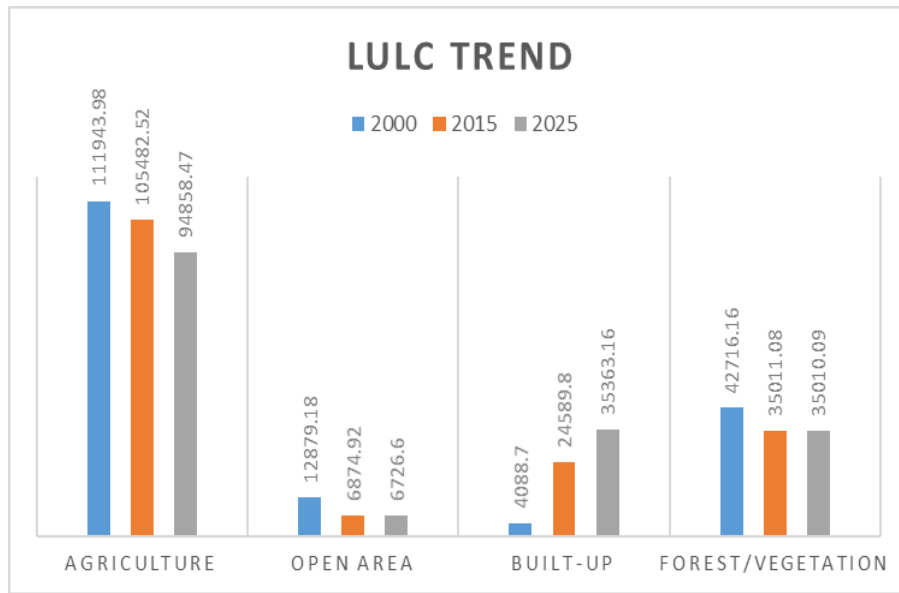
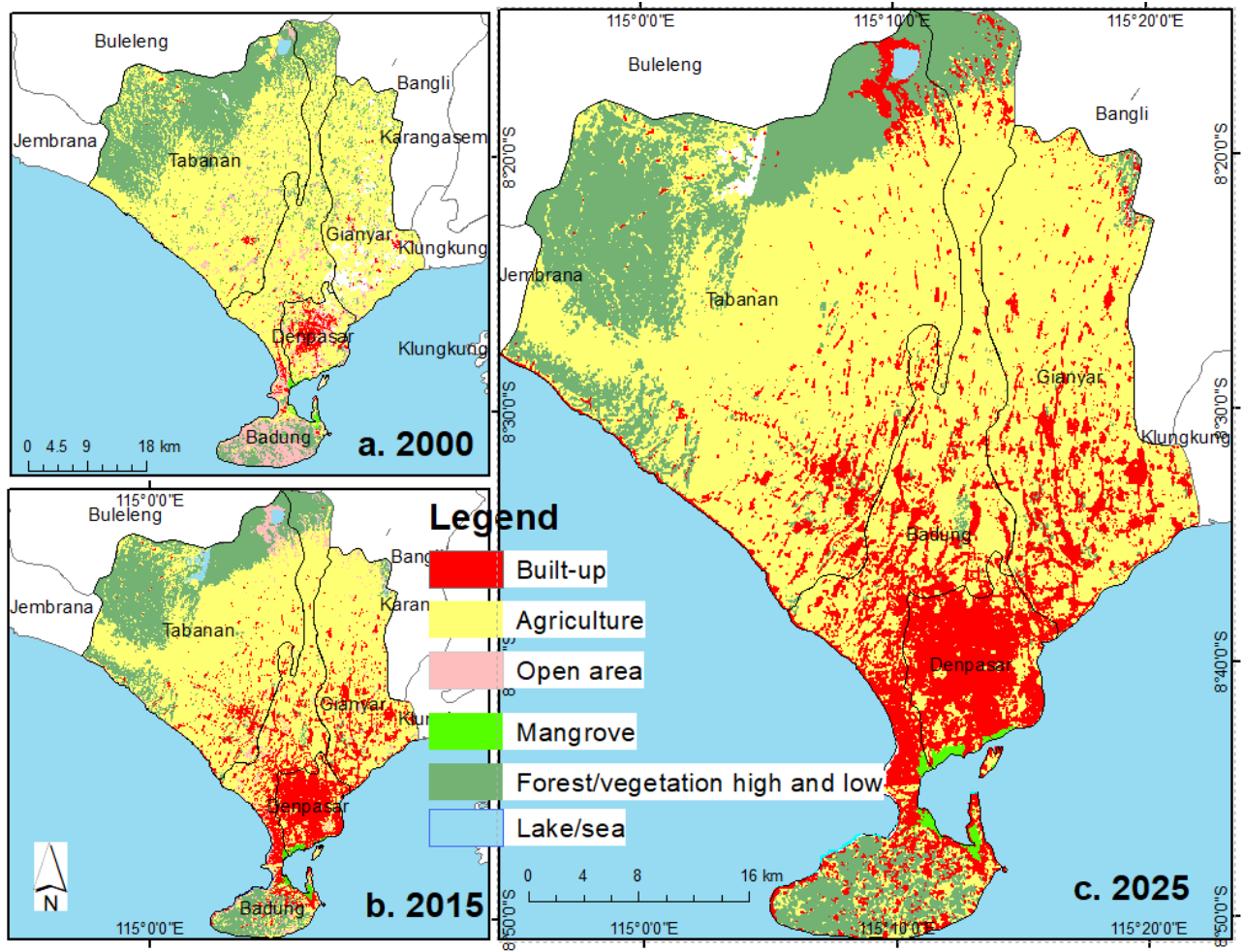Figure 3. LULC trend from 2000 to 2025 (unit in ha)

Figure 4. a. LULC in 2015, b. LULC in 2015, and c. LULC Prediction for 2025

3.3 Bali tourism growth

The increasing number of local and international visitors to Bali island has triggered the rapid growth of neighbouring villages, which has caused uncontrolled land conversion in the Sarbagita area. Generally, the tourism industry is the largest sector in the world, generating 9% of GDP and was associated with 6% of all exports in 2018 (UNWTO, 2014). Tourism contributes to 22.7% of Bali's GDP (Mohan et al., 2018). This industry has triggered urbanization not only from rural to urban areas but also migration from one island to another. Approximately 85% of the tourism sector is in the hands of non-Balinese (Cole, 2012).

Convenience transportation options, good accessibility, and improving emerging markets have made tourism a massive growing industry (UNWTO, 2014). National government development strategies, economic planning, and private investments have strengthened the tourism sector by establishing permits to increase the number of tourism-related businesses (hotels, restaurants, guides, crafts, cultural performances, etc.).

The number of tourists in Bali increases year by year, as shown in Fig.5. The total number of visitors to Bali in 2004 and 2018 were scientifically increased from 2,038,186 and 15,828,464 people, respectively. These visitors were supported by accommodation, as shown in Fig. 6. The number of hotels greatly increased in 2017 by approximately 134 % from 20152015 in total and the average length of stay was 4 to 4.5 days. Moreover, increasing hotel in Sarbagita with 170% excessed Bali's rate in the same period.
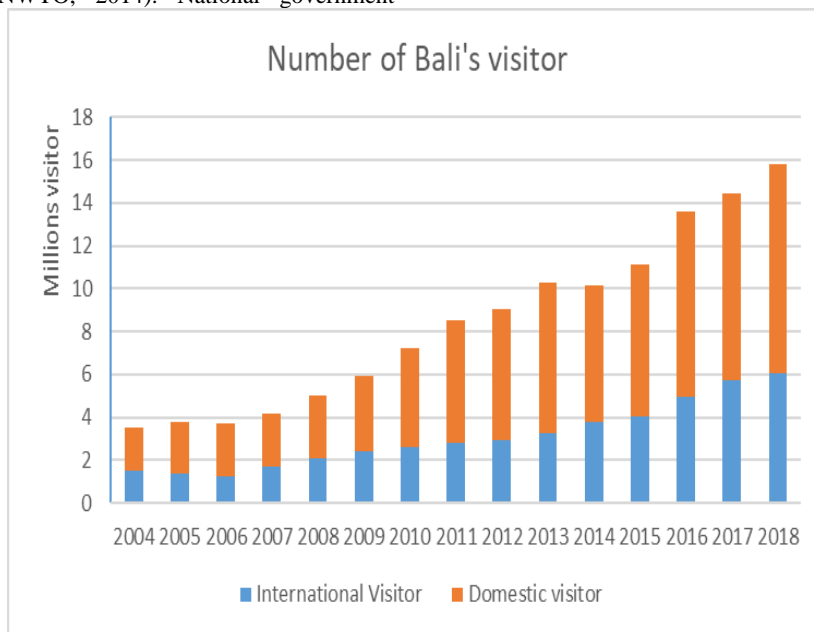

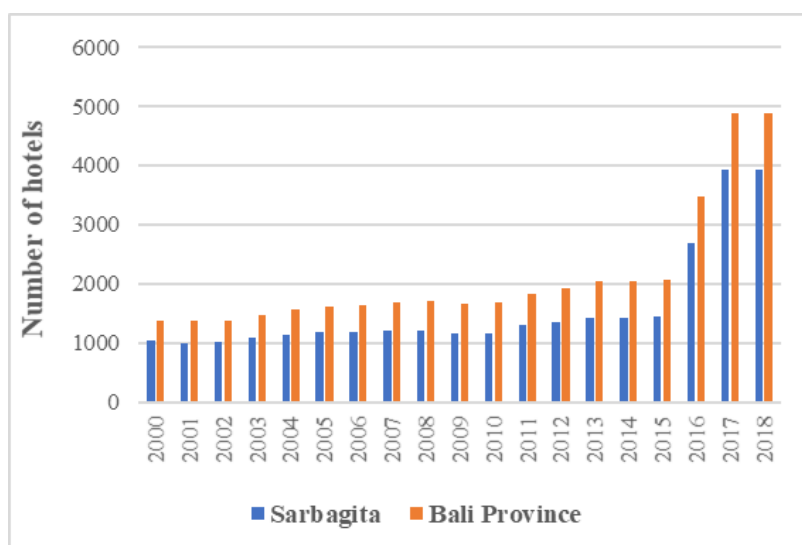Figure 5. Number of international and domestic visitors in Bali (BPS, 2018)

Figure 6. Number of hotels in Sarbagita area and Bali Province

4. CONCLUSION

- Kappa coefficient showed that all models accomplished the standard value of K_{hat}, i.e., 81.25%, 84.12%, and 80.01% in 2000, 2015, and 2025 LULC predictions, respectively. We assumed that the accuracy of the prediction model was constant.
- The trend of LULC change showed that the built-up area had been developed continually, and land conversion was dominated by the agriculture class.
- The urban area expanded by 501% from 4,088.7 Ha in 2000 to 24,589.8 Ha in 2015 and is predicted to have a 43 % increase from 2015 to 2025 (total area for 2025 approximately 35,363.16 Ha).
- The Land Use Model (LCM) is a modern approach to generate LULC predictions; this model could help the decision-makers to issue policies in monitoring LULC.
- The tourism growth triggers the LULC change in the Sarbagita area, and the increase of visitors prompts the development of a tourism-related building.

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