

Land Use/Land Cover Simulation Scenarios in Bogor and Karawang Regencies' Border Area, Indonesia, Using GIS-based Multi-stakeholder Tourism Analysis

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Abstract

Border area development in Indonesia is difficult to oversee because most of the border area is located far away from government centers, therefore the study of land use/land cover (LULC) change in border area is vital to the goal of analyzing a suitable policy for development control, and preventing the environmental problems. This study describes predicted LULC scenarios for 2030 in Bogor and Karawang Regencies' border area based on multi-stakeholder perceptions. Notably, this border area is home to a popular tourist location, Green Canyon Waterfall (GCW). The tourism stakeholder analysis identifies three groups: key players (KP), content setter (CS), and subject (S). Actors representing each stakeholder group were surveyed and interviewed to gather their preferences regarding favorable spatial criteria to determine LULC in 2030. There are nine spatial criteria: altitude (A), water conservation zone (WCZ), water bodies buffer zone (WBBZ), landslide potential disaster zone (LPDZ), distance to border (DB), distance to road (DR), distance to mosque (DM), distance to tourism facilities (DT), and distance to government centers (DG). For each stakeholder group, actors' preferences were input into the Multi-Actor Multi-Criteria Analysis (MAMCA) software. Raster cells containing a suitability index of 0.8 – 1 was reclassified as 1 and replaced with predicted LULC 2030 scenarios from CA-Markov to generate suitable cells for LULC changes. Layer integration between raster cells suitable for change and unsuitable for change resulted in three scenario maps. When superimposed with spatial master plan regulation (SMPR) map, the KP group shows a 73.67% area percentage match, while the S group and CS group reflect a 72.45% match and 72.14% match, respectively. Evaluation of model performance using AUC and ROC curves shows that predicted LULC 2030 based on the S group has the highest AUC with 0.980, followed by the CS group (AUC = 0.974) and KP group (AUC = 0.890).

Keywords: LULC simulation, GIS, CA-Markov, MAMCA

1. Introduction

Land use/land cover change (LULCC) studies have played an important role in understanding anthropogenic driving factors and the environmental impacts of LULCC. Several studies have been performed to identify the propellants of LULCC (Sang *et al.*, 2023; Daba and You, 2022;

Wang *et al.*, 2021), and from this research, a development policy can be devised to address environmental problems such as shrinking green space (Ghosh *et al.*, 2021) and agricultural systems loss (Tolessa *et al.*, 2020). Though the identification of LULCC driving factors is frequently analyzed from a bio-physical

perspective, several previous studies (Boavida-Portugal *et al.*, 2016; Mathewos *et al.*, 2022) have addressed this subject from the viewpoint of stakeholders.

In Indonesia, border area development is difficult to oversee because most of the border area is located far away from government centers. Therefore, some regencies/provinces formed agencies specifically to coordinate the development among adjacent administrative regions, such as BKSP Jabodetabekjur (Greater Jakarta Development Cooperation Agency). Another tactic is to strategize spatial master plan regulation (SMPR) for several bordering regencies through policies such as Government Regulation 66/2022, which coordinates SMPR for Greater Surabaya Megapolitan Area. While cooperation among smaller regencies in the management of border areas has rarely materialized, border area development between Bogor and Karawang Regencies has shown notable growth, a topic discussed among regencies' leaders during the 2019 Borderline Economic Summit (BES). Other topics raised during the summit included tourism cooperation and the planning of new roads that would connect all regencies (Bogor Regency, 2023). Hence, the study of LULC in this border area is vital to the goal of analyzing development, devising a suitable policy for controlling that development, and preventing the environmental problems that might arise.

Many studies have shown that tourism activities in the border area have increased stakeholders' tourism awareness (Kovačević *et al.*, 2018; Wan *et al.*, 2022; Huang *et al.*, 2022). This interest means that tourism facilities will eventually need to expand, which will affect LULC. The Green Canyon Waterfall (GCW) tourism site, located in the middle of Bogor and Karawang Regencies, has become an area of particular interest. Therefore, any studies related to the development and LULC within this border area should involve the tourism stakeholders.

While addressing the issues related to the LULCC in the border area of Bogor and Karawang Regencies, this article has two objectives. The first objective is to predict the LULC in 2030 for the study area based on a multi-stakeholder tourism analysis,

and the second objective is to perform a comparison among the predicted LULC scenarios. This article is divided into four parts; the introduction section addresses the importance of the multi-stakeholder tourism analysis in the prediction of LULC scenarios. The second part describes the methods this study used to predict LULC scenarios and analyze the results. Third, the results section will state the predicted LULC scenarios for 2030, compare these scenarios against the SMPR of both regencies, and illustrate the model performance of those three scenarios. The last section will discuss how the results of this study relate to previous studies and how this research will contribute to future studies.

2. Methodology

Three stakeholder groups in Bogor and Karawang Regencies' border area were identified: key players (KP), content setter (CS), and subject (S). Blad *et al.* (2022) explain that when Geographic Information System (GIS) is combined with Multi-Actor Multi-Criteria Analysis (MAMCA), each stakeholder group then has its own spatial criteria interests resulting from the stakeholder analysis. Hence, when implementing this combination, it is mandatory to create a research framework that accurately represents a GIS-based multi-stakeholder tourism analysis, such as the one illustrated in Figure 1.

Figure 1 reveals nine spatial criteria within the three main factors that influence LULCC. Previous studies (Xiong *et al.*, 2022; Ren *et al.*, 2022; Azizi *et al.*, 2022) identified these three factors as (1) natural factors, (2) specialized regulation planning, and (3) accessibility. Specialized regulation planning is especially relevant to the CS stakeholder group, which comprises Bogor and Karawang Regencies' bureaucrats.

The next step of spatial criteria identification is to determine the polarity of each criterion. According to Chang and Huang (2006), criterion polarity is concerned with whether a criterion functions better as a benefit or a constraint. In other words, researchers should decide whether a criterion should increase or restrict certain measures (Malczewski and Rinner, 2015).

2.1 Study area

The focus of this study is on two villages located in the border area of Bogor and Karawang Regencies, namely Cikutamahi Village within Bogor Regency Zone and Medalsari Village within Karawang Regency (Figure 2). These villages are both located approximately 75 kilometers from Indonesia’s capital city, Jakarta.

Cikutamahi Village has an area of 1,383 hectares, and records from 2019 show 3,725 inhabitants, of which 1,949 were male and 1,776 female (BPS Kabupaten Bogor, 2020). Based on 2021 data from Cikutamahi Village’s

administrative office, the largest educated group comprised those who had graduated from elementary school with 1,420 people (32.71%).

Conversely, Medalsari Village has an area of 1,892 hectares (BPS Kabupaten Karawang, 2020). In 2020, it was recorded that Medalsari Village was inhabited by 3,797 people, consisting of 1,853 males and 1,944 females. According to 2021 data from Medalsari Village’s administrative office, the largest educated group comprised those who had graduated from junior high school with 1,560 people (40.90%).

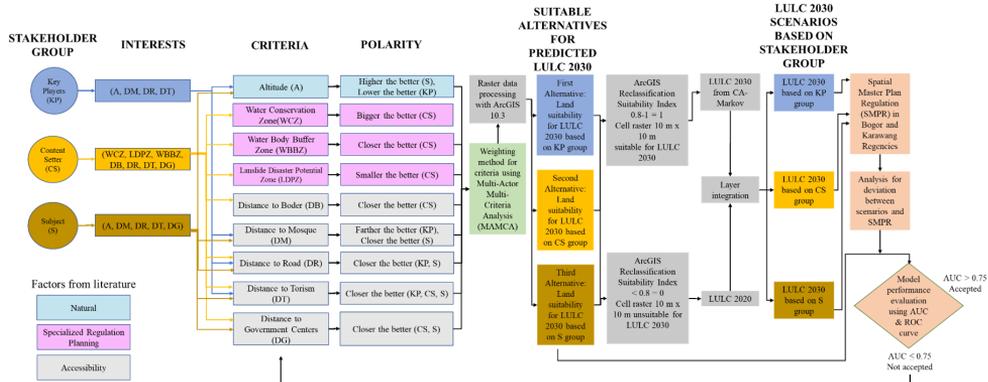


Figure 1. Research framework

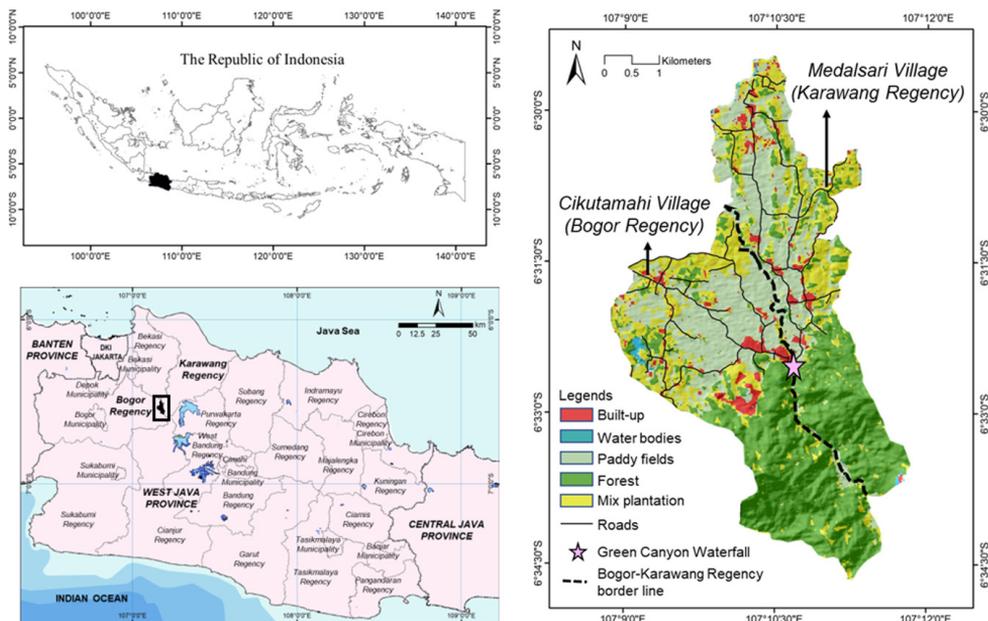


Figure 2. Study area

2.2 Spatial criteria weighting

In this study, A, DR, DM, and DT are the four spatial criteria weighted according to KP group interest. For the CS group, the seven criteria are WCZ, WBBZ, LPDZ, DB, DR, DT, and DG. The S Group's five criteria are A, DM, DR, DT, and DG. These spatial criteria must be processed in order to generate a single map representing suitable raster cells for LULC 2030. Hence, the MAMCA method was employed to generate a weight for each spatial criterion. Professor Cathy Macharris from Vrije Universiteit Brussel (Huang *et al.*, 2020) developed the software that enables this method.

This study conducted questionnaires and interviews for each stakeholder group to obtain sophisticated weight preferences. Six members of Green Canyon's local tourism offices (LMDH and Bumdes) representing the KP group were asked to complete the questionnaires and guided with interviews during the process. In addition, six members representing the CS group from agencies within Bogor and Karawang Regencies were asked to fill out the questionnaires. For the S group, 21 visitors and two local actors were interviewed about their spatial criteria preferences.

The stakeholder groups' answers were input into MAMCA, which uses a 0 – 9 scale. The KP group reflected weights of 0.456 (A), 0.309 (DR), 0.144 (DM), and 0.090 (DT). Meanwhile, the CS group showed weights of 0.409 (WCZ), 0.204 (LPDZ), 0.155 (WBBZ), 0.084 (DR), 0.076 (DB), 0.042 (DT), and 0.030 (DG). As for the S group, weights for A, DM, DR, DT, and DG were all 0.200.

2.3 Suitable locations for predicted LULC 2030 based on the multi-stakeholder tourism analysis

Combining weighted spatial criteria from each stakeholder group generated suitable locations for predicted LULC in 2030. In order to apply each weight for every raster layer, a weighted linear combination (WLC) was used to multiply the weight of each criterion with each cell value

(Malczewski and Rinner, 2015). The formula to generate weighted raster value using WLC can be written as follows:

$$V(A_i) = \sum_{k=1}^n w_k v(ai_k)$$

$V(A_i)$ represents the total of the i -th alternative in a raster cell, w_k is the weight of the k -th criterion, and $v(ai_k)$ is the raster cell value from the k -th criterion. The WLC method was performed using the raster calculator menu in ArcGIS 10.3; each raster cell has a 10 m x 10 m spatial resolution. The WLC operation generated three alternative maps to illustrate suitable locations for predicted LULC in 2030.

Moreover, the three LULC 2030 scenarios representing each stakeholder group appear as suitable raster maps, each containing values from 0 – 1. Raster cells containing values from 0.8 – 1 are assumed suitable for change and can be replaced with predicted LULC 2030 scenarios from CA-Markov. For raster cells with values < 0.8, it is assumed that LULC in these cells will not change and can be replaced with LULC 2020. For each stakeholder group, cells with predicted LULC 2030 and those with LULC 2020 are merged to form a comprehensive scenario of future LULC in 2030.

2.4 Predicted LULC 2030 using CA-Markov

CA-Markov combines two processes: cellular automata (CA) and the Markov transition matrix. CA is a dynamic, discrete system for implementing decision-making rules that operates on a space resembling a grid or box (Malczewski dan Rinner, 2015). For the purpose of predicting LULC 2030 for the border area of Bogor and Karawang Regencies, the CA-Markov method was employed to first simulate the predicted LULC for 2020. Then, LULC 2000 and LULC 2010 were computed together to derive the Markov transition matrix for 2000–2010, which was used to simulate LULC 2020 with a 10-year time span.

LULC 2000 map was generated from Landsat TM dated 06-09-2000 in Google Earth Engine (GEE) using Support Vector Machine (SVM) method.

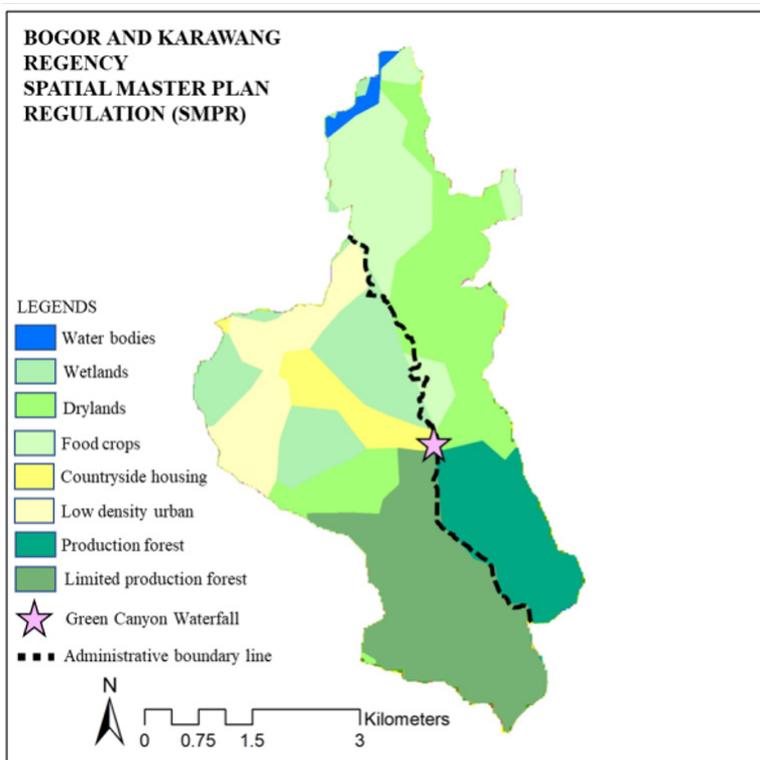
SVM is a classification method based on machine learning algorithm (Nyamekye et al., 2021). Accuracy assessment was performed in GEE using digitized Indonesia's Topographic Map 1999 as a reference. Overall Accuracy value for LULC 2000 map shows 0.76. LULC 2010 map was generated from Landsat TM in GEE using SVM method, and Overall Accuracy value for LULC 2010 map shows 0.78. Furthermore, LULC 2020 map was generated from Landsat 8 OLI in GEE using SVM method, and Overall Accuracy value for LULC 2020 map shows 0.95.

The predicted LULC 2020 was then validated against the actual LULC 2020 using Kappa Hat. According to Koko et al. (2022), if the Kappa Hat value falls within 61 – 80%, the result can be classified as substantially accepted. Any Kappa Hat value over 75% indicates a strong consistency between the simulation result and actual data (Xiong et al., 2022). Hence, if the predicted LULC 2020 reflects a value above 75% during the Kappa Hat validation process, the Markov transition matrix for 2000 – 2010

can be used to predict LULC 2030 based on a 10-year time span from the actual LULC 2020.

2.5 Evaluation of multiple scenarios based on SMPR

Three LULC 2030 scenarios from the three different stakeholder groups were superimposed with Bogor and Karawang Regencies' SMPR. The SMPR map is sourced from two regulations, namely the Perda 11/2016, which controls development in Bogor Regency through spatial planning from 2016 until 2036, and the Perda 2/2013, which administers the spatial master plan in Karawang Regency from 2011 until 2031. LULC prediction in 2030 can be considered as an urgent study since it will provide sufficient time for both governments of Bogor and Karawang Regencies to prepare for the next SMPR. According to these regulations, all development permits must be based on proper land allocation. Figure 3 demonstrates how production forest and limited production forest areas dominate the SMPR map.



Source: Perda 11/2016 and Perda 2/2013

Figure 3. The SMPR of Bogor and Karawang Regencies

3. Results and discussion

3.1 Suitable locations for LULC 2030 based on multi-stakeholder tourism analysis

Figure 4 shows the raster values for each spatial criterion, which have been adjusted according to polarity and stakeholder perspective. There are 11 raster maps in total, each indicating suitable locations for LULC 2030 based on stakeholder polarity.

A suitability map for predicted LULC 2030 was created for each stakeholder

group, as seen in Figure 5. The suitability maps according to the KP group (Figure 5A) and S group (Figure 5C) both display red southern regions, indicating that both stakeholder groups have identified that region as possessing low suitability for predicted LULC 2030. Conversely, for the CS group, low suitability values are located in the middle of the region, where the WCZ, LPDZ, and WBBZ have become the main characteristics, since the CS group prioritizes planning regulation.

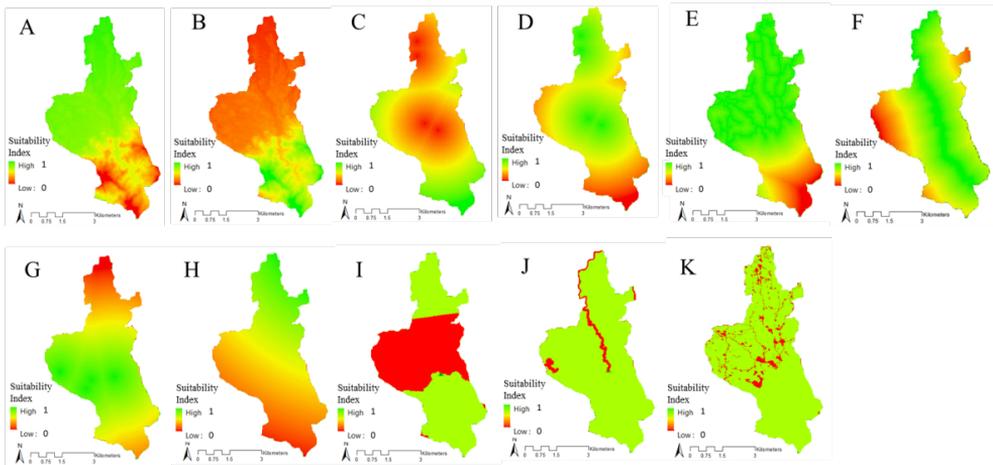


Figure 4. (A) altitude based on KP, (B) altitude based on S, (C) distance to mosque based on KP, (D) distance to mosque based on S, (E) distance to road, (F) distance to border, (G) distance to tourism facilities, (H) distance to government centers, (I) water conservation zone, (J) water body buffer zone, (K) landslide disaster potential zone

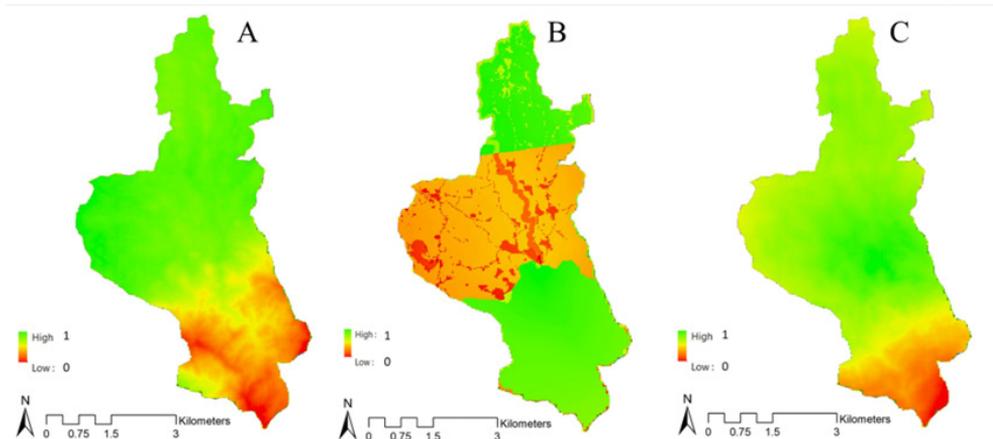


Figure 5. Suitable raster maps for predicted LULC 2030 based on (A) KP group, (B) CS group, (C) S group

3.2 LULC 2030 simulation using CA-Markov

The Markov transition matrix that resulted from two LULC maps (2000 and 2010) can be seen in Table 1. The LULCC with the highest probability in 2000 – 2010 was water bodies changing classification to paddy field (0.6821), while the lowest probability was the change from mixed plantation to waterbodies (0.0007). In Table 1, the Markov transition probability value from built-up class to paddy field reaches 0.4007. This occurs because during the classification process to generate built-up class in LULC 2000 map from Landsat TM, bareland was classified mix with built-up.

In the study area, bareland often within the stage of prepared land before being planted as paddy field by farmers. This can be observed in the Indonesia’s Topographic Map 1999 as a reference where most of bareland is located adjacent to houses or paddy fields. When compared to other LULC classes’ change in Table 1, namely water bodies (0.0028), forest (0.0583), and mixed plantation (0.1530), the probability to change from built-up to paddy field (0.4007) is relatively higher.

Similar conditions have been found in previous studies, Mahamud *et al.* (2019) states that in Kelantan, Malaysia from 1991 to 2000, transition probabilities from built-up to others agriculture is 0.23, and from built-up to paddy is 0.12. Further, Moradi *et al.* (2020) states that in Izeh-Pyon Plain of Iran from 1985 - 2001, transition probabilities from residential to agriculture is 0.1529. However, despite of the higher transition probability value from built-up class to paddy field but the validation between predicted LULC 2020 and actual LULC 2020 using Kappa Hat value shows 0.7710, which is acceptable for this study.

The Markov transition matrix 2000 – 2010 was used to predict 2020 LULC by inputting the matrix and suitable raster images into the CA process. The result of the CA-Markov process can be observed in Figure 6. The predicted LULC 2020 was validated via Kappa Hat by entering it as the input image and the actual LULC 2020 as a reference image in the TerrSet geospatial model. The validation result was 0.7710. According to Xiong *et al.* (2022), Kappa Hat values higher than 75% can be interpreted as demonstrating strong consistency between simulated and actual data. Therefore, it can be concluded that the Markov transition matrix can be used to accurately predict LULC in 2030.

Detailed LULC maps from 2000, 2010, 2020, and predicted 2030 can be observed in Figure 7. From the maps in Figure 7, it is evident that between 2000 and 2020, forests and paddy fields decreased and were replaced with mixed plantations and built-up. The predicted LULC 2030 shows that built-up and mixed plantation areas will only continue to grow and replace more forest and paddy field area (see Figure 7). Furthermore, Figure 8 demonstrates a decreasing trend in the forest class percentage along the Bogor-Karawang Regency border, while the mixed plantation class percentage has an increasing trend for 2000 – 2030.

3.3 LULC 2030 based on GIS-based multi-stakeholder tourism analysis

Three LULC 2030 scenarios in Bogor and Karawang Regencies’ border area are displayed in Figure 9, namely the KP scenario, CS scenario, and S scenario. Visually, the western area of the KP scenario is dominated by the mixed plantation class. Additionally, the northeastern area of the predicted CS and S scenarios show more preservation of the forest class compared to the KP scenario.

Table 1. Markov transition matrix probabilities for LULCC 2000-2010

	Built-up	Water bodies	Paddy field	Forest	Mixed plantation
Built-up	0.3842	0.0028	0.4007	0.0583	0.1539
Water bodies	0.0539	0.1150	0.6490	0.1744	0.0077
Paddy field	0.0777	0.0229	0.4749	0.1268	0.2977
Forest	0.0351	0.0085	0.0518	0.7025	0.2020
Mixed plantation	0.1163	0.0000	0.2737	0.3748	0.2352

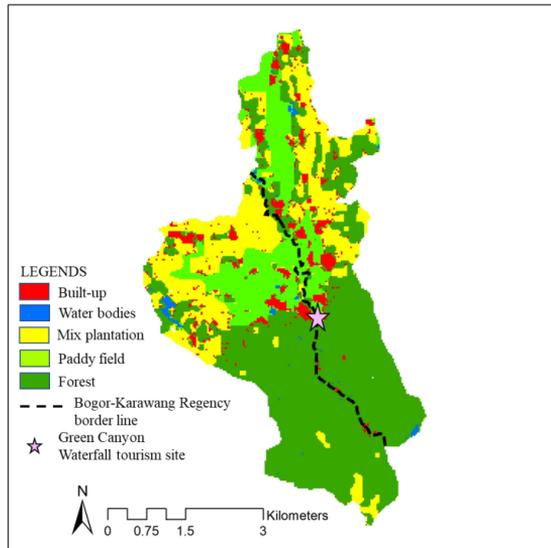


Figure 6. Predicted LULC 2020 using CA-Markov

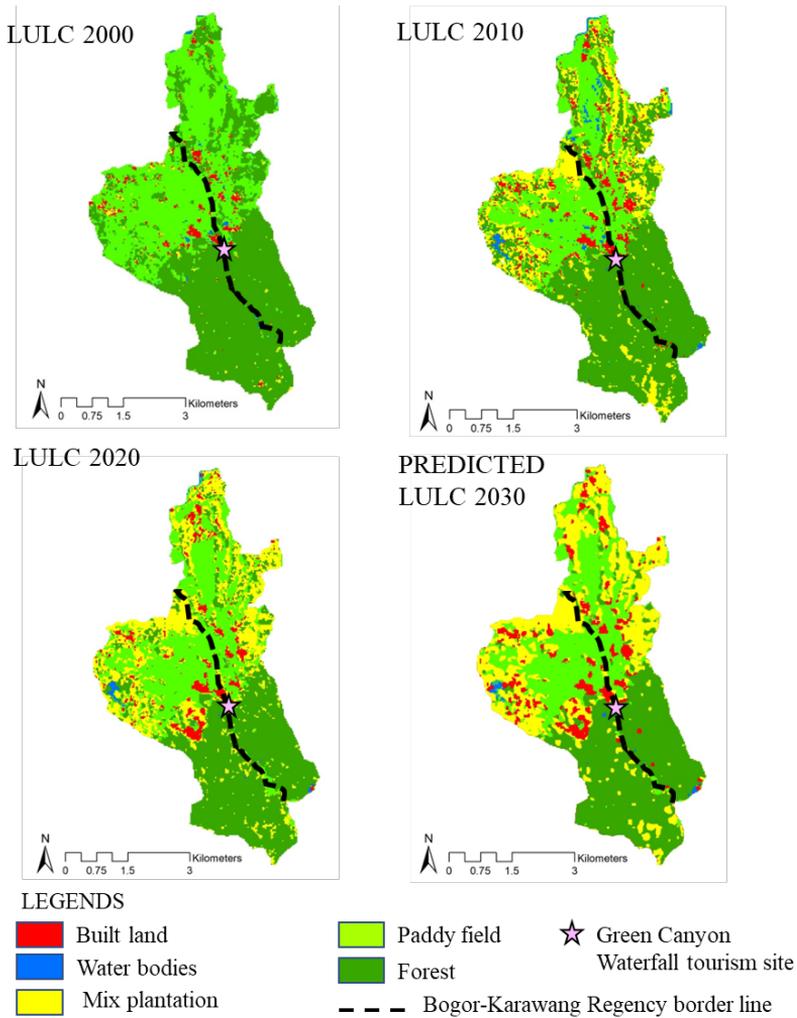


Figure 7. LULC maps of 2000, 2010, 2020, and predicted 2030

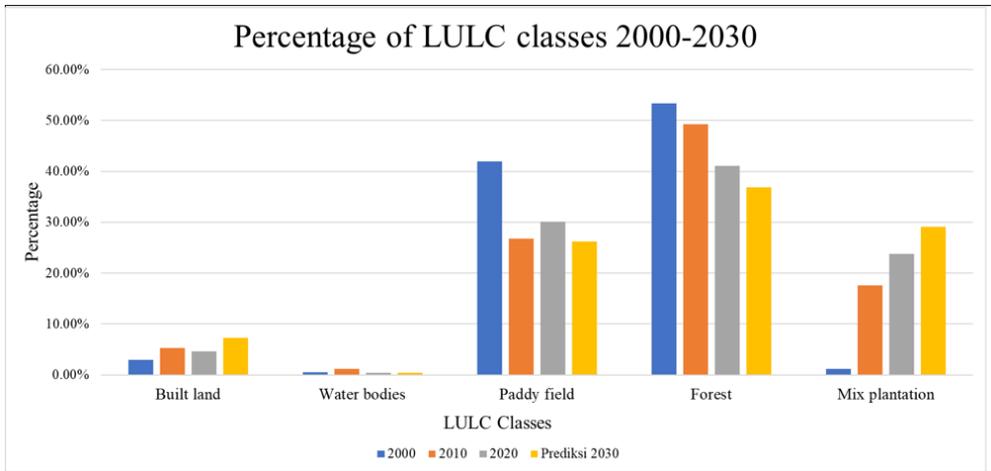


Figure 8. The percentage of LULC classes 2000 – 2030

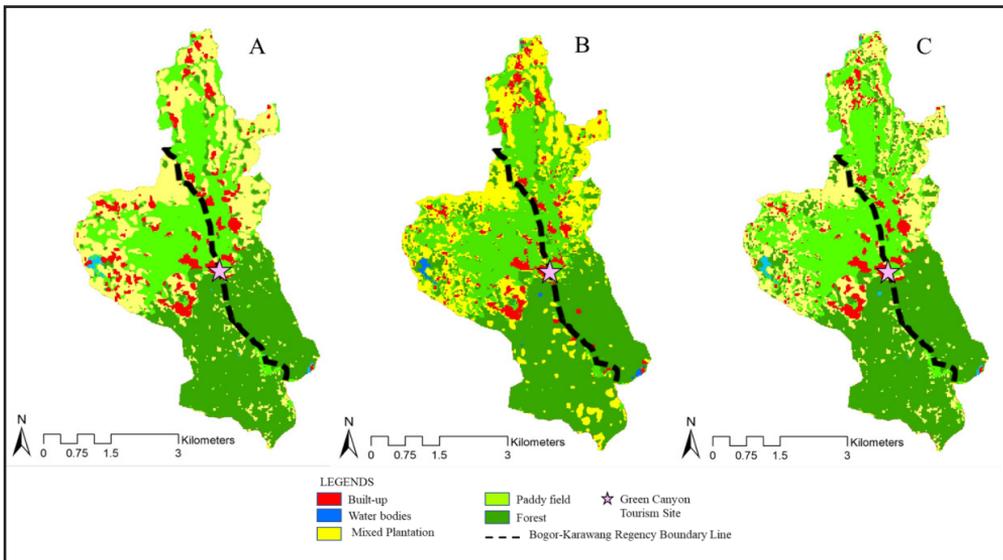


Figure 9. Predicted LULC 2030 based on stakeholder groups: (A) KP, (B) CS, and (C) S

The area for each LULC class is displayed in Figure 10. It can be observed that the KP scenario reflects more built-up and mixed plantation area than the other scenarios. Conversely, the S scenario reflects the most forest and paddy field area compared to the KP and CS scenarios.

3.4 Evaluation of predicted LULC scenarios based on SMPR

The vector data from the three maps representing the LULC 2030 scenarios was superimposed with Bogor and Karawang Regencies' SMPR to determine the extent of

the deviations. This process was performed using ArcGIS 10.3, where a union menu was employed to integrate the vector maps. Further data processing to generate matching classes between the LULC scenarios and SMPR was conducted within the spatial attribute query of ArcGIS 10.3. Figure 11 shows the resulting three maps.

It can be observed from Figure 11 that the KP scenario has the highest match percentage with SMPR (73.67%), while the S scenario has the second highest percentage with a 72.45% match. The CS scenario shows the lowest match percentage with the SMPR with 72.14%.

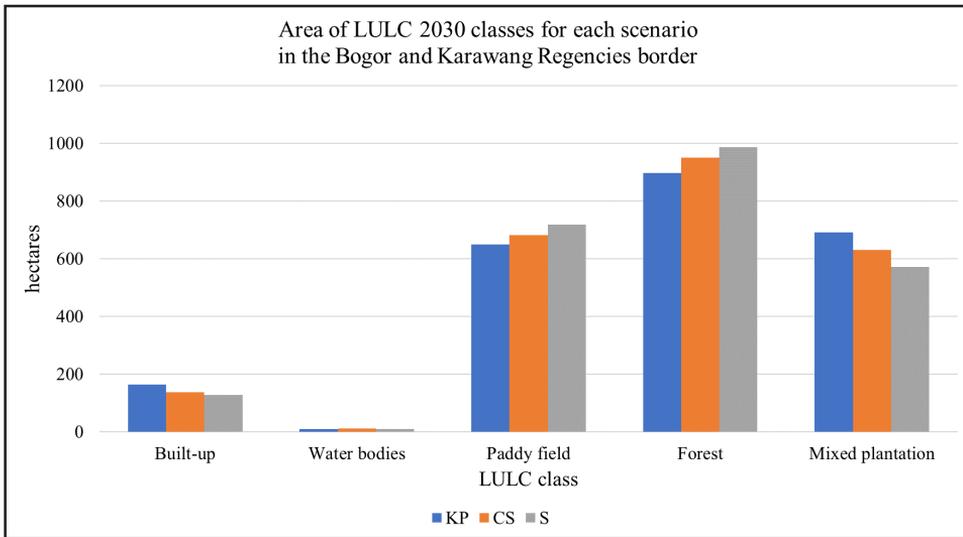


Figure 10. Area of LULC 2030 classes for each scenario

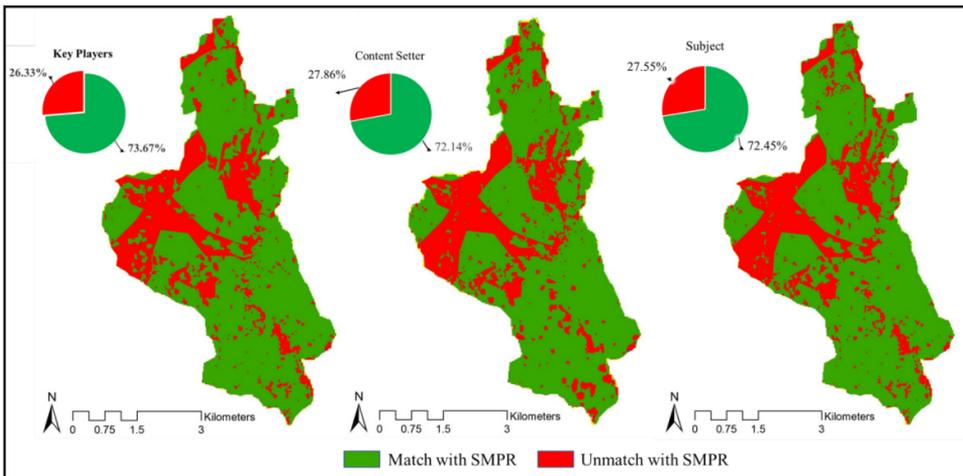


Figure 11. The three LULC scenarios superimposed with Bogor and Karawang Regencies’ SMPR

Based on the ROC curve for each scenario, the S scenario achieved the highest AUC value (0.980) when compared with the KP and CS scenarios. The CS scenario has the second highest AUC value with 0.974, while the KP scenario reflects the lowest value of 0.896. The overall AUC values for each scenario can be seen in Figure 12.

AUC values represent the performance of a model (Talukdar *et al.*, 2020). Figure 12 shows that the S scenario has the highest AUC value when compared to the CS and KP scenarios. In previous studies related to LULC simulation (Li *et al.*, 2016; Gupta and Sharma, 2020), researchers classified $AUC \geq 0.9$ as “outstanding/very good”

and $0.8 \leq AUC < 0.9$ as “excellent”. Based on this value classification, it can be concluded that the model performance of the CS and S scenarios was outstanding, and the performance of the KP scenario was excellent. Thus, all three LULCC scenarios were accepted.

In this study, the suitable raster image for LULCC functioned as the input image, while the matches with SMPR functioned as the reference image. Higher AUC values indicate a higher frequency of suitable raster values that match the SMPR. They also confirm that the spatial criteria employed to generate suitable LULCC raster cells are sufficient to explain the model.

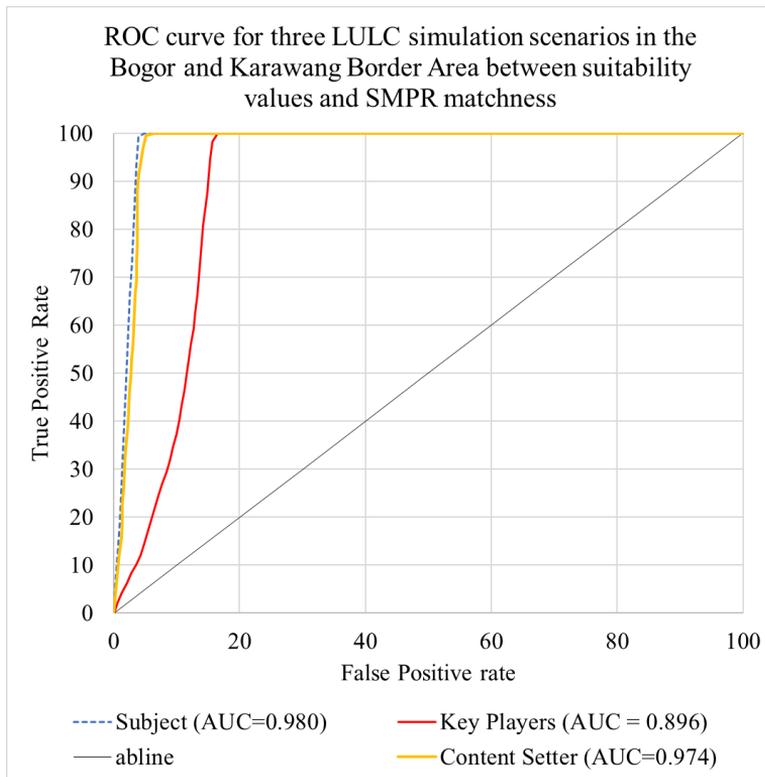


Figure 12. The ROC curve for three LULCC scenarios

Discussion

Though the CS scenario in Figure 11 shows the lowest match percentage between predicted LULC 2030 and SMPR, Figure 12 shows that it has the second-highest AUC value. The reason for this is that in Figure 11, the percentage of matches indicates that the classes of the predicted LULC 2030 map from the CS scenario fall within the same class as the SMPR. Meanwhile, in Figure 12, the CS scenario has a higher AUC value than the KP scenario because of the high suitable raster values within the match map of LULC and SMP. In the CS scenario, many of the spatial criteria used to determine the LULC 2030, such as WBBZ, WCZ, and LPDZ, come from technocratic planning. These spatial criteria are mainly overseen by government or bureaucratic sectors and subject to planning regulations. Interviews with actors in the CS stakeholder group illustrate their adherence to the technocratic planning model.

Putri's (2020) criticism of post-colonial planning practices in Jakarta highlights the interconnectedness of technocratic

and rational planning, which applies the newest science and technology in planning and usually has a firm spatial boundary as its output. Asirin *et al.* (2018) note the importance of public participation in the process, especially after the technocratic planning actors consultants, agencies, and the Regional Peoples's Representative Council (DPRD) have generated the planning products. Based on the technocratic planning literature, it might be assumed that the predicted LULC 2030 from the CS scenario has the highest percentage of match with SMPR. However, Figure 11 shows that the CS scenario has the lowest percentage of matches when compared to other scenarios. Thus, it can be concluded that technocratic, top-down, and rational planning methods cannot always fulfill the implementation of SMPR.

Pătru-Stupariu *et al.* (2016) noted that stakeholders consider the increases in agrotourism and tourism facilities to be the main factors behind landscape changes. During LULC simulations performed by Gomes *et al.* (2020), stakeholders expressed the view that expanding housing

and built-up areas and increasing built surfaces will decrease agricultural areas. These two studies involved stakeholders instead of bureaucrats, indicating that LULCC is more affected by KP and S stakeholder groups.

In this article, predicted LULC scenarios concerning the border of Bogor and Karawang Regencies have been analyzed empirically to prove that KP and S stakeholder groups play a crucial role. This awareness is key to ensuring that LULCC in Bogor and Karawang Regencies is sustainable, environmentally friendly, and aligns with the people's goals. Additionally, sustainable LULCC helps the government implement SMPR and other planning products, which is especially important for border areas located far from the capital city and central government.

When discussing development in border areas, many previous studies examine the border between two countries. However, as a result of the 1998 reforms that ended the Orde Baru regime, the local governments of Indonesian regencies/provinces have been given larger autonomy to manage their own natural resources, including SMPR. Hence, many SMPR products are aimed at maximizing the exploitation of natural resources to finance local development without consideration of adjacent governments' interests. This study empirically proves that stakeholders' goals, as represented by predicted LULC 2030 scenarios, have propelled deviation from government-regulated SMPR in the border between the two regencies. This result can be interpreted in two ways either the formulation of SMPR from the beginning failed to involve all of the stakeholders, or the current aspirations of stakeholders have grown beyond the first formulation of SMPR. This finding should encourage more development studies within the scope of the regencies' border area since the development in this area is closely related to stakeholders' views.

4. Conclusion

The GIS-based multi-stakeholder tourism analysis has successfully yielded three LULC scenarios for 2030 concerning the border of Bogor and Karawang Regencies. For every stakeholder group, it can be predicted that

the paddy field and forest classes will occupy a bigger area than other LULC classes. These two LULC classes are considered indicators of environmental health as well as food security for indigenous people. However, decreases in area for these classes would require rapid attention to monitor and evaluate development in Bogor and Karawang Regencies. When superimposed with SMPR, the KP scenario has the highest match percentage with SMPR (73.67%). The S scenario has a 72.45% match, the second highest, and the CS scenario reflects the lowest match percentage (72.14%). The high reliability of spatial criteria used for each stakeholder group to predict LULC in 2030 can be indicated by high AUC values, where S scenario achieved 0.980 (outstanding), CS scenario 0.974 (outstanding), and KP scenario 0.896 (excellent). The superimposing of predicted 2030 LULC scenarios with SMPR has enabled further measurement of model performance using AUC values. This study's novel findings enable the matches between SMPR and predicted LULC to be used as a tool for analysis.

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References

- Asirin Asbi AM, Pakpahan VH. Stakeholder participation in marine spatial plan making process in Lampung province. *IOP Conference Series. Earth and Environmental Science* 2018; 158(1). doi:<https://doi.org/10.1088/1755-1315/158/1/012030>
- Azizi P, Soltani A, Bagheri F, Sharifi S, Mikaeili M. An Integrated Modelling Approach to Urban Growth and Land Use/Cover Change. *Land* 2022; 11(10): 1715. <https://doi.org/10.3390/land11101715>

- Blad K, Homem de Almeida Correia G, Van Nes R, Anne Annema J. A methodology to determine suitable locations for regional shared mobility hubs. *Case Studies on Transport Policy* 2022; 10(3): 1904-1916. <https://doi.org/10.1016/j.cstp.2022.08.005>
- Boavida-Portugal I, Rocha J, Ferreira CC. Exploring the impacts of future tourism development on land use/cover changes. *Applied Geography* 2016; 77: 82-91. <https://doi.org/10.1016/j.apgeog.2016.10.009>
- Bogor Regency. Borderline Economic Summit (BES) Accelerates Development in Border Area. 2023. [internet]. [cited June 3 2023] available from: <https://diskominfo.bogorkab.go.id/borderline-economic-summit-bes-sarana-percepatan-pembangunan-di-kawasan-perbatasan/>.
- BPS Kabupaten Bogor. Cariu Sub-district in Figures 2020. BPS Kabupaten Bogor, Bogor. 2020.
- BPS Kabupaten Karawang. Pangkalan Sub-district in Figures 2020. BPS Kabupaten Karawang, Karawang. 2020.
- Chang H, Huang W. Application of quantification SWOT analytical method. *Mathematical and Computer Modelling* 2006; 43(1-2): 158-169. <https://doi.org/10.1016/j.mcm.2005.08.016>
- Daba MH, You S. Quantitatively Assessing the Future Land-Use/Land-Cover Changes and Their Driving Factors in the Upper Stream of the Awash River Based on the CA–Markov Model and Their Implications for Water esources Management. *Sustainability* 2022; 14(3): 1538. <https://doi.org/10.3390/su14031538>
- Ghosh S, Das Chatterjee N, Dinda S. Urban ecological security assessment and forecasting using integrated DEMATEL-ANP and CA-Markov models: A case study on Kolkata Metropolitan Area, India. *Sustainable Cities and Society* 2021; 68 : 102773.
- Gomes E, Banos A, Abrantes P, Rocha J, Schlöpfer M. Future land use changes in a peri-urban context: Local stakeholder views. *Science of the Total Environment* 2020; 718: 137381. <https://doi.org/10.1016/j.scitotenv.2020.137381>
- Gupta R, Sharma LK. Efficacy of Spatial Land Change Modeler as a forecasting indicator for anthropogenic change dynamics over five decades: A case study of Shoolpaneshwar Wildlife Sanctuary, Gujarat, India. *Ecological Indicators* 2020; 112. <https://doi.org/10.1016/j.ecolind.2020.106171>.
- Huang H, Lebeau P, Macharis C. The Multi-Actor Multi-Criteria Analysis (MAMCA): New Software and New Visualizations. *Decision Support Systems X: Cognitive Decision Support Systems and Technologies ICDSSST* 2020; 384. https://doi.org/10.1007/978-3-030-46224-6_4
- Huang X, Xu H, Li X. Spatial development of two villages: Bordering, debordering, and rebordering in a community scenic area. *Annals of Tourism Research* 2022; 93: 103370. <https://doi.org/10.1016/j.annals.2022.103370>.
- Koko AF, Han Z, Wu Y, Abubakar GA, Bello M. Spatiotemporal Land Use/Land Cover Mapping and Prediction Based on Hybrid Modeling Approach: A Case Study of Kano Metropolis, Nigeria (2020–2050). *Remote Sensing* 2022; 14(23): 6083. <http://dx.doi.org/10.3390/rs14236083>
- Kovačević ND, Kovačević L, Stankov U, Dragičević V, Miletić A. Applying destination competitiveness model to strategic tourism development of small destinations: The case of South Banat district. *Journal of Destination Marketing & Management* 2018; 8: 114-124. <https://doi.org/10.1016/j.jdmm.2017.01.002>
- Li X, Yu L, Sohl T, Clinton N, Li W, Zhu Z, Liu X, Gong P. A cellular automata downscaling based 1 km global land use datasets (2010–2100). *Science Bulletin* 2016; 61(21): 1651-1661.
- Mahamud MA, Samat N, Tan ML, Chan NW, Tew YL. Prediction Of Future Land Use Land Cover Changes Of Kelantan, Malaysia, *Int. Arch. Photogramm. Remote Sens. Spatial Inf. Sci.* 2019; XLII-4/W16: 379–384. <https://doi.org/10.5194/isprs-archives-XLII-4-W16-379-2019>,

- Malczewski J, Rinner C. *Multicriteria Decision Analysis in Geographic Information Science*. Multicriteria Decision Analysis in Geographic Information Science. Springer. Berlin. 2015. <https://doi.org/10.1007/978-3-540-74757-4>
- Mathewos M, Lencha SM, Tsegaye M. Land Use and Land Cover Change Assessment and Future Predictions in the Matenchose Watershed, Rift Valley Basin, Using CA-Markov Simulation. *Land* 2022; 11(10): 1632. <https://doi.org/10.3390/land11101632>
- Moradi F, Kaboli HS, Lashkarara B. Projection of future land use/cover change in the Izeh-Pyon Plain of Iran using CA-Markov model. *Arabian Journal of Geosciences* 2020; 13: 1-17.
- Nyamekye C, Ghansah B, Agyapong E, Kwofie S. Mapping changes in artisanal and small-scale mining (asm) landscape using machine and deep learning algorithms.-a proxy evaluation of the 2017 ban on asm in ghana. *Environmental Challenges* 2021; 3: 100053.
- Pătru-Stupariu I, Tudor CA, Stupariu MS, Buttler A, Peringer A. Landscape persistence and stakeholder perspectives: The case of Romania's Carpathians. *Applied Geography* 2016; 69: 87-98. <https://doi.org/10.1016/j.apgeog.2015.07.015>
- Putri PW. Insurgent planner: Transgressing the technocratic state of postcolonial Jakarta. *Urban Studies* 2020; 57(9): 1845–1865. <https://remote-lib.ui.ac.id:2075/10.1177/0042098019853499>
- Ren Y, Li Z, Li J, Ding Y, Miao X. Analysis of Land Use/Cover Change and Driving Forces in the Selenga River Basin. *Sensors* 2022; 22: 1041. <https://doi.org/10.3390/s22031041>
- Sang CC, Olago DO, Ongeri ZJ. The factors driving land cover transitions and land degradation and the potential impacts of the proposed developments in the Isiolo dam watershed, LAPSSSET Corridor, Kenya. *Discover Sustainability* 2023; 4(1). doi:10.1007/s43621-023-00126-w
- Talukdar S, Singha P, Mahato S, Shahfahad Pal S, Liou YA, Rahman A. Land-Use Land-Cover Classification by Machine Learning Classifiers for Satellite Observations A Review. *Remote Sensing* 2020; 12(7): 1135. <http://dx.doi.org/10.3390/rs12071135>
- Tolessa T, Dechassa C, Simane B, Alamerew B, Kidane M. Land use/land cover dynamics in response to various driving forces in Didessa sub-basin, Ethiopia. *GeoJournal* 2020; 85: 747-760. <https://doi.org/10.1007/s10708-019-09990-4>
- Wan YKP, Li X, Lau VM, Dioko L. Destination governance in times of crisis and the role of public-private partnerships in tourism recovery from Covid-19: The case of Macao. *Journal of Hospitality and Tourism Management* 2022; 51: 218-228. <https://doi.org/10.1016/j.jhtm.2022.03.012>
- Wang F, Yuan X, Xie X. Dynamic change of land use/land cover patterns and driving factors of Nansihu Lake Basin in Shandong Province, China. *Environ Earth Sci* 2021; 80(180). <https://doi.org/10.1007/s12665-021-09476-y>
- Xiong N, Yu R, Feng Y, Wang J, Feng Z. Land Use and Land Cover Changes and Prediction Based on Multi-Scenario Simulation: A Case Study of Qishan County, China. *Remote Sensing* 2022; 14(16): 4041. doi:<https://doi.org/10.3390/rs14164041>