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Prediction of Bandung District Land Use Change Using Markov Chain Modeling

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***Abstract*— Land conversion has occurred and converted into non-agricultural purposes in Bandung district, Indonesia. Consequently, the availability of agricultural land has decreased. The tendency of accessibility to infrastructure, natural resources, and population growth contribute to land-use change. This study aims to identify the relationship between distance accessibility factors such as distance to road, river, city center, slope and population density, and the land conversion in Bandung district. In this study, three multitemporal land use data (2007, 2012, and 2017) were used to determine transition probability matrix land-use change and predict land use in 2027. ArcGIS and Idrisi Selva software were used to simulate the land-use change in 2007–2017 and land use projection in 2027 using the Markov Chain model. The study resulted in Bandung district during 2007 to 2017 there was a decline in the areas of forest (0.03%), garden/plantation (7.02%), dryland (3.48%), paddy field (3.07%), and bushes (3.56%). Meanwhile, 34.57% of settlement and 11.44% of water bodies area increased in 2017. Land use was converted into settlement/built-up (18%), paddy fields (2.6%), water bodies (0.3%) and forest (0.1%). Distance to road, river, city center, and slope factor tended a negative correlation, while population density factor obtained positively correlated to the extent of land-use change. Land use prediction in 2027 resulting the most extensive land use was for paddy fields (22.58%), followed by forest (19.00%), garden/plantation (18.13%), settlement/built-up area (16.38%), dryland (12.32%), bushes (11.21%), and water bodies area (0.38%).**

***Keywords*—Land use; conversion; projection; Markov Chain; Bandung district.**

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I. Introduction

Food availability relates to food supply through production, distribution, and exchange. There is a relationship between hunger and food insecurity to household food supplies and individual food and nutrient intake [1]. The stability of food systems may be at risk under short-term variability in supply and influences on food security [2]. To achieve food stability, the obstacle that has become a global issue is diminishing land availability for agricultural purposes by land-use change/conversion.

The phenomenon of land-use changes in developing countries is in harmony with socio-economic activities and priority development activities, and it has also become global change research. There are some factors of land-use change, including natural factors by demographic changes and climate variability [3] and artificial factors by resource conservation policies, and socioeconomic factors [4]. The continuous expansion of the residential area in developing countries in the last few decades has led to the loss of productive agricultural land and biodiversity [5].

Land-use conversion has occurred in Bandung district, Indonesia. Consequently, the availability of agricultural land has decreased. Many rice field areas have been converted into non-agricultural purposes (settlements, industries, infrastructure for international airport development) [6]. Land use conversions often negatively affected the soil quality and resulting land degradation [7]–[9], although land degradation occurred in the upper watershed of Bandung district in 2013, reached 20.2% of the total upstream area, and increased to 59.3% in 2015 [10]. In the Bandung district, the most difficult challenge faced by farmers connected to land problems is a decrease in land availability and soil fertility.

Identification of the land conversion causal factor and future land projection is needed to provide policy considerations for maintaining land availability for the Bandung district. There has been a lot of modeling research for simulating and land-use dynamics changes around the world, such as cellular automata (CA) model [11], the Clue-s model [12], regression models [13], Markov Chain model [14]–[17], agent-based models [18] and machine learning algorithms [19].

Markov Chain method as a land-use change modeling has been used in several countries to find land-use change and land use projection. In Jiangle, China, the Markov Chain method was used to simulate and predict the spatial change and driving factors of land use change using remote sensing and GIS techniques [20]. During 2010-2020 in northern China, the Markov Chain method was used to simulate land use [21]. In the Su-Xi-Chang region, China, the method was used to find the changes temporally and spatially during 1990–2010 [22], Dongying city, China [23], Bangladesh [24] Tanzania [25], and others countries [26]–[29]. In Indonesia, the Markov Chain method was also used to predict the land-use change in Makasar [30], Komering watershed [31], Citarum Watershed [32], Tondano watershed [33], and North Sumatra [34].

In the Bandung district, is still a lack of information on driving factors of land-use change (distance accessibility, slope, and population density factors). This study aims to find the relationship between distance accessibility factors such as distance to road, river, city center, slope and population density, and the land conversion in Bandung district. Besides, a land-use simulation was carried out to estimate the land use in 2027 with the Markov chain model. Knowing the driving factors of land-use change is useful for sustainable management of natural resources; it also serves as information in future spatial planning, especially for the availability of land and supporting food stability in the future.

II. Materials and Method

A. Study Area

The study was carried out in Bandung district, which is geographically located at coordinates 6°41' to 7°19' South Latitude and between 107°22' to 108°5' East Longitude with an area of 172,303 ha (Fig. 1). The study area is located in West Java province, Indonesia, consisting of 31 sub-districts and 275 villages with 3,657,701 inhabitants [35]. The soil types in the study area are dominated by *Inceptisols* (59.11%), *Andisols* (40.55%), and *Entisols* (0.20%) [36]. The topography in the Bandung district varies from flat to mountainous, with elevations ranging from 600-2.500 meters above sea level. Bandung district has a tropical climate influenced by monsoon with an average rainfall ranging from 1500 to 4000 mm year^{-1}, with temperature ranges at 19-24 °C [35].

B. Data Analysis

The land use data is obtained from three different time periods in the form of remote sensing datasets. Landsat satellite images [37] in 2007, 2012, and 2017 with a resolution of 30x30m were used as the main data sources. Other supporting database was population data in 2007-2017 [35], topographic map scale 1:25,000, toponym/RBI map (1209-311 sheet) scale 1:25,000 [38] and soil map scale 1:25,000 [36].

The topographic map was used as auxiliary data in the interpretation of the slope map. Road, river, and the city center maps were obtained from the RBI map. Population density maps were obtained from tabulation data into spatial data processing. Distances to roads, rivers, city centers, slope, and population density were made by inserting these maps into the distance module by selecting the GIS analysis (Distance menu) in Idrisi Selva software. The distance was calculated based on Euclidean, the distance from one object to another with meters (m) and kilometers (km) for distance units.

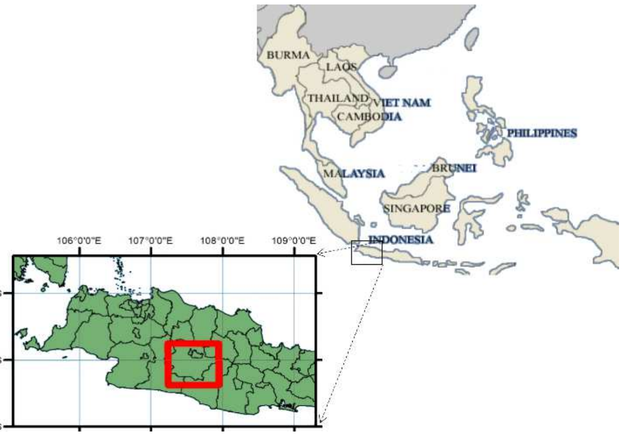

Fig. 1 Geographical location of the study area

Multi-temporal land use data analysis (image interpretation results) was carried out to produce a land-use change map in 2007, 2012, and 2017. The analysis of land-use changes transition probabilities using cross-tabulation was used to produce a land-use change transition matrix between 2007 and 2017. Transition probability on land use is choosing the possibility of land-use change from a category to another category. The land-use change driving factor was analyzed based on the distance variable (road, river, city center, slope, and population density). Multiple regression analysis stepwise methods were used to determine the factors that influence changes in land use. The last stage is land use simulation and prediction in 2027 using the Markov Chain model (Fig. 2).

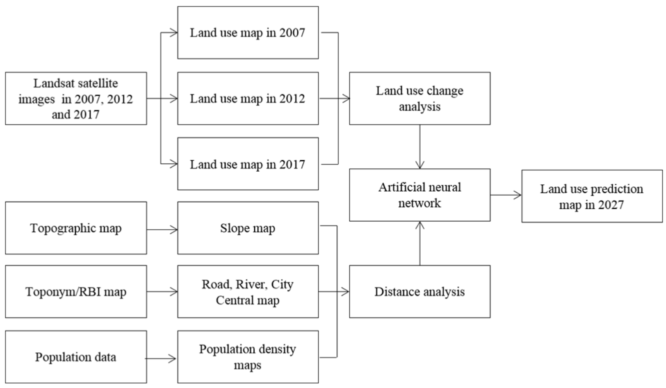

Fig. 2 A systematic research stage

The land use simulation was carried out in two stages. The first step was to simulate the land-use change in 2007–2017 and then followed by land-use projection simulation in 2027 using the Markov Chain model. The first simulation aims to determine the model's ability to simulate changes that have occurred. The basis of the simulation input was the 2007 land use map and transition probability matrix land-use change in 2007–2017. Kappa index value or index of agreement was used to evaluate and reduce uncertainties in remote sensing image simulation precision. The Kappa value of 0.81-1.00 indicates very high consistency, 0.61-0.80 is high consistency, 0.41-0.60 is medium consistency, 0.21-0.40 is less than medium consistency, and the value <0.21 is poor consistency [39], [40]. The data were analyzed using ArcGIS and Idrisi Selva software. Data processing was carried out in the land evaluation laboratory, Department of Soil Science and Land Resources, Faculty of Agriculture, Padjadjaran University.

III. Results and Discussion

A. The Land Use Condition

The condition of land use in the Bandung district from 2007 to 2017 is presented in Table I and Fig. 3a and 3b, and also land use prediction in 2027 (Fig. 3d). In 2007, the prominent land-use type in Bandung district was the paddy field, covering 25% of the total land area but decreased in 2017 to 24%. Land use with the declining area during 2007 to 2017 was forest (0.03%), garden/plantation (7.02%), dryland (3.48%), paddy field (3.07%), and bushes (3.56%). The largest percentage of land-use change was for settlements. Settlement/built-up area increased 21.64% from 2007 to 2012 and 34.57% in 2017. The forest expanded at 0.17% in 2012 due to the trees planting program in the upstream area of the Bandung district. However, during 2012-2017 the forest's 0.2% decline seemed due to trees logging and other uses. Waterbody area maintained an increase of 0.03% from 2007 to 2017.

TABLE I
THE AREA OF LAND USE IN BANDUNG DISTRICT FROM 2007 TO 2017

Land Use	Area (Ha)			Change (Ha)
	2007	2012	2017	2007-2017
Forest	34,462	34,522	34,451	-11
Garden	41,047	40,156	38,166	-2,881
Dryland	21,990	21,239	21,226	-764
Settlement	15,819	19,242	21,288	5,469
Paddy Fields	43,084	42,130	41,759	-1,324
Bushes	15,377	14,432	14,829	-548
Water	524	582	584	60
Total	172,303	172,303	172,303	

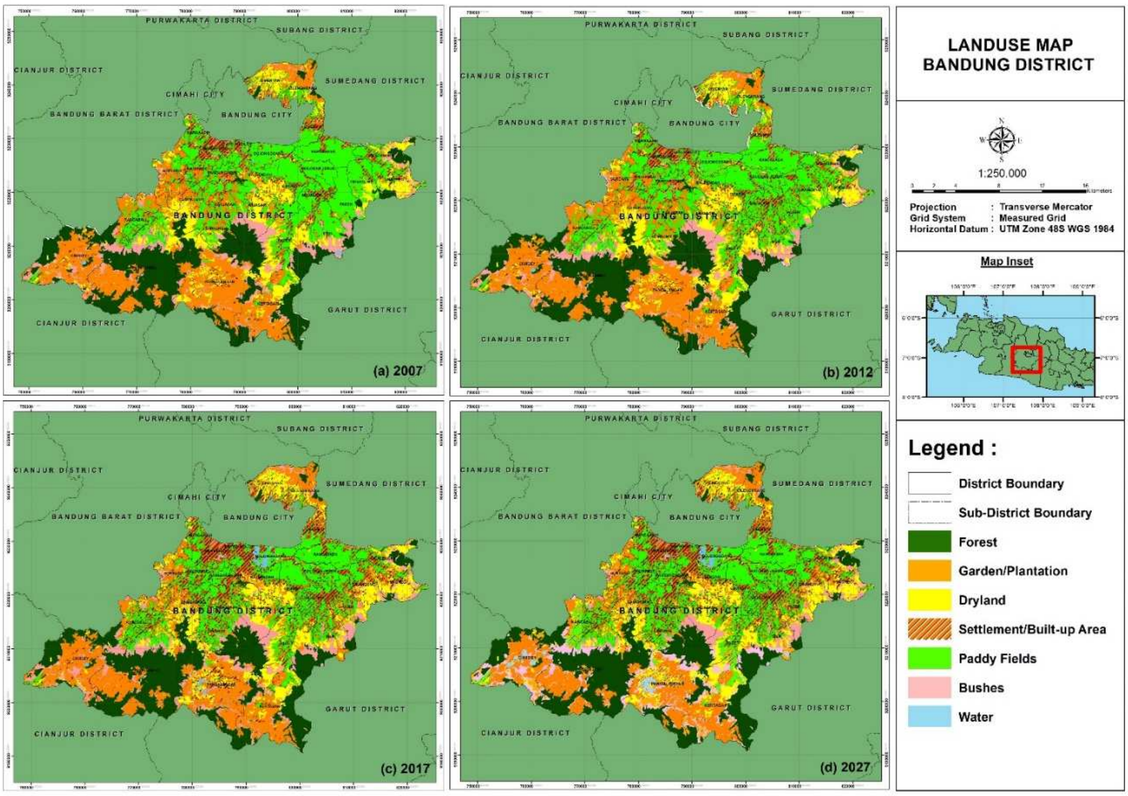

Fig. 3 Land use maps in 2007 (a), 2012 (b), 2017 (c), and 2027 prediction (d)

Table II shows the transition matrix of land-use change during 2007-2017. The garden/plantation has the largest conversion into built-up areas (6.4%) and paddy fields (0.6%). Wetland for paddy fields was converted 4.2% into built-up areas. Bushes area was converted 3% into built-up areas and 0.5% into wetlands. Dryland was converted 2.5% into built-up/settlement areas, 0.6% into wetlands, 0.3% into water bodies and 0.1% into forested area. Water bodies area was converted 1.8% into built-up areas and 0.9% into wetlands. Forest area was also converted 0.1% into built-up areas in the Bandung district. Overall, land use in Bandung district during 2007-2017 was dominantly converted into a settlement/built-up area, which reached 18%. The rest were 2.6% to wetland/paddy fields, 0.3% to water bodies, and 0.1% to forested areas.

TABLE II
TRANSITION MATRIX OF LAND USE CHANGE FROM 2007-2017 IN HECTARES

Land Use	Forest	Garden/ Plantation	Dryland	Settlement/ Built-up	Paddy Fields	Bushes	Water	Total in 2007
Forest	34,438	0	0	24	0	0	0	34,462
Garden/Plantation	0	38,166	0	2,635	245	0	0	41,047
Dryland	12	0	21,226	540	137	0	75	21,990
Settlement/Built-up Area	0	0	0	15,818	0	0	0	15,819
Paddy Fields	0	0	0	1,794	41,290	0	0	43,084
Bushes	0	0	0	466	82	14,829	0	15,377
Water	0	0	0	10	5	0	509	524
Total in 2017	34,451	38,166	21,226	21,288	41,759	14,829	584	172,303

B. Driving Factors and Land Use Projection

Fig. 4 shows the relationship between the extent of land-use change by distance to the road, river, and city center. A negative correlation was obtained from the driving factor of land-use change.

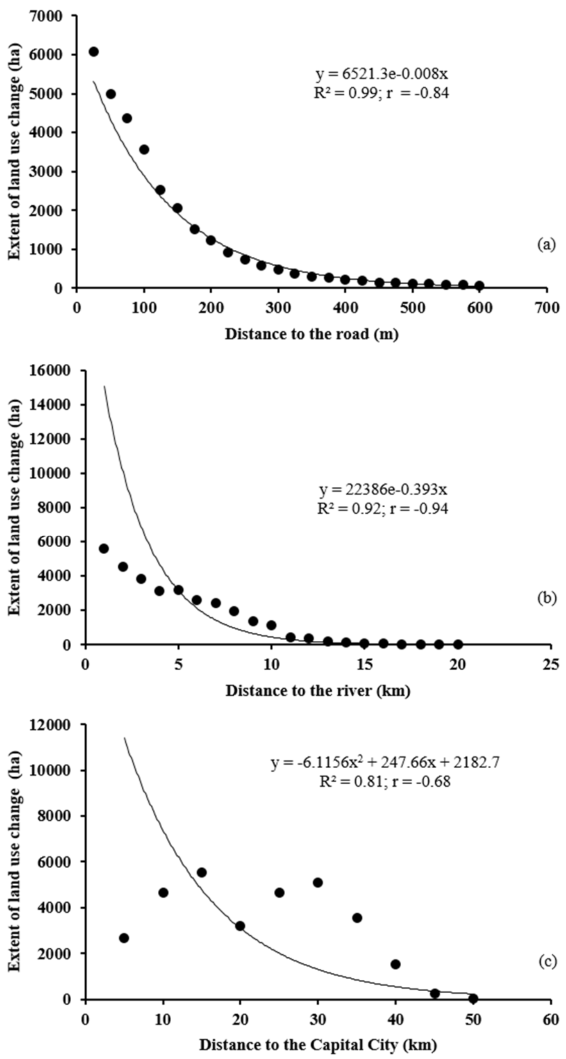

Fig. 4 The relationship between land-use change with distance to the road (a), river (b), and city center (c)

The factor of road distance gave -0.84 of coefficient correlation (r) in the extent of land-use change (Fig. 4a), while the distance to the river gave -0.94 (Fig. 4b) and to the city center gave -0.68 (Fig. 4c). This situation indicates that the closer to the road, the more rapid the change in land use. Like the distance to the river and the city center, the closer to the river and the city center, the more rapid the change in land use. Distance to road, river and city center tends to affect the extent of changes in land use. In Fig. 4a, the change obtained is 65 ha area with 600 m distance, while 100 m the changing area is greater (3,563 ha). The distance of 1 km to the river, the land-use change reaches 5,569 ha, compared to 20 km distance to the river only 2 ha has changed (Fig. 4b). There are several land-use change locations where the farthest distance is around 50 km. The distance of 50 km to the city center, the land-use change reaches 17 ha, while with 20 km distance, the change is 3,194 ha.

The relationship between the extent of land-use changes and distance to the road, which is stated by a coefficient of determination (R^2) is equal to 0.99 (Fig. 4a). This value indicates the ability of the distance factor to the road in influencing the area of change in land use by 99%, while other factors influence the remaining 1%. Regions that have a lot of road access generally encourage land-use changes because of the easy access. Land-use changes are influenced by accessibility or adequate road networks [27], [41]. Accessibility to the transport network has influenced land-use conversion in Shanghai, China [22], [23], [42]. Distance to roads is a driving factor for economic factors where the closer to the trade center, the cheaper transportation costs. The main road is located close to the industrial center, making it easier for the public to access services trading activities. Some sub-districts such as Cimenyan, Cileunyi, Rancaekek, Bojongsoang, are sub-districts that support activities in trade and services, as well as office or educational activities.

Distance to the river is a driving factor for land-use change in terms of the people's culture. The people are dominantly concentrated and live near to the water source (river). The river is the water resource for domestic, agricultural, and industrial needs. The location of several sub-districts adjacent to rivers such as Baleendah, Bojongsoang, Rancaekek sub-districts has encouraged the area to make a change in land use. The ability of river distance factor in influencing the change of land use was 92%, while the remaining 8% was influenced by other factors (R^2 = 0.92), as shown in Fig. 4b. The city center distance factor obtained had smaller relation in land-use change than road and river factors. The city center distance in Fig. 4c influenced 81% land use change while the remaining 19% was influenced by other factors (R^2 = 0.81). The city center of Bandung district is located in Soreang city. Farther from the city center, the changes of land use are more difficult due to the remote supervision of the local government. The further distance of the sub-district from the city center causes the low supervision of the authorities over all forms of spatial deviation [43]. The number of offices and trade activities in the city center, so the distance to the city center becomes a factor influencing land-use changes. Accessibility to the city center also has been mainly influenced by land-use conversion in Shanghai, China [22], [23], [42].

The relationship between the extent of land-use change by slope and population density factors is shown in Fig. 5. A negative correlation was obtained from the slope driving factor in land-use change. The factor of slope gave -0.79 of coefficient correlation in the extent of land-use change (Fig. 5a). Based on the coefficient of determination, the relationship of land use changes with a slope (Fig. 5a) was 0.95. The change of land use decreased as the slope became steeper. Flat slope operational costs were relatively lower compared to steep slope costs. Land rent value on steep slopes decreased compared to the flat slope. The land rent optimal value is on a flat slope [44]. As shown in Fig. 5a, at 2% slope conditions, the change reached 3,513 ha, while on a steep slope (40%) only 318 ha were changed.

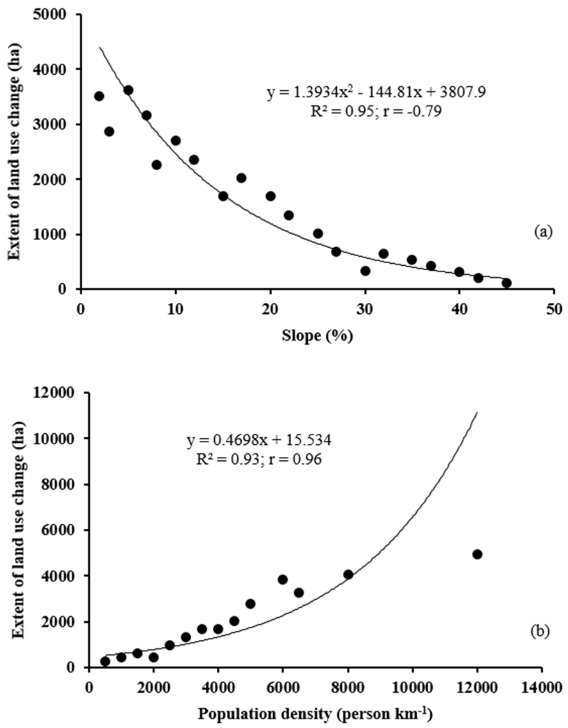

Fig. 5 The relationship between land-use change with slope (a) and population density (b)

Meanwhile, the population density factor was in positive correlation (0.96) to the extent of land-use change with 0.93 of coefficient of determination (Fig. 5b). The population density in Bandung district is a major factor in land-use changes. People need physical activity space, including settlements, agricultural land, and industries, to support their lives. The population density in the Bandung district tends to be concentrated in the north area with medium to high population densities. The southern Bandung district has several changes in land use with moderate population density. The land value of agricultural land that is relatively low in the Bandung district encourages people to convert it into a settlement/built-up area. The high population density in a region was the trigger for agricultural land changes in the north Bandung district [45]. Population affects the change of agricultural land into non-agricultural purposes [46]. Urbanization has mainly influenced of land use conversion [14], [27], [47].

Based on the land use change map trend in 2007, 2012 and 2017 (Fig. 3a-c), a prediction map in 2027 (Fig. 3d) was generated using the Markov Chain method. Predictive maps for 2027 were validated using the existing map in 2017. Validation using Idrisi selva software were obtained by Kappa Index of Agreement with *Kno*, *Klocation*, and *Klocationstrata* index value (0-1 scale). *Kno* is an indicator value to measure overall agreement, *Klocation* measures the level of agreement between all inputs and *Klocationstrata* measures the level of agreement based on the total number of inputs [40]. The validation obtained in this study was *Kno* 0.90, *Klocation* 0.91 and *Klocationstrata* 0.91 meaning the simulation model showed high consistency and reliability to predict in 2027.

Land use prediction in 2027 (Fig. 3d and Table III) shows the most extensive land use was for paddy fields with 22.58% areas that were concentrated on flat slope in the central of Bandung district. The forested area in southern Bandung district covered 19.00% and cultivated dry land covered 30% areas.

TABLE III
LAND USE PREDICTIONS IN 2027

Land Use	**Area**	
	Ha	**%**
Forest	32,737	19.00
Garden/Plantation	31,230	18.13
Dryland	21,236	12.32
Settlement/Built-up Area	28,225	16.38
Paddy Fields	38,907	22.58
Bushes	19,312	11.21
Water	655	0.38
Total	172,303	100

Several land use areas decreased in 2027 compared to 2017, such as forest, plantation, and paddy field areas. Based on the total area in 2017, at least 5.0% of forested areas, 18.2% of plantation areas, and 6.8% of paddy field areas declined in 2027. Settlement and bushes were the most extensive land use that increased in 2027 compared to 2017, with 32.6% and 30.2% each. Water bodies and dryland purposes area increase at 12.3% and 0.05%, respectively, in 2027. In terms of supporting land availability planning for food crop stability, wetlands for rice did not appear to be large enough. The mechanism for increasing food stability is expected to be employing an agricultural intensification system and zoning of existing agricultural land. A large forest area in Bandung district is expected to be made industrial forestry and protection policy for forest products.

This result is expected to be a scientific tool for regional spatial exploration, supporting land availability planning and making spatial policies supporting food stability in the Bandung district. The shortcomings of this study were various land-use change models were not compared, and the impact of climate change was not taken into account. The study used Landsat satellite imagery maps with an accuracy of 30x30m certainly has a weakness in land use interpretation. Therefore, more detailed satellite imagery is needed for further study.

IV. Conclusion

The land use in Bandung district for ten years (2007 to 2017) has been changed. The transition of land-use changes during 2007-2017, was converted into settlement/built-up (18%), paddy fields (2.6%), water bodies (0.3%) and forest (0.1%). Distance accessibility (road, river, city center) and slope factors are negatively correlated, while population density positively correlated to the extent of land-use change in the Bandung district. Land use prediction in 2027 resulting the most extensive land use was for paddy fields covered 22.58% areas of Bandung district, followed by forest (19.00%), garden (18.13%), settlement (16.38%), dryland (12.32%), bushes (11.21%), and water bodies area (0.38%).

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References

[1] N. Larson, M. N. Laska, and D. Neumark-Sztainer, "Food insecurity, diet quality, home food availability, and health risk behaviors among emerging adults: Findings from the EAT 2010–2018 study," *American Journal of Public Health*, vol. 110, no. 9, pp. 1422–1428, 2020.

[2] T. Hasegawa *et al.*, "Risk of increased food insecurity under stringent global climate change mitigation policy," *Nature Climate Change*, vol. 8, no. 8, pp. 699–703, 2018.

[3] H. Temesgen, W. Wu, X. Shi, E. Yirsaw, B. Bekele, and M. Kindu, "Variation in ecosystem service values in an agroforestry dominated landscape in ethiopia: Implications for land use and conservation policy," *Sustainability*, vol. 10, no. 4, p. 1126, 2018.

[4] F. Handavu, P. W. C. Chirwa, and S. Syampungani, "Socio-economic factors influencing land-use and land-cover changes in the miombo woodlands of the Copperbelt province in Zambia," *Forest Policy and Economics*, vol. 100, pp. 75–94, 2019.

[5] A. P. Durán *et al.*, "A practical approach to measuring the biodiversity impacts of land conversion," *Methods in Ecology and Evolution*, vol. 11, no. 8, pp. 910–921, 2020.

[6] A. N. Chaidar, I. Soekarno, A. Wiyono, and J. Nugroho, "Spatial analysis of erosion and land criticality of the upstream citarum watershed," *International Journal of GEOMATE*, vol. 13, no. 37, pp. 133–140, 2017, doi: 10.21660//2017.37.34572.

[7] M. I. Onwuka, "Land–use change effects on soil quality at Umudike area, Abia State, South-East Nigeria," *Nigeria Agricultural Journal*, vol. 51, no. 1, pp. 109–118, 2020.

[8] F. Raiesi, "A minimum data set and soil quality index to quantify the effect of land use conversion on soil quality and degradation in native rangelands of upland arid and semiarid regions," *Ecological Indicators*, vol. 75, pp. 307–320, 2017.

[9] P. Yu, S. Liu, H. Yang, G. Fan, and D. Zhou, "Short-term land use conversions influence the profile distribution of soil salinity and sodicity in northeastern China," *Ecological Indicators*, vol. 88, pp. 79–87, 2018.

[10] Ministry of Agriculture, *Integrated Land Conservation Development Management Support*. Ministry of Agriculture, 2015.

[11] H. Wu *et al.*, "Examining the sensitivity of spatial scale in cellular automata Markov chain simulation of land use change," *International Journal of Geographical Information Science*, vol. 33, no. 5, pp. 1040–1061, 2019.

[12] M. Zare, A. A. N. Samani, M. Mohammady, H. Salmani, and J. Bazrafshan, "Investigating effects of land use change scenarios on soil erosion using CLUE-s and RUSLE models," *International journal of environmental science and technology*, vol. 14, no. 9, pp. 1905–1918, 2017.

[13] Y. Feng and X. Tong, "Using exploratory regression to identify optimal driving factors for cellular automaton modeling of land use change," *Environmental monitoring and assessment*, vol. 189, no. 10, p. 515, 2017.

[14] M. G. Munthali, S. Mustak, A. Adeola, J. Botai, S. K. Singh, and N. Davis, "Modeling land use and land cover dynamics of Dedza district of Malawi using hybrid Cellular Automata and Markov model," *Remote Sensing Applications: Society and Environment*, vol. 17, p. 100276, 2020.

[15] B. Rimal, L. Zhang, H. Keshtkar, B. N. Haack, S. Rijal, and P. Zhang, "Land use/land cover dynamics and modeling of urban land expansion by the integration of cellular automata and markov chain," *ISPRS International Journal of Geo-Information*, vol. 7, no. 4, p. 154, 2018.

[16] V. Nasiri, A. A. Darvishsefat, R. Rafiee, A. Shirvany, and M. A. Hemat, "Land use change modeling through an integrated multi-layer perceptron neural network and Markov chain analysis (case study: Arasbaran region, Iran)," *Journal of Forestry Research*, vol. 30, no. 3, pp. 943–957, 2019.

[17] C. J. Geyer, "Practical markov chain monte carlo," *Statistical Science*, pp. 473–483, 1992.

[18] J. Groeneveld *et al.*, "Theoretical foundations of human decision-making in agent-based land use models–A review," *Environmental Modeling & software*, vol. 87, pp. 39–48, 2017.

[19] M. Samardžić-Petrović, M. Kovačević, B. Bajat, and S. Dragićević, "Machine learning techniques for modeling short term land-use change," *ISPRS International Journal of Geo-Information*, vol. 6, no. 12, p. 387, 2017.

[20] C. Liping, S. Yujun, and S. Saeed, "Monitoring and predicting land use and land cover changes using remote sensing and GIS techniques—A case study of a hilly area, Jiangle, China," *PloS One*, vol. 13, no. 7, p. e0200493, 2018.

[21] M. Wang, L. Cai, H. Xu, and S. Zhao, "Predicting land use changes in northern China using logistic regression, cellular automata, and a Markov model," *Arabian Journal of Geosciences*, vol. 12, no. 24, p. 790, 2019.

[22] E. Yirsaw, W. Wu, X. Shi, H. Temesgen, and B. Bekele, "Land use/land cover change modeling and the prediction of subsequent changes in ecosystem service values in a coastal area of China, the Su-Xi-Chang Region," *Sustainability*, vol. 9, no. 7, p. 1204, 2017.

[23] C. Wang, Y. Wang, R. Wang, and P. Zheng, "Modeling and evaluating land-use/land-cover change for urban planning and sustainability: a case study of Dongying city, China," *Journal of Cleaner Production*, vol. 172, pp. 1529–1534, 2018.

[24] K. Islam, M. F. Rahman, and M. Jashimuddin, "Modeling land use change using cellular automata and artificial neural network: the case of Chunati Wildlife Sanctuary, Bangladesh," *Ecological Indicators*, vol. 88, pp. 439–453, 2018.

[25] C. Hyandye and L. W. Martz, "A Markovian and cellular automata land-use change predictive model of the Usangu Catchment," *International Journal of Remote Sensing*, vol. 38, no. 1, pp. 64–81, 2017.

[26] A. K. Hua, "Application of Ca-Markov model and land use/land cover changes in Malacca River Watershed, Malaysia," *Applied Ecology and Environmental Research*, vol. 15, no. 4, pp. 605–622, 2017.

[27] E. Zadbagher, K. Becek, and S. Berberoglu, "Modeling land use/land cover change using remote sensing and geographic information systems: case study of the Seyhan Basin, Turkey," *Environmental Monitoring and Assessment*, vol. 190, no. 8, p. 494, 2018.

[28] E. Gidey, O. Dikinya, R. Sebego, E. Segosebe, and A. Zenebe, "Cellular automata and Markov Chain (CA_Markov) model-based predictions of future land use and land cover scenarios (2015–2033) in Raya, northern Ethiopia," *Modeling Earth Systems and Environment*, vol. 3, no. 4, pp. 1245–1262, 2017.

[29] Y. Trisurat, H. Shirakawa, and J. M. Johnston, "Land-use/land-cover change from socio-economic drivers and their impact on biodiversity in Nan Province, Thailand," *Sustainability*, vol. 11, no. 3, p. 649, 2019.

[30] A. M. Y. Hakim, S. Baja, D. A. Rampisela, and S. Arif, "Modeling land use/land cover changes prediction using multi-layer perceptron neural network (MLPNN): a case study in Makassar City, Indonesia," *International Journal of Environmental Studies*, pp. 1–18, 2020.

[31] E. Kusratmoko and S. D. Y. Albertus, "Modeling land use/cover changes with markov-cellular automata in Komering Watershed, South Sumatera," in *IOP Conference Series: Earth and Environmental Science*, 2017, vol. 54, no. 1, p. 12103.

[32] F. Yulianto, T. Maulana, and M. R. Khomarudin, "Analysis of the dynamics of land use change and its prediction based on the integration of remotely sensed data and CA-Markov model, in the upstream Citarum Watershed, West Java, Indonesia," *International Journal of Digital Earth*, vol. 12, no. 10, pp. 1151–1176, 2019.

[33] F. Yulianto, I. Prasasti, J. M. Pasaribu, H. L. Fitriana, N. S. Haryani, and P. Sofan, “The dynamics of land use/land cover change modeling and their implication for the flood damage assessment in the Tondano watershed, North Sulawesi, Indonesia,” *Modeling Earth Systems and Environment*, vol. 2, no. 1, p. 47, 2016.
[34] M. H. Saputra and H. S. Lee, “Prediction of land use and land cover changes for north sumatra, indonesia, using an artificial-neural-network-based cellular automaton,” *Sustainability*, vol. 11, no. 11, p. 3024, 2019.
[35] Central Bureau of Statistics, *Bandung District in 2017*. 2018.
[36] Research Center for Development of Agricultural Land Resources, “Bintan island semi-detailed soil map at 1: 50,000 scale. Center for Agricultural Land Resources, Ministry of Agriculture, Bogor.,” 2017.
[37] P. G. USGS, “Landsat Climate Data Record (CDR) Surface Reflectance,” *US Geological Survey, version*, vol. 3.
[38] Geospasial Information Agency, “Toponym map of Bandung district scale 1:25.000,” *Jakarta: Permendagri*, 2015.
[39] D. G. Altman, “Mathematics for kappa,” *Practical statistics for medical research*, vol. 1991, pp. 406–407, 1991.
[40] R. G. Pontius, D. Huffaker, and K. Denman, “Useful techniques of validation for spatially explicit land-change models,” *Ecological Modeling*, vol. 179, no. 4, pp. 445–461, 2004.
[41] R. Nuraeni, S. R. P. Sitorus, and D. R. Panuju, “Analisis perubahan penggunaan lahan dan arahan penggunaan lahan wilayah di Kabupaten Bandung,” *Buletin Tanah dan Lahan*, vol. 1, no. 1, pp. 79–85, 2017.
[42] J. Han, Y. Hayashi, X. Cao, and H. Imura, “Evaluating land-use change in rapidly urbanizing China: Case study of Shanghai,” *Journal of Urban Planning and Development*, vol. 135, no. 4, pp. 166–171, 2009.
[43] B. Susilo, “Pemodelan Spasial Probabilistik Integrasi Markov Chain dan Cellular Automata untuk Kajian Perubahan Penggunaan Lahan Skala Regional di Provinsi Daerah Istimewa Yogyakarta,” *Jurnal Geografi Gea*, vol. 11, no. 2, 2011.
[44] B.-J. Fu *et al.*, “Temporal change in land use and its relationship to slope degree and soil type in a small catchment on the Loess Plateau of China,” *Catena*, vol. 65, no. 1, pp. 41–48, 2006.
[45] A. Ruswandi, E. Rustiadi, and K. Mudikdjo, “Dampak konversi lahan pertanian terhadap kesejahteraan petani dan perkembangan wilayah: studi kasus di daerah Bandung Utara,” *Jurnal Agro Ekonomi*, vol. 25, no. 2, pp. 207–219, 2016.
[46] E. F. Lambin and P. Meyfroidt, “Land use transitions: Socio-ecological feedback versus socio-economic change,” *Land Use Policy*, vol. 27, no. 2, pp. 108–118, 2010.
[47] T. Yuan, X. Yiping, Z. Lei, and L. Danqing, “Land use and cover change simulation and prediction in Hangzhou city based on CA-Markov model,” *International Proceedings of Chemical. Biol. Environ. Eng*, vol. 90, pp. 108–113, 2015.