Land cover modelling of Pelabuhanratu City in 2032 using cellular automata-markov chain method

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Abstract. Pelabuhanratu located in strategic coastal area, make it as the Centre of Growth in Sukabumi District. In this regard, landcover changes continue to occur and could trigger unsustainable environmental. The purpose of this study is to analysis the land cover change of Pelabuhanratu city until 2032. The Cellular Automata-Markov is used to identify the spatial growth, several factors that encourage the landcover change used as an input. The driving factor was build based on fuzzy logic, the variables are proximity to road, proximity to river, proximity to coastline proximity to point of interest, elevation, slope and landcover. Then, suitability area for built up area as input for Cellular Automata-Markov tools. Landcover was obtained from google earth in 2002, 2010 and 2017 then used as the basis for model calculation. The prediction result shows that land cover change in Pelabuhanratu city is very significant with the Kappa Standard level reach 91% accuracy. Built up area has extended from the previous condition that coming from agricultural area. Moreover, the area growth with linear pattern at south area, spread pattern at north area and crowded at west area.

1. Introduction
The population in pelabuhanratu city increased continuously and caused a landcover change from open space to built-up area while the land is so limited that land shortage will occur in the future [1]. The complexity of physical, social, political, economic and biology in the same space and time dimensions is major cause of the landcover change process [2,3]. Basically, the land area has not changed as long as there is no expansion that treat the limit of cities [4]. Landcover change should always be monitored and controlled. One of the way to monitor and manage the land is to create quality planning so that it can analysis the interrelated components in order to make the right policy [5]. Understanding urban growth is crucial for sustainable growth planning and management [6].

The purpose of this study is to predict landcover changes in 2032 in pelabuhanratu city by using cellular automata method integrated with Markov chain. Results are expected to provide support for future land planning. Cellular automata is a modelling method that can be used as a tool in supporting land-use planning and spatial and temporal policy analysis by analysis the complexities of urban growth resulting in simulation, prediction and planning [7]. Other methods used in making predictive models of land including Agent Based modelling, Spatial Statistics Modelling, Artificial Neural Network (ANN) Models, Fractal-based modelling and Chaotic and catastrophe modelling.

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The research related to landcover modelling usually use auto classification in the image either with supervised or unsupervised, but in this research using manual digitization technique. The data used is a high-resolution image on google earth. Spatial, temporal and statistical analysis were used in analyzing the results of the study.

**Area of Study and Data**

Pelabuhanratu City is located in Sukabumi Regency, West Java which is adjacent to the Pelabuhanratu bay. There are 10 Subdistrict in this city, namely, Buniwangi, Cibodas, Cikadu, Cimanggu, Citarik, Citepus, Jayanti, Pelabuhanratu, Pasirsuren and Tonjong. In the south of the city, there is a cimandiri river that flows into the bay of Pelabuhanratu. The area of the Pelabuhanratu City is 9,214.80 Ha.

![Figure 1. Location of study area](image)

This research used multi-temporal landcover data to process cellular automata-**Markov** chains models. The imagery obtained from Google Earth 7.3.0 and geo referenced with Elshayal smart GIS software. This study uses physical data such as coastline, river network, elevation, slope and infrastructure data such as road network and point of interest. Point of interest in this research such as health facilities, education, government offices and worship (i.e. churches, mosque). Physical and infrastructure data is overlaid with fuzzy to create a driving factor. The detail of each parameters is shown in Table 1.

| No | Data                | Date or year | Source                        |
|----|---------------------|--------------|-------------------------------|
| 1  | Google Earth Imagery| 2002, 2010 and 2017 | Google Earth                  |
| 2  | Digital Elevation Model | 2015       | ALOS Palsar                   |
| 3  | Road Network map    | 2015         | Geospatial Information Agencies |
| 4  | Boundary map        | 2015         | Geospatial Information Agencies |
| 5  | River map           | 2015         | Geospatial Information Agencies |
| 6  | Point of interest   | 2015         | Geospatial Information Agencies |

**2. Method**

Markov chains is a dynamic processes based on **markovian** random process that calculate the probability of changes from particular object [8]. Markov chain produces a transition probability matrix that explains the probability of landcover change. Markov chains cannot analysis land cover changes spatially. Cellular automata method is a dynamic system that operates with space in raster data where the value of the raster data can be defined into binary or discrete data and its behaviour is influenced by neighbours [9]. The procedure of cellular automata-**Markov** chains model is presented in figure 2.
Driving factor is very important in cellular automata-Markov chains modeling to develop a framework analysis of the model [10]. Fuzzy Logic is the concept of Boolean logic to make anything into a binary expression in which the input in the cellular automata process uses binary units (0 or 1, black or white, yes or no) [11]. Driving factor made by scoring and fuzzy each data with fuzzy membership in Arcmap 10.1. Each fuzzy value on variable overlaid with fuzzy gamma to be a single file driving factor.

Accuracy test is important to know the reliability and capability of models of landcover changes. It can be standard evaluation model whether the result of the model can be used for policy maker or not [8]. In this research, the accuracy test was performed using validate on Idrisi-Selva edition 17 with kappa index.

3. Result and Discussion
3.1 Land Cover Changes Analysis
3.1.1 Spatial Pattern of land cover changes
The classification of landcover divided into 8 types (i.e. built-up area, forest, cultivated area, water body, bare land, paddy field, shrubs and moor). Cultivated area is the most dominant in the study area. The forest located in the north and centre of study area and shows no changes since 2002 until 2017. However, over past decade, built-up area growing quickly in Pelabuhanratu City. Built-up area growth with linear pattern at south area, spread pattern at north area and crowded at west area.

3.1.2 Transitional probability matrix
Markov chains process chain produces a transition probability matrix that explains the probability of landcover change. The matrix shown the probability of landcover to change in 0-1 range which 0 value means impossible to change and 1 means certainly happening [8]. The transitional probability matrix is presented in table 2.
Table 2. Transitional probability matrix

| Landcover     | Built Up Area | Paddy Field | Cultivated Area | Bare Land | Moor | Shrubs | Forest | Water Body |
|---------------|---------------|-------------|-----------------|-----------|------|--------|--------|------------|
| Built Up Area | 0.93          | 0.01        | 0.05            | 0.00      | 0.00 | 0.00   | 0.00   | 0.00       |
| Paddy Field   | 0.19          | 0.75        | 0.02            | 0.00      | 0.03 | 0.00   | 0.00   | 0.00       |
| Cultivated    | 0.11          | 0.01        | 0.87            | 0.00      | 0.01 | 0.00   | 0.00   | 0.00       |
| Bare Land     | 0.82          | 0.00        | 0.00            | 0.18      | 0.00 | 0.00   | 0.00   | 0.00       |
| Moor          | 0.06          | 0.00        | 0.02            | 0.92      | 0.00 | 0.00   | 0.00   | 0.00       |
| Shrubs        | 0.03          | 0.00        | 0.25            | 0.00      | 0.00 | 0.72   | 0.00   | 0.00       |
| Forest        | 0.05          | 0.00        | 0.00            | 0.00      | 0.00 | 0.95   | 0.00   | 0.00       |
| Water Body    | 0.00          | 0.00        | 0.00            | 0.06      | 0.00 | 0.00   | 0.00   | 0.94       |

3.2 Landcover Prediction

3.2.1 Driving factor

Driving factor is very important in cellular automata-Markov chains modeling [10]. It used to determine the probability changes with pixel value. In this research, driving factor made by proximity to road network, proximity to point of interest, slope, elevation, proximity to river and proximity to coastline. Each driving factor data classified to identify the level of suitability. Table 3 present the suitability classification of driving factor.

Table 3. Classification of driving factor

| No. | Driving factor         | Class       | Suitability   |
|-----|------------------------|-------------|---------------|
| 1   | Proximity to road      | 0 – 100     | Very Suitable |
|     |                        | 100 – 200   | Suitable      |
|     |                        | 200 – 500   | Quite Suitable|
|     |                        | 500 – 1000  | Less Suitable |
|     |                        | >1000       | Not Suitable  |
| 2   | Proximity to POI       | 0 – 500     | Very Suitable |
|     |                        | 500 – 1000  | Suitable      |
|     |                        | >1000       | Less Suitable |
| 3   | Proximity to river     | 0 – 25      | Not Suitable  |
|     |                        | 25 – 50     | Less Suitable |
|     |                        | >50         | Suitable      |
| 4   | Proximity to coastline  | 0 – 100     | Not Suitable  |
|     |                        | 100 – 500   | Less Suitable |
|     |                        | >500        | Suitable      |
| 5   | Elevation              | 0 – 25      | Suitable      |
|     |                        | 25 – 100    | Very Suitable |
|     |                        | 100 – 500   | Quite Suitable|
|     |                        | >500        | Not Suitable  |
| 6   | Slope                  | 0 – 2       | Very Suitable |
|     |                        | 2 – 15      | Suitable      |
|     |                        | 15 – 40     | Less Suitable |
|     |                        | >40         | Not Suitable  |
3.2.2 Landcover Change Prediction
Landcover change prediction in 2032 spatially shown in figure 3. Built-up area growth happen in suitable area which has high value in driving factor. Generally, the expansion happen in the area that close to road network, flat slope and low to moderate elevation. Figure 3 also shows the paddy field and cultivated area converted into built-up area in 2032. Figure 4 shown the landcover changes. Built-up area is growing from 1308 Ha in 2017 to 1994 Ha in 2032. Built-up area is predicted increasing 52% from 2017 to 2032.

**Figure 3. Landcover Prediction**

**Figure 4. Landcover changes prediction**
3.2.3 Accuracy Test
Accuracy test in this research using validate tool in Idrisi-Selva Edition 17 which all pixels of the image are part of the analysis [12]. The output of validating tool is K-standard value that in this research which shows 0.9175 kappa index.

4. Conclusion
This study shows that cellular automata-Markov chains and land cover data from the digitation on google earth data was successfully executed to predict the spatial growth of Pelabuhanratu city with high kappa value. The result of projection models shows that the built-up area will increase 52% from 2017 to 2032. Built up area growth with linear pattern at south area, spread pattern at north area and crowded at west area. Agriculture area such as paddy field and cultivated area are the most changed into built-up area.

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