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Spatial Analysis of Kulon Progo District Development from 2007-2030 with Cellular Automata Markov Model

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Abstract

The construction of a new airport in Kulon Progo District as an embodiment of improving transportation infrastructure will have an effect on changes in spatial planning and land use. These changes can cause several impacts, so planning is needed as a preventive measure. Forms of planning are very diverse, ranging from the simplest to very complex. One of the alternatives is to make a simulation through a model approach with the Cellular Automata (CA) method, while the pattern of the direction of physical development of residential areas with the Global Moran's Index. The research location focuses on three sub-districts in Kulon Progo District, which are the closest sub-districts to the airport construction sites, namely Kokap, Temon, and Wates Sub-districts. The main data used in this research are multi-temporal land use data, namely in 2007, 2012, and 2017. The data from the years of 2007 and 2012 are projected to become in the year 2017 and compared with the original data of 2017 to determine the level of suitability, resulting suitability of 91.53%. The final results of this research show predictions of the development of Kulon Progo District in 2030. In the span of 23 years, from 2007 to 2030, the allocation of residential land increased by 7.98% leaning west and south side. Results from the Global Moran's Index show that the pattern of development in the Kulon Progo Regency area is random.

Keywords: CA markov, global moran's index, Kulon Progo, regional development, land use

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1. Introduction

Increasing population mobility along with the development of globalization requires adequate transportation infrastructure [1]. The Special Province of Yogyakarta provides a solution by building a new airport in Kulon Progo District to support the functioning of Adisutjipto Airport, which is already overcapacity and has a density of flight schedules. The most felt impact from the construction of this airport is that there are changes in spatial planning and land use that have a sustainable impact, such as increasing population density in Kulon Progo [2].

This increase in population density will be offset by an increase in the needs of the population for the availability of needs for housing, goods, food, and services. The rapid increase in population density supported by increasing demand will trigger a rapid economic rate. This also directly affects the existence of land conversion to support economic development and to meet their needs [2]. Careful planning is needed to prevent this negative impact.

The problem of growth in a region is the integration of spatiotemporal and socio-economic processes [3]. Land use planning is a form of activity that has been going on for a long time throughout the history of human civilization. Forms of planning are very diverse, ranging from the simplest to the most complex and applying various multi-concept approaches. One of the alternatives is to make a simulation using the model approach [4]. The model will produce a simulation of growth patterns in an area and play an important role in sustainable development [5].

The method used to predict the development of the area in Kulon Progo District is Cellular Automata (CA) Markov, while the pattern of the direction of physical development of residential areas with the Global Moran's Index. Cellular Automata (CA) Markov was chosen because it has a good ability to integrate dynamic and spatiotemporal aspects and to model complex dynamic systems [5].

This research aims to simulate and predict the development of the region in terms of the growth of residential areas. Prediction of the development of Kulon Progo District is needed to conduct spatial analysis so that it can be used to support further planning.

2. Methodology

The following section will describe and discuss the methodology used in this study, including the study area, the data processing, and the method used.

2.1. Study Area

Kulon Progo District is one of five regencies in the Special Province of Yogyakarta which is the westernmost and borders with Purworejo District, Central Java Province. The construction location of the new DIY airport is precisely located in the southern part of Kulon Progo District, which is a lowland with an altitude of 0-100 meters above sea level. The study area in this research focused on the sub-districts closest to the airport construction sites, namely Kokap, Temon, and Wates Sub-districts. Study area shown in the following Figure 2:

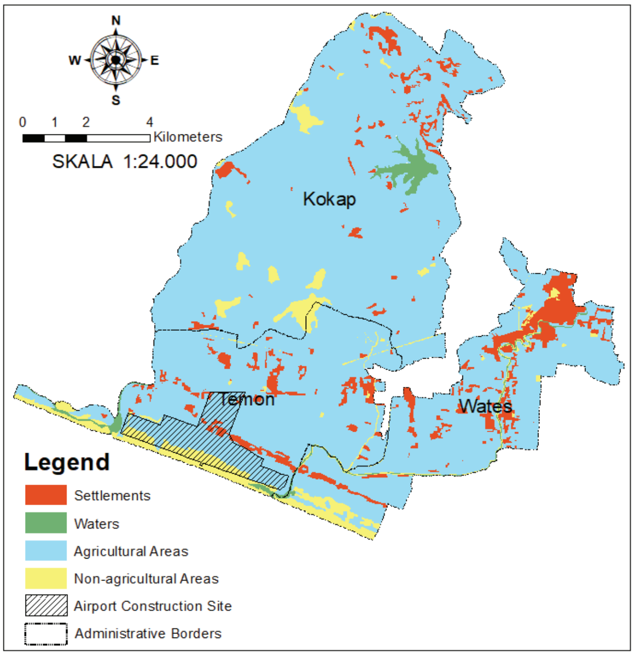


Figure 1: Study Area.

2.2. Materials and Methods

The data used in this study are multi-temporal land use, namely in 2007, 2012, and 2017. The method used to predict the development of the area in Kulon Progo District is Cellular Automata (CA) Markov, while the pattern of the direction of physical development of residential areas with the Global Moran's Index.

2.2.1. Data Collection

This research uses land use maps obtained from the Kulon Progo Dsitrict Land and Spatial Planning Agency. The data given is a vector type and has a shapefile format. The land use data is classified into ten, namely brackish water, fresh water, shrubs, buildings, gardens, settlements, grasses, irrigated rice fields, rainfed rice fields, and moors. The data then reclassified in accordance with SNI 7645:2010 concerning Land Cover Classification into four, namely waters, settlements, agricultural areas, and non-agricultural areas.

2.2.2. The Simulation based CA-Markov Model

CA-Markov is a spatial model that can be used to simulate urban growth [6]. Simulations with the cellular automata method are integrated with the Markov model by applying transition rules that not only depend on the previous situation, but also on the state of the surrounding environment. CA-Markov projects a land use map by considering changes that continue to be made repeatedly to meet the entire research area [10]. In this research, CA-Markov is applied to predict the development of regions in KulonProgo District until 2030. The data used are from the years of 2007, 2012, and 2017. The Iterations used are 13 because they are calculated from 2017. To ensure that the model is appropriate, a trial is conducted by making a prediction of land use in 2017 using data from 2007 and 2012. The original 2017 land use is compared with the results of the trial to see its suitability. Furthermore, by using data in 2007 and 2017, land use predictions were made in 2030.

2.2.3. Regional Development Pattern

The distribution of spatial objects is often described as a pattern [7]. The pattern formed is very dependent on previous forms of development [8]. In general, there are three patterns that can be formed, namely dispersed, random, and clustered [9]. In this research, regional development patterns were identified by global methods using Spatial Autocorrelation (Moran's I). Spatial autocorrelation describes the approximate correlation between values related to spatial location. Positive spatial autocorrelation tends to be grouped because it shows the similarity of values from adjacent locations, while negative spatial autocorrelation tends to spread because the values in adjacent locations have differences [10]. The value produced in the Moran index calculation ranges from -1 <I <1. The value of I is expressed by:

1. I_0 = -1 / n - 1 near zero means there is no spatial autocorrelation.
2. I> I_0 means that there is a positive spatial autocorrelation.
3. I <I_0 means that there is a negative spatial autocorrelation.

3. Result and Discussion

Land use data obtained from agencies have ten classifications, so it needs to be reclassified to facilitate processing. Classifications from agencies include brackish water, fresh water, shrubs, buildings, gardens, settlements, grasses, irrigated fields, rainfed rice fields, and moorings. In accordance with SNI 7645: 2010 concerning Land Cover Classification, brackish water and fresh water are categorized in waters; buildings and settlements are categorized as settlements; irrigated rice fields, rainfed rice fields, moors, and gardens are categorized as agricultural areas; and grass and thickets are categorized as non-agricultural areas.

Reclassification is divided into four and given a code, namely Waters with code 1, Settlements with code 2, Agricultural Region with code 3, and Non-Agricultural Regions with code 4. Coding is needed because CA-Markov processing uses data in raster format. Reclassification and coding are carried out on land use data from all years (2007, 2012, and 2017) resulting in land use shown in the following Figure 2:

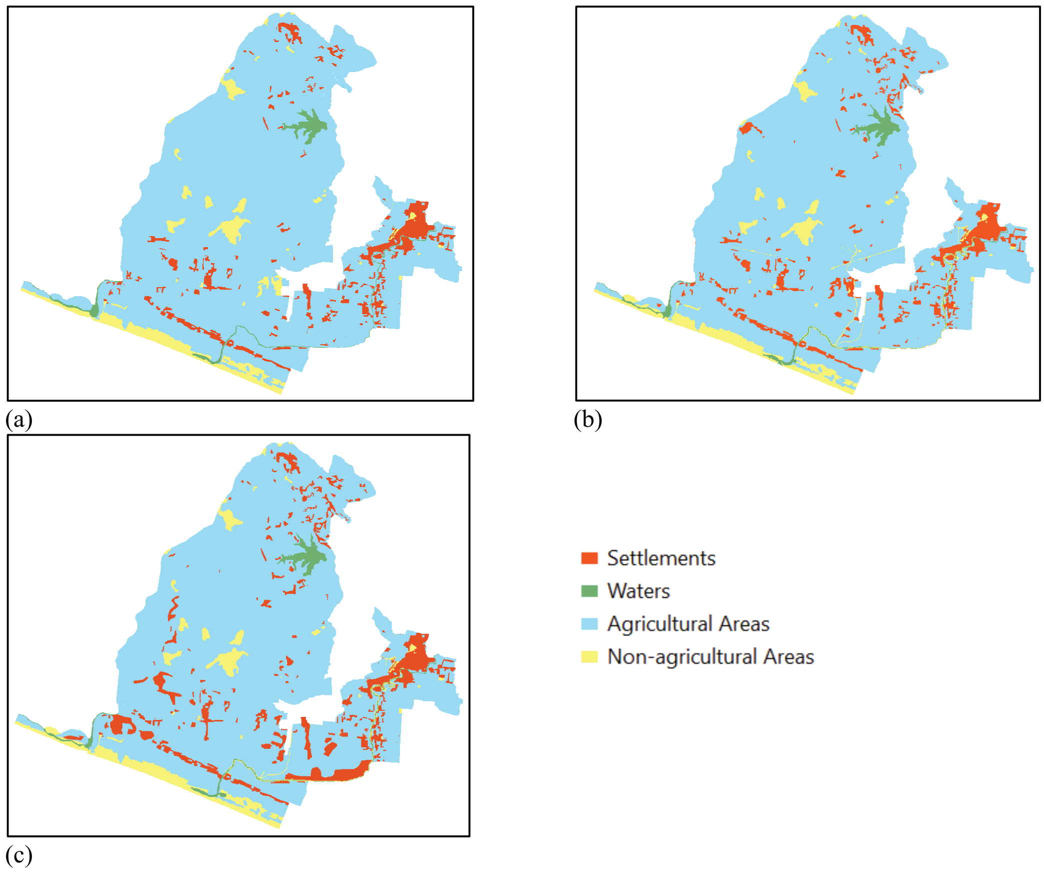


Figure 2: Land use of Study Area 2007 (a), 2012 (b), 2017 (c).

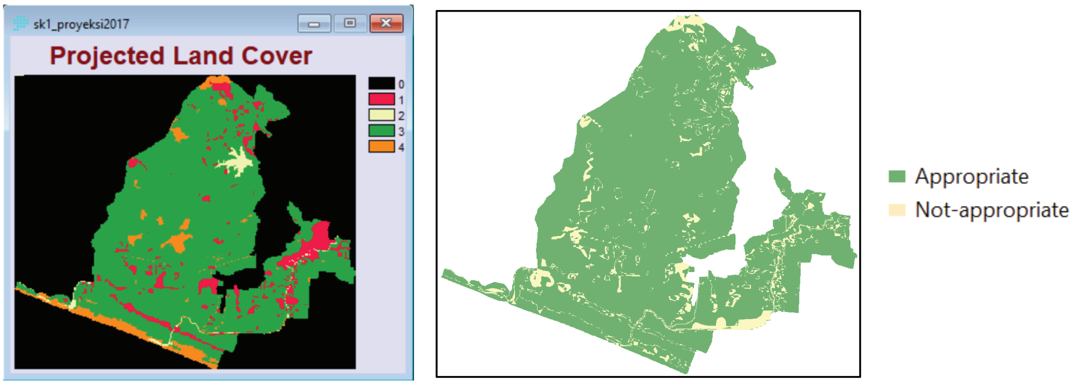
Based on the process carried out previously, each land use has a wide area. Extensive percentage of each land use classification per year available land use classification for each year, 2007, 2012, and 2017 is presented in the following Table 1:

Table 1: Comparison of area land use classifications.

Years	Land use Classifications (%)			
	Settlements	Waters	Agricultural Areas	Non-Agricultural Areas
2007	5,96	1,56	87,18	5,31
2012	7,25	1,69	85,35	5,71
2017	9,37	1,63	83,48	5,52

Based on Table 1, from 2007 to 2012 residential land use increased by around 1.29% and from 2012 to 2017 there was an increase of around 2.12% so that the increase from 2007 to 2017 (within ten years) was 3.41%. The agricultural area has decreased over the past ten years, while the non-agricultural areas and waters are relatively fixed in value.

Before conducting a prediction simulation for 2030, a prediction simulation in 2017 was carried out using 2007 and 2012 data. This simulation was conducted aimed to determine the suitability of simulations with actual data. Data from the simulation results in 2017 are then compared with the original data in 2017 to see the suitability of the intersect process. The results obtained from the comparison are 81.23% appropriate, and 18.77% is not appropriate, with visualization shown in the following Figure 3:



(a) (b)

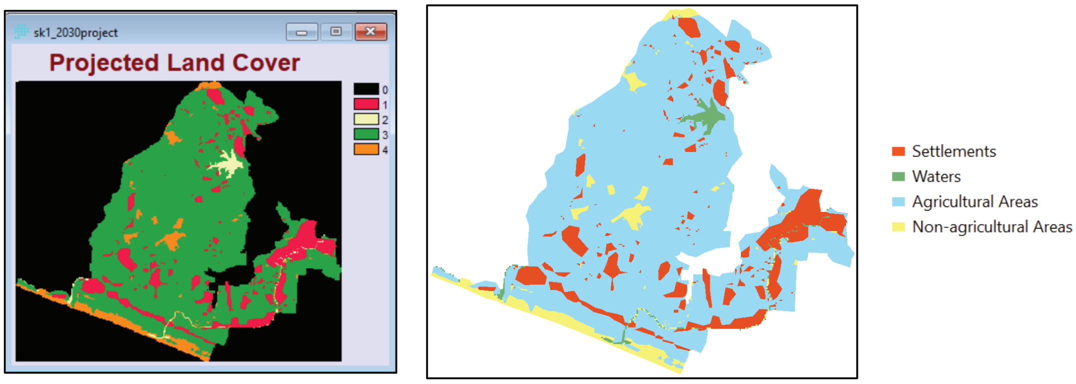
Figure 3: Land use in 2017 simulation results (a), Original 2017 land use suitability and simulation results (b).

Next is to do a simulation for 2030 starting in 2007. Iterations carried out in the CA-Markov process are 13 times, because the process carried out was started in 2007 and ended in the year 2030. The simulation is done with raster type input data and produces output with raster data types as well. In order to calculate the area for further analysis, the simulation data is converted into vector format, in this case, shapefile. Visualization of simulation results in 2030 can be seen in the following Figure 4:

Figure 4 (a) is a simulation result that is still in the raster data format, while Figure 4 (b) is a simulation result that has been converted into shapefile data. Furthermore, the data can be calculated in accordance with the classification that has been done before.

The results of the simulation in 2030, when compared with the preliminary data in 2007, will see the development of the area in the research location marked by increasing settlements, including the centre of economic and social activities. Differences between the initial data and simulation results are presented in the following Table 2:

The growth of settlements influences the development of the region, namely by the existence of settlements the social and economic activities of the surrounding



(a) (b)

Figure 4: Simulation results in 2030 original results (a), export results become shapefiles (b).

TABLE 2: Comparison of area of land use in 2007 and simulation in 2030.

Years	**Land use Classifications (%)**			
	Settlements	**Waters**	**Agricultural Areas**	**Non-Agricultural Areas**
2007	5,96	1,56	87,18	5,31
2030	12,93	1,48	79,92	5,67

community will increase so that the area can be more developed than other non-residential areas [11]. Settlements at the research site experienced growth in the span of 23 years, starting from 2007 to 2030 at 7,98%.

The simulation results in 2030 saw the pattern of regional development using the Global Moran's Index, with the value range of the Moran's Index ranges from -1 and 1 ($-1 \leq I \leq 1$). A value of $-1 \leq I < 0$ indicates a negative spatial autocorrelation, while a value of $0 < I \leq 1$ indicates a positive spatial autocorrelation, the value of Moran's Index is zero indicating there is no autocorrelation.

This research provides a Moran's Index of 0.003205. This value is in the range $0 < I < 1$, so that indicates a positive autocorrelation, but because the value is close to zero, it can be said that the correlation is very weak. So it can be concluded that the pattern formed is random. The results of these calculations are shown in the following Figure 5:

4. Conclusion

This research was conducted using the Cellular Automata (CA) Markov method because it is good for integrating dynamic and spatiotemporal aspects. The research locations were three sub-districts in Kulon Progo District, namely Kokap, Temon, and Wates Sub-district. The development of the region in this research is illustrated by the increase

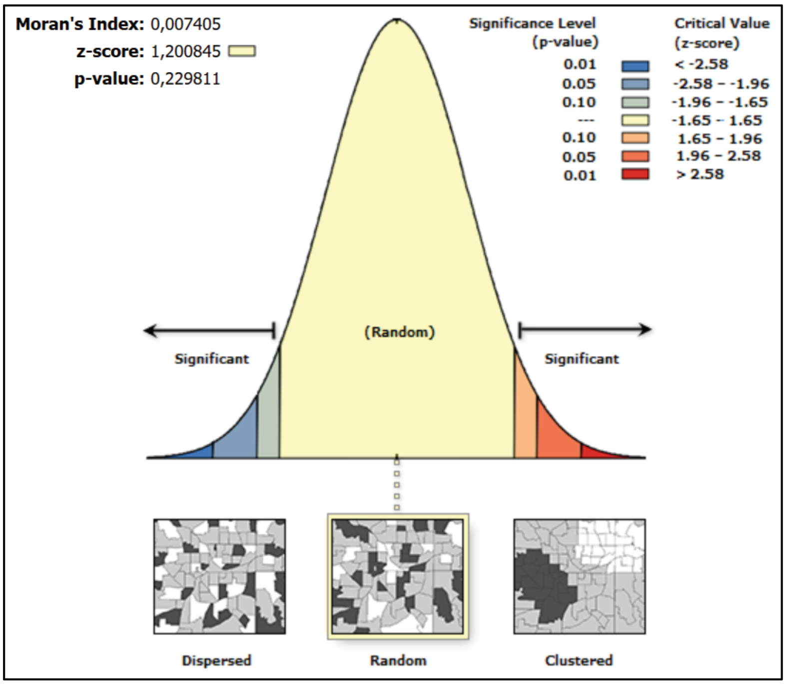


Figure 5: The Moran's Index on the simulation results in 2030 produces a random pattern.

in the number of settlements, which amounted to 7.98% in the span of 23 years. The direction of development of the region is to the west in accordance with the direction to the capital of Kulon Progo District, namely the Wates Sub-district and the south according to the location of the construction of the new airport. The pattern of regional development measured by the Global Moran's Index produces a value of 0.003205 so that it is included in the random pattern.

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