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Prediction of Land Cover Changes in Evaluation of Regional Spatial Planning in the Keduang Sub-Watershed, Wonogiri Regency

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Abstract

River watersheds have an important function for water absorption for human life. The Pemudang sub-watershed is a national priority because its condition is increasingly critical due to land degradation. This research aims to carry out spatial modeling of land cover changes in 2031 in the Uangng Sub-watershed which will be compared with the 2011-2031 Regional Spatial Plan scenario. The method used uses the Cellular Automata-Markov Chain method. Based on predictions of land cover in 2031, agricultural areas dominate in the Uangng Sub-watershed covering an area of 14,783.4 ha (37.5%). Agricultural area according to the model in 2031 is estimated to increase by 97.5 ha. The difference between the 2031 model area and the region spatial plan is 5,168.9 ha, which means that the region spatial plan settlements are not expected to be able to accommodate future settlements. The forest area in the 2031 model is 12,351.6 ha, while in the region spatial plan it is 12,300.3 ha with an area difference of 51.2 ha. This shows that controlling the use of space in forests is not in accordance with the policies in the region spatial plan.

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Abstrak

Daerah Aliran Sungai memiliki fungsi penting bagi resapan air untuk kehidupan manusia. Sub DAS Keduang menjadi prioritas nasional karena kondisinya yang semakin kritis akibat degradasi lahan. Penelitian ini bertujuan melakukan pemodelan spasial perubahan tutupan lahan tahun 2031 di Sub DAS Keduang yang akan di komparasi dengan skenario Rencana Tata Ruang Wilayah (RTRW) 2011-2031. Metode yang dipakai menggunakan metode Cellular Automata-Markov Chain. Berdasarkan prediksi penutup lahan tahun 2031, kawasan pertanian mendominasi di Sub DAS Keduang seluas 14.783,4 ha (37,5%). Luas pertanian menurut model tahun 2031 diperkirakan meningkat 97,5 ha. Selisih luas model tahun 2031 dengan RTRW adalah 5.168,9 ha yang berarti permukiman RTRW diperkirakan tidak bisa mewadahi pemukiman di masa depan. Luas hutan dalam model tahun 2031 adalah 12.351,6 ha, sedangkan dalam RTRW seluas 12.300,3 ha dengan selisih luasan sebesar 51,2 ha. Ini menunjukkan bahwa pengendalian pemanfaatan ruang di hutan belum sesuai dengan kebijakan dalam RTRW.

INTRODUCTION

Indonesia's population growth is centered on Java Island in the 2020 population census results. Java Island ranks first for population with a percentage of 56.19% or the equivalent of 151.6 million people (BPS, 2021). Meanwhile, Java Island only makes up 7% of the total land area of Indonesia (Rafiudin et al., 2016). Based on this reality, the availability of land area in the context of land and population experiences an imbalance in capacity. The ever-increasing population dynamics will certainly influence the increasing need for land for living. The occurrence of land exploitation indicates a change in the function of land cover to artificial land use which could disrupt the environmental ecosystem in the area.

Land conversion is the phenomenon of changing natural land cover into built-up land which is used to support the primary needs of society such as settlements, rice fields, plantations, and industrial areas (Kusumastuti et al., 2018). Changes in land use, such as cases of uncontrolled deforestation and without paying attention to conservation requirements, have a destructive effect on the surrounding environment. This has a negative impact on land quality, such as reducing the quality and quantity of land. The further effects of this cause land degradation which will later lead to critical land. The extent of critical land in the River Watershed (DAS) causes the function of the area to decline.

The Bengawan Solo watershed is one of the critical watersheds on the island of Java which is listed on Indonesia's super priority watershed list. As a super national priority, the Bengawan Solo watershed is very important to pay attention to and requires special attention in its management. Due to the condition of land cover in the form of forests which is quite worrying (Nugroho, 2003). The Bengawan Solo Watershed has six sub-watersheds, one of which is the Keduang Sub-watershed with an area of 42,644 ha (Lastiantoro & Cahyono, 2015). The Keduang Sub-watershed is an area in critical condition which is starting to lose its water absorption capacity. This is influenced by land degradation due to changes in forest land cover to built-up land (Hastono et al., 2012). This is not in accordance with Law no. 41 of 1999 concerning forestry, which states that each watershed is required to have a forest area of at least 30% of its land area. The reduction in forest area in the Bengawan Solo Hulu watershed causes a decrease in the absorption function due to the minimal area of forest cover. Apart from that, the sedimentation problem of 1,218,580 m^3/year especially also occurs in the Keduang Sub-watershed (Maridi et al., 2015)

Misuse of the Keduang sub-watershed which is located upstream can have a negative impact on the downstream. This is related to the water catchment ecosystem which is a series of natural processes of the hydrological cycle, the upstream and downstream parts have a biophysical connection through the hydrological cycle (Asdak, 2014). Continuously ignoring land damage in the upstream part of the watershed will cause the land to lose its function. The occurrence of these problems has attracted the government's attention by formulating several policies to resolve existing problems, for example, Republic of Indonesia Law No. 37 of 2014 concerning Soil and Water Conservation. This policy explains watershed management, which is handled holistically from upstream to downstream.

Problems that occur in watersheds need to receive more attention, especially in the upstream part, especially in spatial planning. Currently, problems in spatial planning are also having a big influence on river watersheds, for example land transformation. Spatial planning does not seem to be an important instrument in sustainable development. Meanwhile, the reality is that if changes in land use are not properly regulated and based on the principles of preserving environmental functions and sustainable development, watersheds will remain threatened. This situation has implications for efforts to maintain the extent of forest areas with provisions for watershed protection becoming difficult to realize and forest areas will continue to be degraded significantly. Changes in land use are not only changes in forest areas to agriculture or plantations but most are also changed to industrial and other commercial areas.

Economic development is still the main orientation of various regions today. Economic development is used as a benchmark for the welfare of a region so that development prioritizes regional economic growth and ignores sustainability aspects. If this situation continues to be prioritized and the environment is ignored in development, the threat of environmental problems will become increasingly difficult to avoid, for example, floods, landslides, or drought.

Efforts can be made to face this challenge, Cellular Automata-Markov Chain (CA-MC) was introduced as a method that is quite effective in estimating the rate of land use change (Rahnama, 2021). This approach combines the concept of cellular automata in representing spatial and temporal changes in Markov chains as a form of transition between land cover categories (Mustafa et al., 2021). This approach can make predictions while still considering the complex interactions between factors that influence land cover (Manakane et al., 2023). Land use changes in this study include the conversion of forests into agricultural land or settlements. Mwabumba et al. (2022) highlight the importance of understanding these types of changes and their implications. Predictions within a certain period into the future are quite relevant in planning sustainable land management (Wang et al., 2022). Therefore, land analysis is needed that can describe the condition of land damage in the Keduang Sub-Watershed using the use of Geographic Information Systems and Remote Sensing.

METHOD

Research Area

The Keduang Sub-watershed is part of the Bengawan Solo Hulu Watershed with an area of 39,408.8 ha. Geographically, the Keduang Sub-watershed is located between 110º57'00"E − 111º13'24" E and 7º42'30" S − 7º55'29" S (Figure 1). Administratively, the Keduang Sub-Watershed is located in Wonogiri Regency and Karanganyar Regency. The Keduang Sub-watershed area in Wonogiri Regency covers 12 sub-districts, while in Karanganyar Regency there is 1 sub-district. Serious land use changes have been reported in this area. These changes cause an increase in river flow and runoff coefficient (Marhaento et al., 2021; Wuryanta et al., 2023), water balance (Marhaento et al., 2017), changes in food security (Ningsih & Ramandani, 2024). It is feared that changes without control efforts will trigger serious problems in the future.

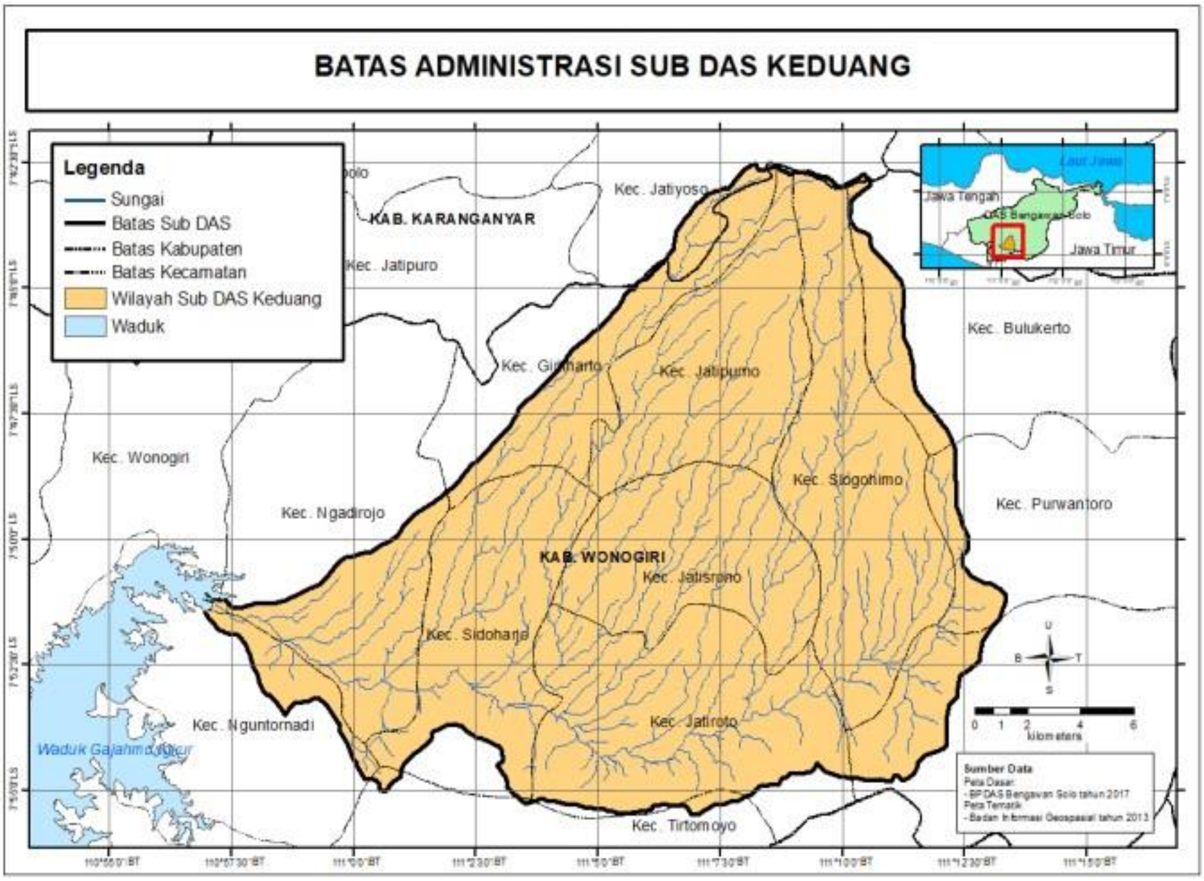

Figure 1. Map of Administrative Boundaries of Keduang Sub-watershed

Cellular Automata Markov Chain

Cellular Automata - Markov Chain (CA-MC) can make predictions for modeling based on spatial data of past, existing, and future conditions with what are called driving factors (Ebrahimipour & Farshchin, 2016; Gharaibeh et al., 2020). The use of this method is usually easily processed in IDRISI software to calculate probabilities based on the number of pixels in the raster originating from remote sensing data for determining model parameters (Bedawi & Shariff, 2016; Song et al., 2020). Models using the CA-MC method are very popular for modeling geographic study phenomena starting from physical and social aspects such as deforestation, urban sprawl, and changes in land cover due to land use (Ozturk, 2017; Hasani et al., 2020).

This spatial model has been widely used in several studies and provides quite accurate results in predicting land cover and urban growth (Ghosh et al., 2017). This is because this model can be used to study predictions of complex land cover distribution with a simple algorithm that is easy to apply.

The MC model assumes that the current state of a cell depends on the history of land use and the probability of its change to another form of land use class (Ghosh et al., 2017). The probability of change is determined by a transition probability matrix, which is calculated from a series of historical land use maps for each pixel change (Alqurashi et al., 2016; Ghost et al., 2017). Therefore, the land use transition probability between time t and t − 1 is calculated as

$$P(t) = P(t-1)P_{ij} \quad (1)$$

where $P(t)$ and $P(t-1)$ are the state probability of a cell at present and the previous point in time, respectively. P_{ij} is the probability matrix of land-use type i changing into land-use type j:

$$P_{ij} = \begin{bmatrix} P_{11}P_{12}\cdots P_{1n} \\ P_{21}P_{22}\cdots P_{2n} \\ P_{31}P_{32}\cdots P_{3n} \end{bmatrix} \quad (2)$$

each transition probability value in this matrix denotes the persistence/conversion probability of a particular land-use type (rows: land-use type of a previous time point) to another land-use type (columns: land-use type of a later time point), with the assumption of there being constant land-use conversion probabilities (Mosammam et al., 2017). The principal diagonal values represent the probabilities of LUC continuity: the likelihood of the specified land-use class remaining unchanged while the off-diagonal values show the land-use conversions across land-use classes (Rimal et al., 2017).

Data Collection

The data used in this research is divided into two types based on the source, namely primary data and secondary data (Sugiyono, 2007). The main data in this research utilizes secondary data obtained from digitizing land cover from satellite images, and other spatial data collected through literature studies related to research studies. Land cover data was obtained from Google Earth imagery for October 2005, 2011, and 2018. Slope and elevation were extracted from Digital Elevation Model Shuttle Radar Topography Mission 30 × 30 meter data. The road network was obtained from the Geospatial Information Agency in 2017. The river network was obtained from the Bengawan Solo River Basin Management Center (BPDAS) in 2017. The Regional Spatial Planning of Wonogiri Regency was obtained from BAPPEDA and Research and Development of Wonogiri Regency. The above data used in this research is open-access data that can be accessed intensively.

Data Processing

Driving Factors

The driving factors data in this research are spatial data on distance from roads, distance from rivers, distance from settlements, slope, and elevation. All driving factors data is processed using ArcGIS 10.8.1. Driving factors data in the elevation and slope are classified. Meanwhile, driving proximity factors in the form of distance from roads, distance from rivers, and distance from settlements are processed using buffering techniques. All driving factors are then given a score based on predetermined class criteria (Table 1). Each driving factor value is then converted into a fuzzy value. After that, we perform fuzzy overlay to combine the data.The fuzzy overlay will provide a membership degree between 0 to 1. The closer membership is to 1, the higher the opportunity for an area to change.

Table 1. Driving Factors Classification

No.	Variable		Class	Score	Source
1	Elevation (m)	< 500	Very potential	4	Yudarwati, 2016
		500-750	Potential	3	
		750-1000	Less Potential	2	
		>1000	Not Potential	1	
2	Slope (%)	< 2	Very potential	4	Akbar & Supriatna, 2019
		2-15	Potential	3	
		15-40	Less Potential	2	
		>40	Not Potential	1	
3	Distance from River (m)	< 25	Not Potential	1	Akbar & Supriatna, 2019
		25-50	Potential	2	
		>50	Very potential	3	
4	Distance from Road (m)	< 100	Very potential	5	Akbar & Supriatna, 2019
		100-200	Potential	4	
		200-500	Quite Potential	3	
		500-1000	Less Potential	2	
		>1000	Not Potential	1	
5	Distance from settlement (m)	< 100	Very potential	4	Yudarwati, 2016
		100-500	Potential	3	
		500-1000	Less Potential	2	
		>1000	Not Potential	1	

Land Cover Modeling

Land cover modeling was carried out to obtain land cover data for 2031. Land cover modeling was carried out in IDRISI Selva software. The data used is land cover data for 2005, 2011, and 2018 and fuzzy driving factors data. Land cover modeling and fuzzy driving factors data must have the same metadata (resolution, columns, and rows). This was completely done using ArcGIS 10.8.1 software. In processing land cover data in IDRISI software, it is necessary to name the data via assign to define each land cover. The Markov Chain process of land cover data for 2005 and 2011 was carried out with an error proportion of 0.15 to obtain a probability matrix for the 2018 land cover model.

The CA-MC process was carried out with the help of driving factors data to produce land cover data for the 2018 model year. Next, validation was carried out on the actual 2018 land cover data and the 2018 model to test the accuracy of the model created with the actual 2018 land cover as a baseline by referring to kappa accuracy. The kappa coefficient is considered a general technique for measuring the accuracy of thematic maps produced by the classification process. The kappa coefficient is calculated using the following equation.

$$K_{APPA} = \frac{N \sum^{k} X_{ii} \sum^{k} (X_{i+} \times X_{+i})}{N^2 - \sum^{k} (X_{i+} \times X_{+i})} \quad (3)$$

where K_{APPA} is Kappa index, k is the number of matrix files, X_{ii} is observation number on row i and column I (along the diagonal), X_{i+} and X_{+i} are total marginal for row i and column i, respectively, N is a total number of observations.

After accurate modeling, the 2031 land cover model was carried out. The stages carried out are the same as the previous modeling but the probability matrix is created from land cover in 2005 and 2018 with a span of 13 years. The research flow can be seen in Figure 2.

RESULT AND DISCUSSION

Land Cover Changes

The dominant land cover in 2005 in the Keduang Sub-watershed was agriculture covering an area of 20,150.8 ha (51.1%) (Figure 3). The largest agricultural land cover is in the Cuwo sub-sub-watershed covering an area of 4,477 ha, while the smallest is in the Cebongan sub-sub-watershed covering an area of 957.4 ha. The other dominant land cover is forest covering an area of 15,205.9 ha (38.6%).

Forests in the Keduang sub-watershed dominate in the north and south, which have

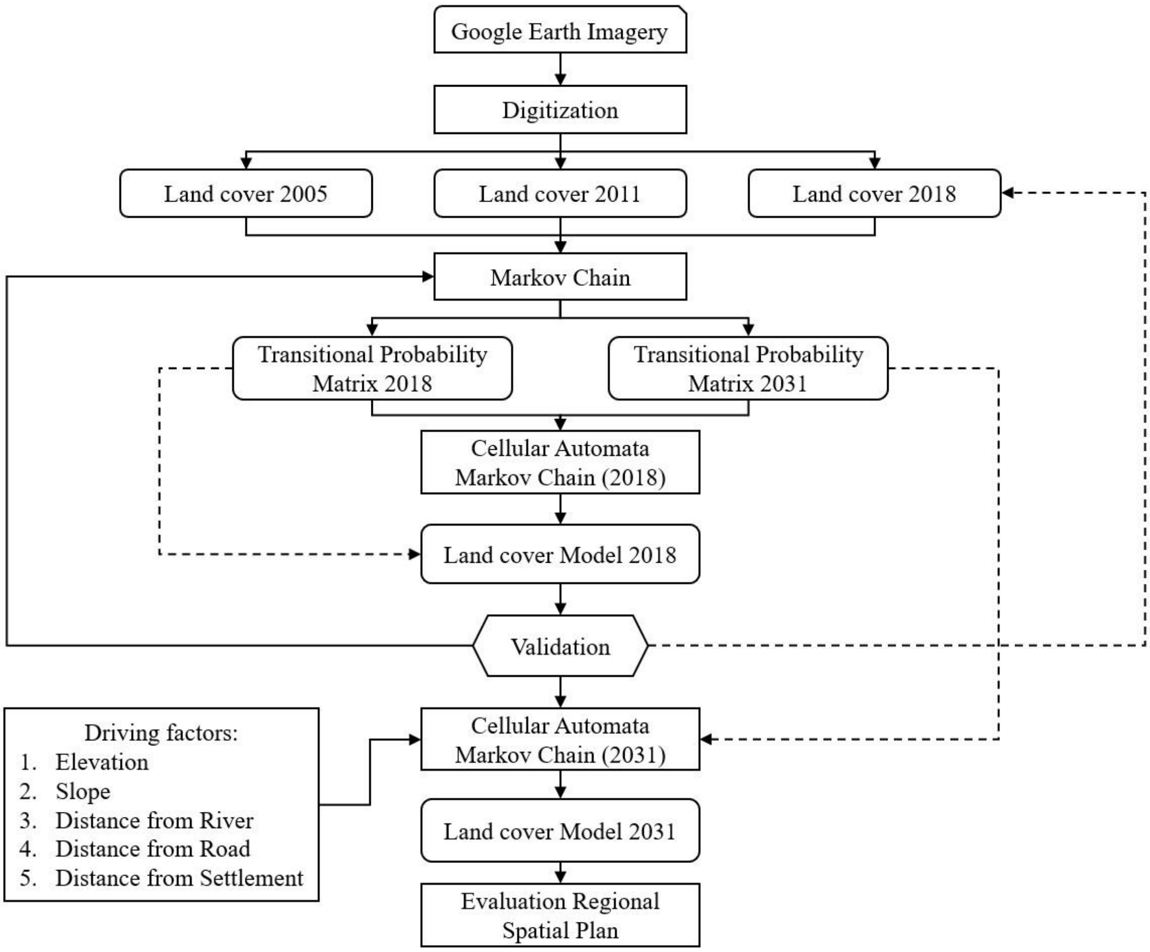

Figure 2. Overall Research Workflow

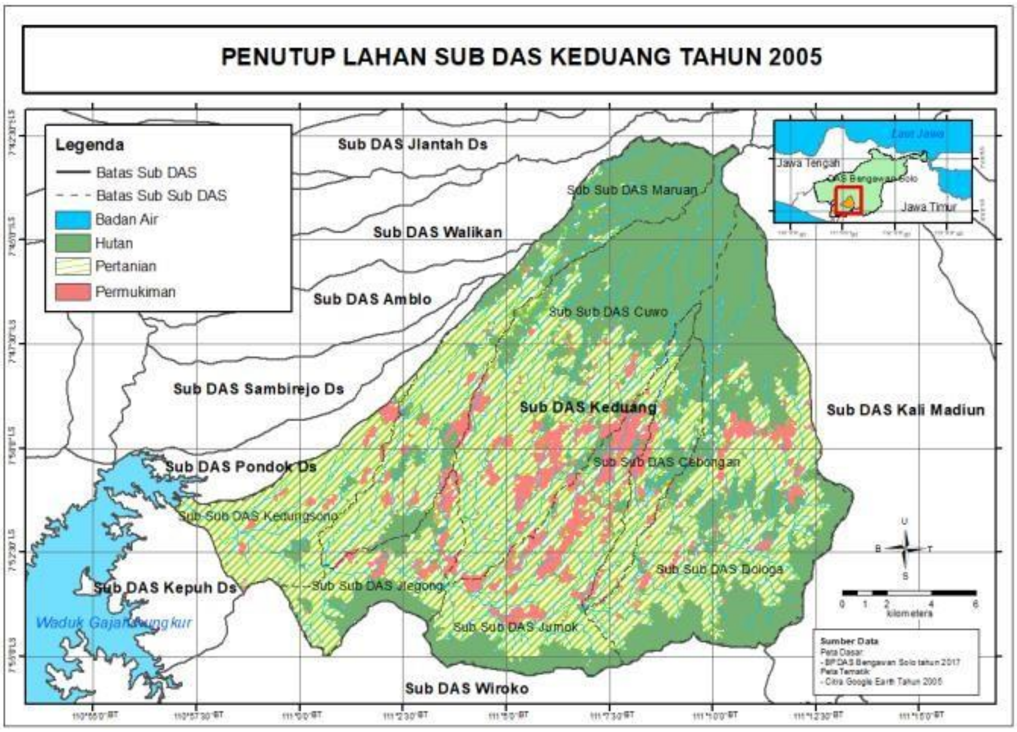

Figure 3. Land Cover in 2005 in the Keduang Sub-Watershed

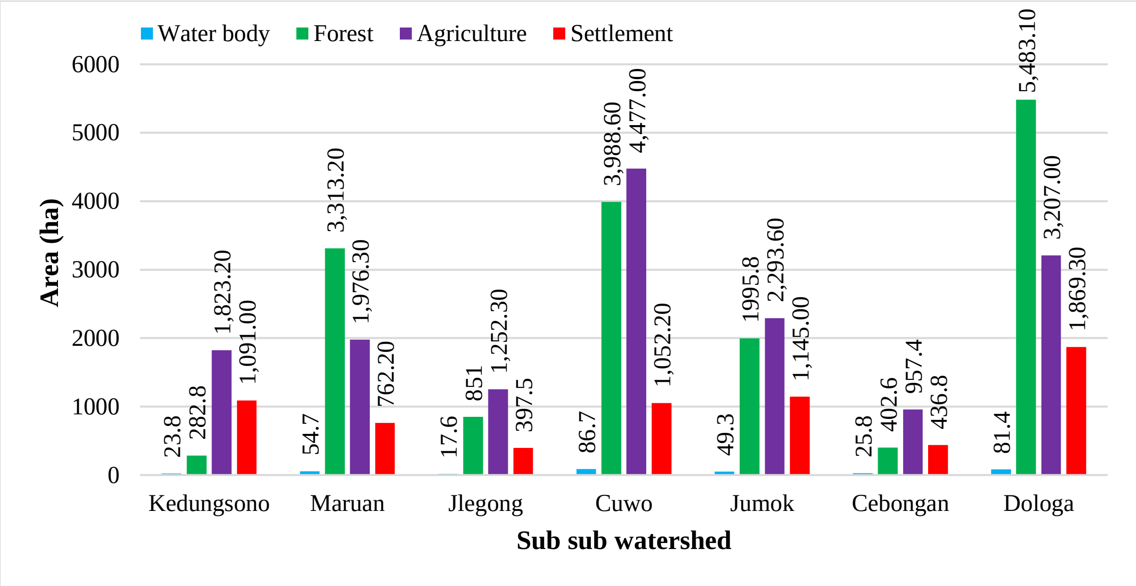

Figure 4. Land Cover Area in 2005 in the Keduang Sub-Watershed

topographical conditions with steep slopes so that development of areas into settlements is still rare. The largest forest land cover is in the Dologa sub-sub-watershed covering an area of 5,483.1 ha. Residential land cover is 3,712.8 ha (9.4%). The most extensive residential land cover is in the Jumok sub-sub-watershed covering an area of 1,145 ha with a slope of 0-8% (flat) making it suitable for the development of settlements (Figure 4).

The dominant land cover in 2011 in the Keduang sub-watershed was agriculture with an area of 15,391.4 ha (39.1%) (Figure 5). This is still the same as in 2005 when agricultural land cover was the most dominant in the Keduang sub-watershed. Agriculture has experienced a decrease in area from 2005–2011 covering an area of 4,759.4 ha. This is quite worrying because, within 6 years, much of the agricultural land has been turned into residential areas. This is due to the increase in population and the need for land for residence. The most extensive agriculture is in the Dologa sub-sub-watershed covering an area of 3,907 ha. The other dominant land cover is forest covering an area of 13,836 ha (35.1%). Forests dominate in the northern and southern parts of the Keduang Sub-watershed. Forests have decreased in area from 2005–2011 to an area of 1,369.9 ha. The most dominant forest in the Dologa sub-sub-watershed covers an area of 4,581 ha. Settlements in 2011 of the Keduang sub-watershed were known to cover an area of 9,842.1 ha (25%). Settlements have experienced an increase in area from 2005–2011 covering an area of 6,129.3 ha. The most extensive settlements are found in the Jumok Sub-sub-watershed, covering an area of 2,127.3 ha (Figure 6). The increase in settlements may continue to occur in the coming years so land conversion that occurs needs to be considered because it can cause environmental damage. The increase in population is in line with the increase in human activities in various sectors, especially the economic sector, so the need for land resources will also increase, while the existence of land is fixed (He et al., 2018) and will ultimately reduce the carrying capacity of the environment (Kurniawan & Ramadhan, 2024).

The most dominant land cover 2018 in the Keduang Sub-watershed was agriculture with an area of 14,685.5 ha (37.3%) (Figure 7). Agriculture has experienced a decrease in the area from 2005–2018 by 5,465.3 ha, while the decrease in the area 2011–2018 was 705.9 ha. Therefore, the greatest decrease in agricultural area occurred from changes in 2005–2011 compared to changes in 2011–2018. Agriculture dominates most in the Dologa sub-sub-watershed covering an area of 3,487.1 ha. The other dominant land cover is forest covering an area of 12,508.9 ha (31.7%). Forests have decreased in area from 2005–2018 by 2,697 Ha, while the decrease in area from 2011 – 2018 was 1,327.1 ha. Therefore, the largest decrease in forest area occurred from 2005–2011 compared to 2011–2018, the same as the decrease in agricultural area. Forests dominate in the north and south of the Keduang Sub-watershed. The most dominant forest is in the Dologa sub-sub-

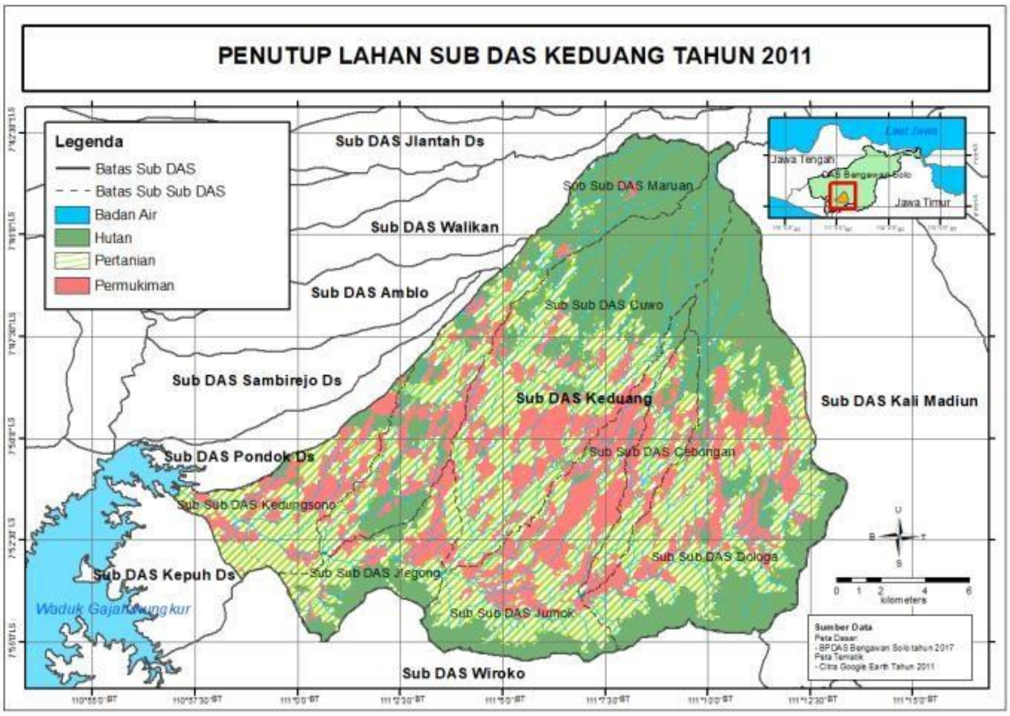

Figure 5. Land Cover in 2011 in the Keduang Sub-Watershed

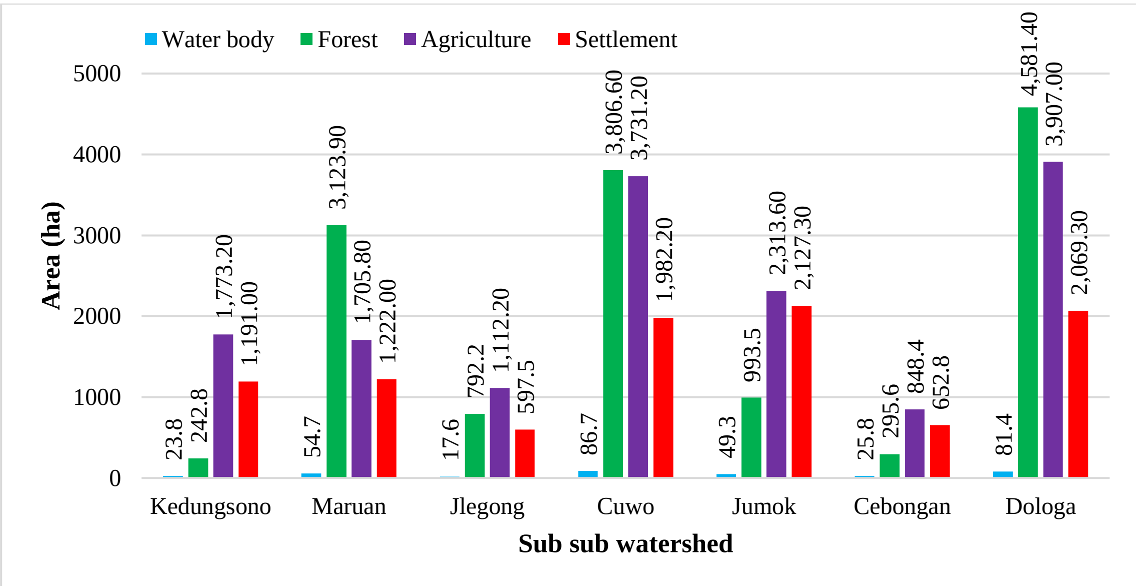

Figure 6. Land Cover Area in 2011 in the Keduang Sub-Watershed

watershed covering an area of 4,514 ha. In 2018, settlements in the Keduang sub-watershed covered an area of 11,881.2 ha (30.1%).

Settlements have experienced an increase in area from 2005 – 2018 covering 8,168.4 ha, while a decrease in area from 2011 – 2018 covering 2,039.1 ha. Therefore, the largest increase in settlement area occurred from changes in 2005 - 2011 compared to changes in 2011 - 2018. The most dominant settlements were in the Jumok sub-sub-watershed covering an area of 2,418.6 ha (20.4%) (Figure 8).

Based on the graph of gains and losses, land conversion can be seen by showing the increase and decrease in the area of each land cover in the Keduang sub-watershed (Figure 9). From 2005 – 2018, settlements became the most significant land cover, experiencing an increase of 8,804 ha and only a decrease of 560 ha.

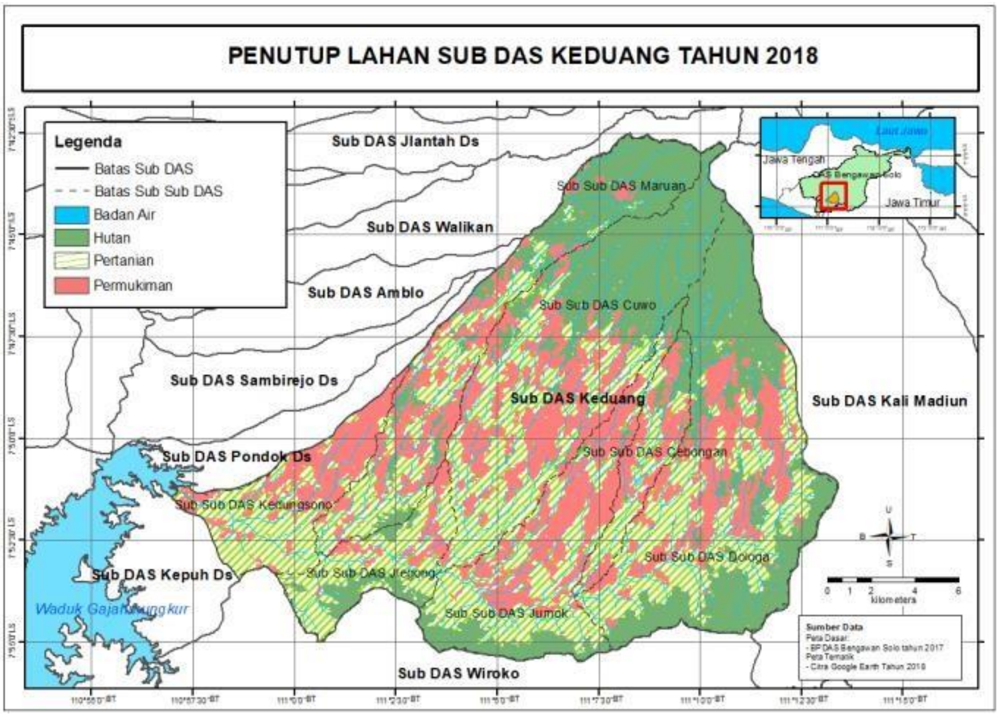

Figure 7. Land Cover In 2018 in the Keduang Sub-Watershed

The 2,210 ha settlement came from the conversion of forest and agricultural functions over a period of 13 years covering an area of 498 ha. Agriculture, the most significant land cover, experienced a decline of 7,261 ha. Changes in agricultural area are caused by increasing residential area and decreasing forest area. Agriculture covering an area of 6,035 ha has been converted into residential areas and 498 ha of agricultural land came from forest conversion. The more dominant forest experienced a decline, namely 1,725 ha. Changes in forest area are caused by increasing areas of settlement and agriculture. A forest area of 2,210 ha has been converted into settlements and 498 ha has been converted into agriculture. The land cover of water bodies has not been identified as having changed.

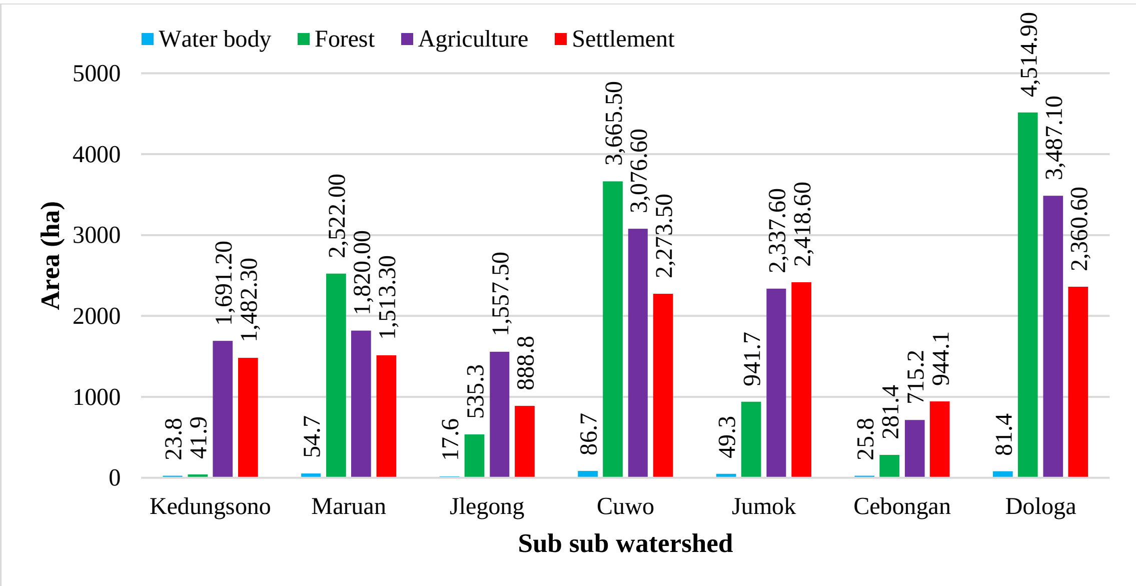

Figure 8. Land Cover Area In 2018 in the Keduang Sub-Watershed

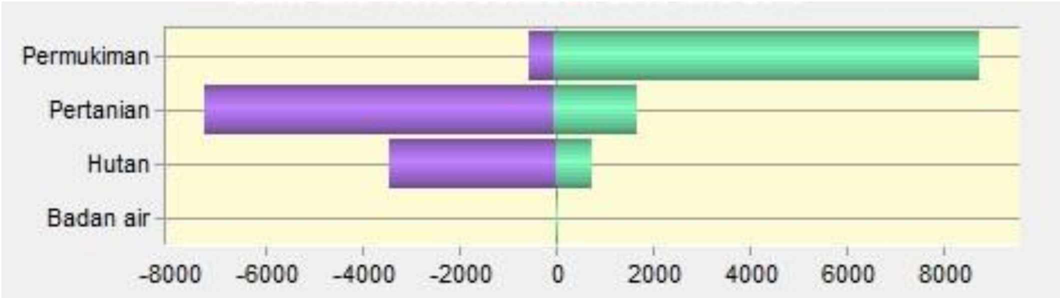

Figure 9. Land Cover Changes Area in 2005 – 2018 in the Keduang Sub-watershed

Land Cover Prediction in 2031

The land cover modeling in 2031 was obtained by validating the 2018 model with the actual 2018 land cover. The kappa accuracy test results obtained were 81% or very good suitability (Ridwan et al., 2017), because the results exceed the 75% threshold, so that data used for model predictions in 2018 can be continued for land cover predictions in 2031. Land cover in 2005 is used as the baseline and 2018 as the final data which produces a probability matrix (Table 2).

Forests have the possibility of remaining forests (probability 0.7743), changing to agriculture (probability 0.0788), and settlements (probability 0.1470). Agriculture has a probability of turning into a settlement (probability 0.3188), while agriculture has a smaller probability of turning into a forest (probability 0.0345). Settlements have a higher probability of remaining as settlements (probability 0.8520), changing to agriculture (probability 0.1366), and becoming forests (probability 0.0114). Water bodies have the possibility of remaining a water body (probability 0.9808), and changing into agriculture (probability 0.0192), but do not have the possibility of changing into forests and settlements.

The modeling results show that agricultural land in 2031 will dominate the Keduang Sub-Watershed, namely 14,783.4 ha (37.5%) (Figure 10). The agricultural area in 2031 is estimated to increase by 97.5 ha. Agriculture is mostly found in the Dologa sub-sub-watershed (3,501.8 ha). Land cover in the form of forest still dominates the northern and southern parts of the Keduang Sub-watershed covering an area of 12,351 ha (31.3%). The forest area is estimated to decrease in 2031 by 151.2 ha. The most forests are found in the Dologa sub-sub-watershed (4,493 ha). Settlements in 2031 are expected to increase to 11,934.6 ha. This shows that within 13 years, settlements are expected to expand by 53.4 ha. Most settlements are found in the Cuwo sub-sub-watershed (2,787.2 ha) (Figure 11).

Evaluation of Regional Spatial Plan with Land Cover Predictions in 2031

The most dominant land cover in the regional spatial plan is agriculture covering an area of 20,003 ha (50.8%) (Figure 12). Agriculture according to the regional spatial plan is the same as actual land cover which is the largest land cover compared to others. Agriculture is mostly found in the Cuwo sub-sub-watershed (6,029.3 ha). The other dominant land cover is forest with an area of 12,300.3 ha (31.2%). The most extensive forest is in the Dologa sub-sub-watershed covering an area of 4,650.4 ha. Settlements in the Keduang sub-watershed based on the regional spatial plan cover an area of 6,765.6 ha. Most settlements are found in the Cuwo sub-sub-watershed (2,486.6 ha) (Figure 13).

Table 2. Land Cover Change Probability Matrix

Land Cover	Water Body	Forest	Agriculture	Settlement
Water Body	0.9808	0.0000	0.0192	0.0000
Forest	0.0000	0.7743	0.0788	0.1470
Agriculture	0.0000	0.0345	0.6466	0.3188
Settlement	0.0000	0.0114	0.1366	0.8520

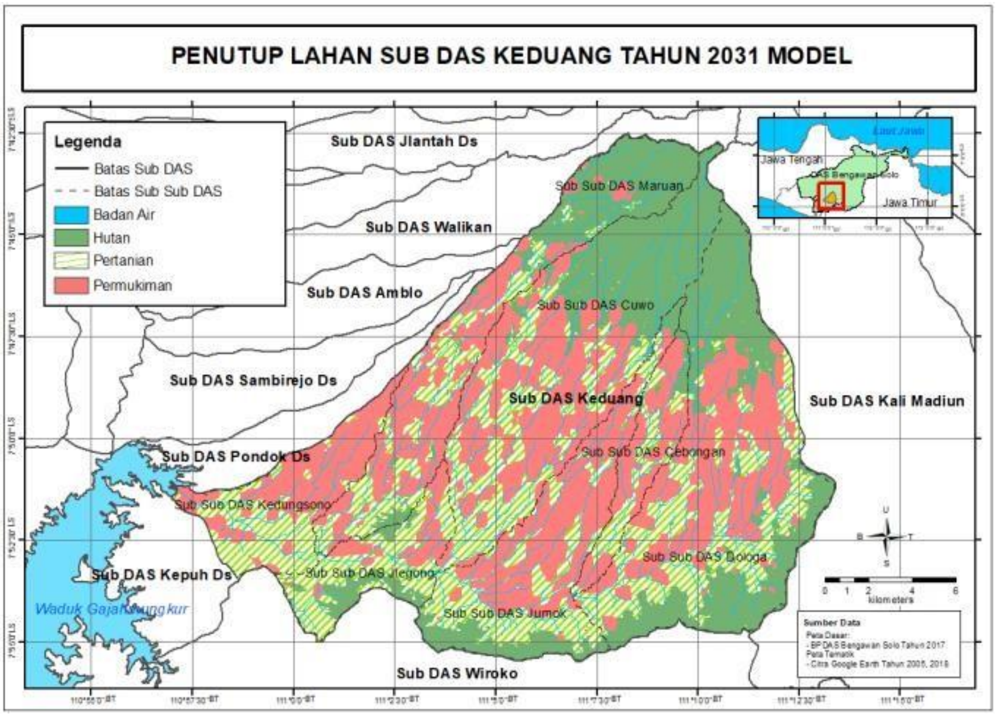

Figure 10. Land Cover 2031 Model in the Keduang Sub-watershed

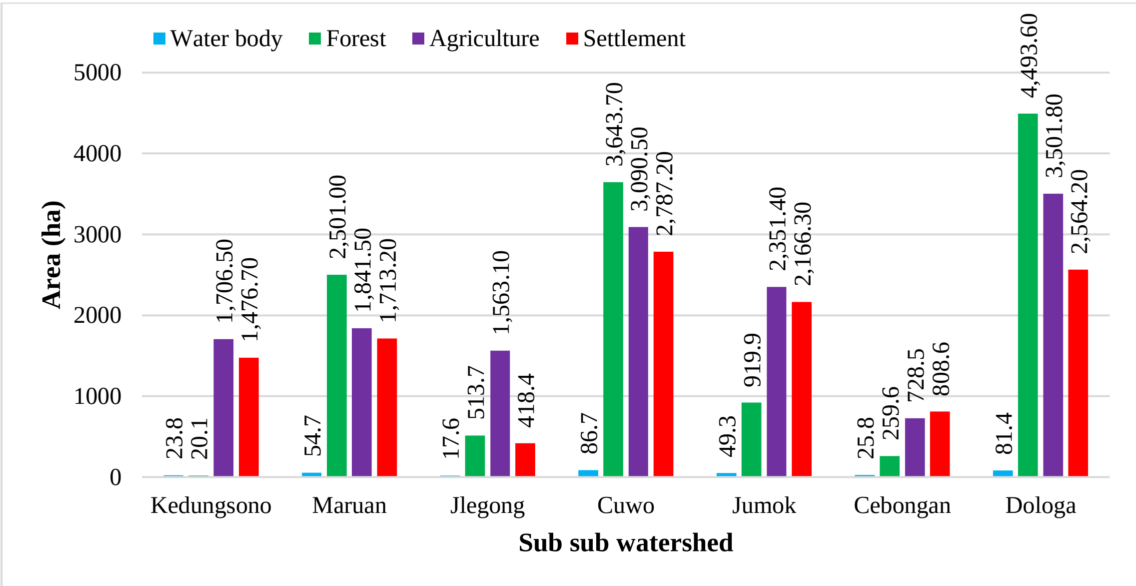

Figure 11. Land Cover Area 2031 model in the Keduang Sub-watershed

According to the land cover 2031 model and regional spatial plan, forests are still dominant in the northern and southern parts of the Keduang sub-watershed. However, the forest area in the northern part of the regional spatial plan is smaller and in the south, it is larger. The forest area in the 2031 model is larger than in the regional spatial plan. Agriculture in the regional spatial plan has a larger area than the 2031 model. Settlements in the regional spatial plan have a smaller area compared to the 2031 model (Table 3). This shows that there is a lack of land provision and management by the government compared to the potential for land changes in the future. Carrying capacity reaches good quality if the land area for the built-up area is between 30 - 70% of the total land that can be used (Soerjani et al., 1987).

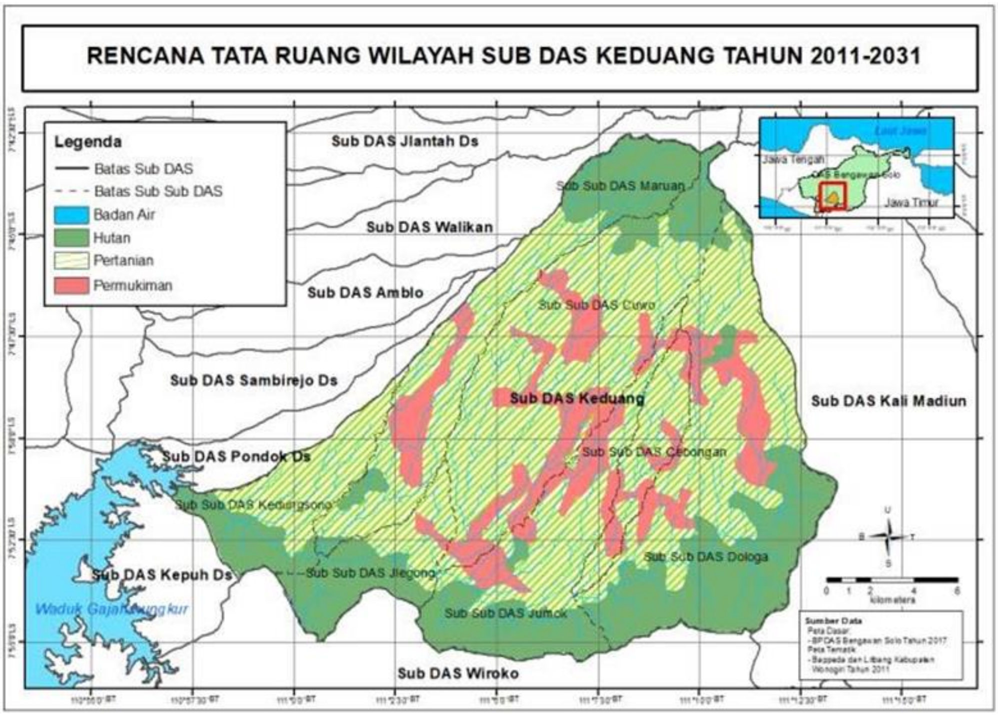

Figure 12. Regional Spatial Planning 2011 - 2031 in the Keduang Sub-watershed

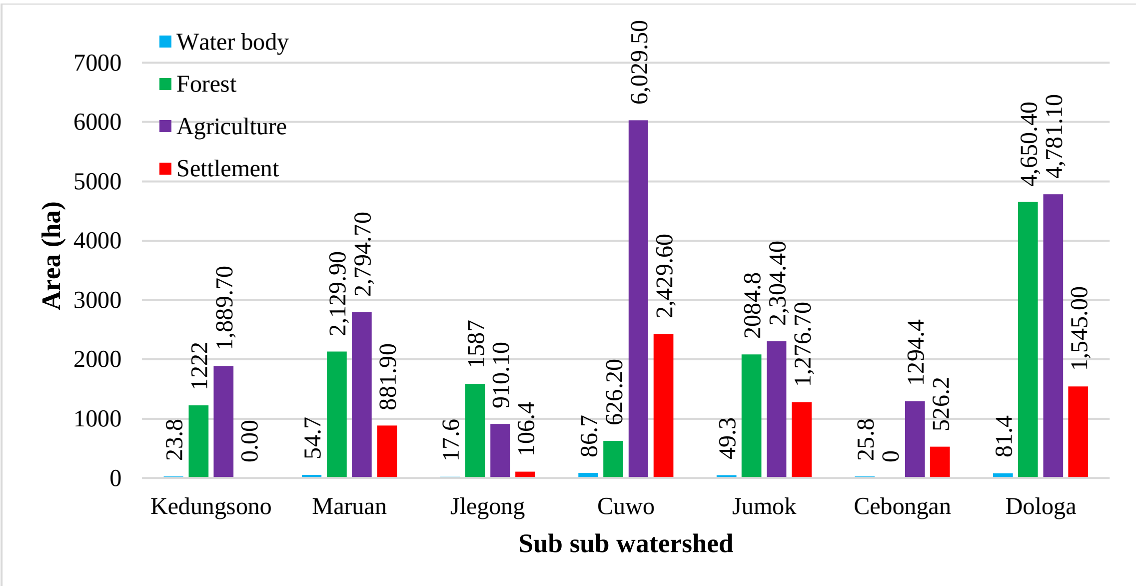

Figure 13. Regional Spatial Planning Area 2011 - 2031 in the Keduang Sub-watershed

Table 3. The Difference in Area Between The 2031 Model and The Regional Spatial Planning

Land Cover	2031 Model	2031 RTRW	Difference
Water Body	339,3	339,3	0,0
Forest	12.351,6	12.300,3	51,2
Agriculture	14.783,4	20.003,6	5.220,2
Settlement	11.934,6	6.765,6	5.168,9
Total	39.408,8	39.408,8	10.440,4

The biggest difference in area is the agricultural land cover in the 2031 model and the 2031 regional spatial plan model. The 2031 model has a smaller area compared to the regional spatial plan which reaches 5,220.2 ha. The results of the 2031 modeling can be estimated that the agricultural area is still inadequate if based on the regional spatial plan which wants to provide sufficient food production for regional communities so that expansion of agricultural land can still be carried out for annual regional spatial plan evaluations. Research conducted by Pratama (2023) at Ciawi Dam shows that there is moderate suitability of agricultural areas to the regional spatial planning where for suitability to the regional spatial plan there is at least 46% permitted with conditions, 49% corresponds to 5% of areas that are not suitable. Aldiansyah & Supriatna (2024) also found the suitability of agricultural land expansion for the vision and mission of Unaaha City as an Agropolitan City.

The second biggest difference in area is settlements between the 2031 and regional spatial plan models. The Wonogiri Regency Government has calculated that the area of settlements in the Keduang Sub-Watershed is only 6,765.6 ha, but in the 2031 model, the settlement area in 2031 will reach 11,934.6 ha. This will cause land inequality due to the need for land as a result of the population growth of the Keduang Sub-Watershed which continues to increase. Therefore, active community participation in the process of planning and controlling space use is important. The difference in settlement area between the model and the regional spatial plan is 5,168.9 ha, which means that the settlements prepared in the regional spatial plan cannot meet the need for land as a place to live. The same case was also found by Nessa et al. (2021) in which the area of residential land planned in the regional spatial planning exceeds capacity and reaches 17,946.03 hectares of the total existing land use area. Another case was also found by Manakane et al. (2023) that residential land will continue to increase until it reaches 116.96 ha, which is triggered by increasing population and demand for land.

The difference in forest area in the 2031 model and regional spatial plan only reaches 51.2 ha. The forest area in the 2031 model is 12,351.6 ha, while in the regional spatial plan, it's 12,300.3 ha. Modeling has illustrated that controlling the use and management of space in forests is almost following the policies in regional spatial planning. Aldiansyah & Wibowo (2022) also found that the regional spatial planning evaluation found deviations in the actualization of spatial planning, especially in Protected Areas and Cultivation Areas in Southeast Sulawesi Province. Arimjaya et al. (2022) also found irregularities in the actualization of spatial planning, especially on the Kapuas River border in Central Kalimantan Province.

The regional spatial plan was created for policy direction and space utilization strategies which serve as guidelines for spatial planning (Wonogiri Regional Regulation No. 9 of 2011). The CA-MC model integrated with GIS can be used as a guide in evaluating land use changes in an area. The CA-MC model has proven to be accurate in evaluating the suitability of phenomena to regional spatial plans such as disasters (Ramadhan & Kurniawan, 2021, Pratiwi et al., 2022; Aldiansyah et al., 2023), fisheries cultivation (Yunita et al., 2022) and agriculture (Hambali et al., 2022; Aldiansyah & Supriatna, 2024), land use (Mauliddama, 2021; Ramadhan & Wibowo, 2021), and rainfall (Setiawan et al., 2021). The wide difference between the 2031 land cover model and the regional spatial plan can be a further consideration in preparing the regional spatial plan because the CA-MC model does not take into account economic activities, disasters, and so on. This evaluation will provide an overview of the suitability of the predicted land cover with the policies that have been made so that existing land cover discrepancies can be considered further.

CONCLUSION

Changes in land cover from 2005 - 2018 occurred dynamically with forests decreasing significantly every year. The land cover that experiences a significant increase in the area every year is the settlement. The increase in residential area is one of the causes of the conversion of other land into residential areas, especially agriculture into residential areas. This will not be following the fulfillment of raw materials and the increasing population. The area of forest also continues to decrease due to the expansion of agriculture as a result of land that should have been designated for agriculture has been turned into residential areas, so that forest land has finally been converted into agricultural areas.

The results of the regional spatial plan evaluation with predictions of changes in land cover illustrate that there is still a discrepancy between the use of space regulated in the regional spatial plan and the predicted land cover in 2031. Agricultural land and settlements in the 2031 model provide a larger area than planned in the regional spatial plan, so the planning carried out needs to be re-evaluated so that it can meet the community's need for land. The forest has a small difference in area between the 2031 model and the regional spatial plan, so forest use is almost by what has been prepared in the regional spatial plan for Wonogiri Regency in the Keduang Sub-watershed.

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