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Modeling land cover dynamics using Markov chain and cellular automata in Batang Regency

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ABSTRACT

Land cover change is one of the impacts of the economic development process, also marked by urbanization. One form of urbanization is industrialization. Batang Regency is an area currently carrying out much industrial development, such as the steam power plant and the Batang integrated industrial area (KITB), which can become a centre of economic growth. Accessibility in Batang Regency is currently passed by the Toll Road and National Road, which can be one of the attractions for changes in land cover. This study aims to predict land-cover changes due to economic activities and compare the prediction results with applicable regulations. The method used is the cellular automata algorithm for 2032 and 2039. Land cover modelling is carried out based on data from 2015 to 2023. The selection of years is based on the Batang Regency spatial planning (RTRW) regulations. Accuracy test results using the relative operating characteristic (ROC) method show that the number is 0.86. The results of land cover predictions show that open land and agriculture tend to decline. Changes in land cover tend to occur in areas close to economic centres and highways. The agricultural area in the prediction results is lower than the planned area, indicating that the program to maintain agricultural land has been considered in the RTRW. The conversion of land that tends to be used as settlements is done in non-agriculture fields, such as forest areas and plantation areas.

Keywords: industrialization, land cover, cellular automata, regional spatial planning, urban sprawl.

INTRODUCTION

Regional economic development will cause changes in land use due to the construction of buildings or buildings that are economically useful. The problem of changing land cover from plants or vegetation to buildings is a global problem that needs to be resolved (OECD, 2018; Sun et al., 2024). Many losses are caused by this problem, such as air pollution (Yi et al., 2024), water pollution (Dou et al., 2024; Gule et al., 2023), reduction in carbon stocks (Jiang et al., 2024; L. Zhu et al., 2022), and decreased food production (Ashiagbor et al., 2024). Changes in land cover are one of the impacts of the economic development process, which is also marked by urbanization (Liang et al., 2022; Long et al., 2014). The presence of certain activity centres, such as industry, will encourage many changes in land cover and settlements around industrial areas (Wang et al., 2019; Xu & Zhang, 2021; F. Zhu et al., 2018). Observations of industrial centres and surrounding land use are necessary to assess the impacts that will arise in the future (Veldkamp & Lambin, 2001).

Remote sensing (RS) imagery makes observing land cover in an area easier. Information from RS imagery can be taken every year so that it can be used to identify temporally and to predict changes in land cover (Bao Pham et al., 2024; Islam et al., 2021; Jafarpour Ghalehteimouri et al., 2022). Changes in land cover can also occur quickly, making the use of remote sensing imagery more efficient (Weslati et al., 2023). The availability of RS data is now easy to access and free to use (open source). One way to provide RS data is through Google Earth Engine (GEE). GEE makes it easier to acquire and process RS data due to *cloud-based processing.* So that there is no memory burden on the device used (Gorelick et al., 2017). Data obtained through GEE can be multi-resolution spatial, multi-temporal, and multi-source (Velastegui-Montoya et al., 2023). The application of GEE has been widely carried out in various fields, such as calculating TSS waters (Sanjoto et al., 2020; Zhang et al., 2023), sedimentation (Sanjoto et al., 2019), forest land degradation (Halder et al., 2024), flood mapping (Cian et al., 2024), dan land cover dynamics (Susilo, 2016).

Future land cover changes can be measured using prediction methods. Various methods can be used to study land changes and predict their development, including the Markov model chain and cellular automata (CA) models (Huang et al., 2020). CA and Markov models can be combined to determine land use changes by estimating the probability of possible changes. The CA model can simplify a simple to complex pattern (Susilo, 2016).

Batang Regency has many new growth centres and national strategic projects (PSN). The PSN established in Batang Regency is the power plant (PLTU) located on the north side of Batang Regency (Rencana Tata Ruang Wilayah Kabupaten Batang Tahun 2019–2039). The development of PSN is to develop the region and reduce the gap according to the Second National Priority Agenda and the Fifth National Priority Agenda, namely to strengthen infrastructure in supporting economic development and essential services (Kementerian Perencanaan Pembangunan Nasional/Badan Perencanaan Pembangunan Nasional Republik Indonesia, 2020).

PSN is one of the government's efforts to develop the regional economy at the national level for individual communities by adding jobs. Another significant development being planned by the government is the Batang integrated industrial area (KITB), which is also located in the northern part of Batang Regency (Peraturan Menteri Koordinator Bidang Perekonomian, 2017). Therefore, the existence of PSN and large projects in Batang Regency can trigger population growth and increase the need for housing. The development of PSN in Batang Regency is also inseparable from the existence of toll roads, which are an accessibility factor that facilitates interaction between goods in Batang Regency and its surroundings.

Batang Regency issued a regional spatial planning (RTRW) regulation in 2019. RTRW is a guide and regulation owned by Batang Regency that determines the land use that can be developed. Land cover changes are dynamic, while RTRW is static because it has been in effect for 20 years (Arfah et al., 2024). Therefore, a comparison is needed between the modelling results and the RTRW regulations to accommodate and consider the impact of current activities

Phenomena such as PSN can be a driving factor of land cover change. CA and Markov modelling can predict land cover using certain driving factors (Veldkamp & Lambin, 2001). This study will use PSN factors and toll road accessibility as driving factors to determine land cover changes. Land cover changes are predicted using the CA and Markov model. The study aims to determine the prediction of land cover changes due to economic activities and compare the prediction results with applicable regulations.

MATERIAL AND METHODS

Study area

The research was conducted in Batang Regency, Central Java, which has an area of 78,864 hectares. Batang Regency is located on the north coast of Java Island. Batang Regency is one of the regencies with a national strategic project. The PSN in Batang Regency is a power plant and Batang integrated industrial area. The existence of PSN can cause a more significant land conversion, so it needs to be predicted. The increasingly massive land conversion can cause agricultural land and forest land to change, which can cause other disaster impacts such as flooding and food deficits (Figure 1).

Data

Land cover data is obtained through supervised classification results. from Landsat-8. The classification was done using Google Earth Engine (GEE). GEE is used because it can directly overlapped with Google images. Earth makes it possible to know the conditions in the field, has large storage access, is lightweight because it is web-based, and is easy to apply (Gorelick et al., 2017; Putri & Sibarani, 2023). RTRW data was obtained from the Batang Regency Government. Land cover predictions are made until 2039. The prediction time is from 2002, 2015, 2023, 2032 and 2039. The year 2019 is used to obtain land cover change trends and can be used as a basis for prediction. Another factor that influences the prediction is the driving factor. The driving factors used are the existence of PLTU, KITB, and

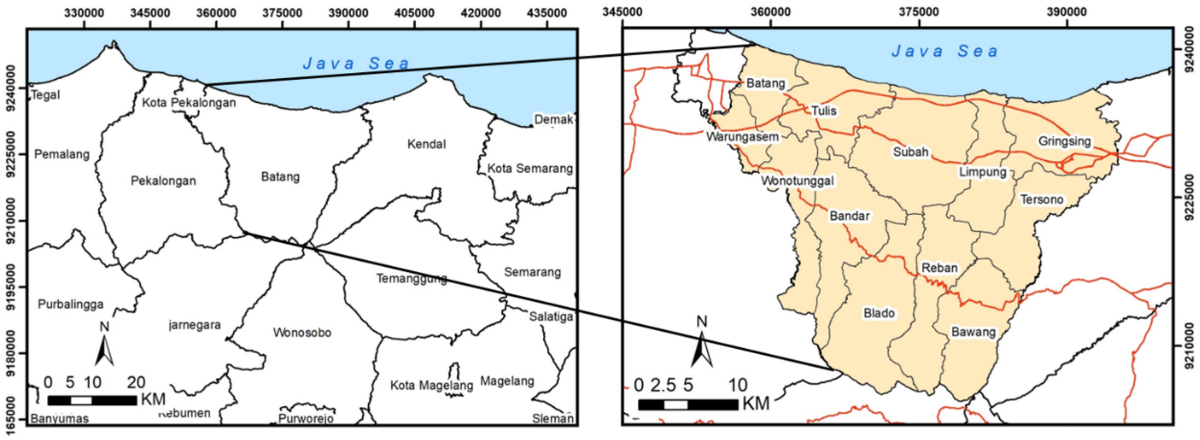

Figure 1. Maps of study area

toll roads. Cellular model automata is used to predict land cover.

Methods

Supervised classification is a process carried out with guidance from an analyst where the class classification criteria are determined according to class characteristics. through area sampling activities *(training area)* (Purwanto & Lukiawan, 2019). The remote sensing imagery used is Landsat-8, acquired in August 2015, 2021, and 2023. In those months, cloud coverage is estimated to be low or is expected to be cloud-free. By standard, the image will undergo image correction, which includes geometric correction, radiometric correction, and atmospheric correction.

Cellular automata is dynamic spatial modelling related to time elements and includes various variables systematically arranged in space. CA modelling has spatial characteristics that are based on cells. Changes in a cell will affect neighbouring cells nearby. The dynamic CA model is relevant for analysis, change studies, and land change predictions. The CA model is obtained from various transition probability matrix models that are useful for encouraging changes in one condition *(state)* to another condition*)* within a specific period according to desire. CA modelling is carried out in specific scenarios. The scenario considers the existence of PLTU, KITB, and toll roads. The scenario considers the occurrence of rapid economic growth in Batang Regency. The results of this scenario will show the impact of economic growth centres such as PLTU and KITB on land cover.

The results of supervised classification will be tested with the groundcheck method. The Groundcheck method is to compare the mapping results with the conditions in the field directly. The accuracy test uses a confusion matrix to obtain the mapping accuracy value. There are 50 observation location points for land cover divided randomly. The prediction test uses the relative operation characteristic (ROC) method on TerrSet software. The results of ROC are also known as area under curve (AUC) of ROC. The AUC concept operates using the results *of the soft predictions obtained* through land cover prediction modelling.

RESULTS AND DISCUSSION

The results of the land cover classification in Batang Regency are divided into five classifications: open land, agriculture field, non-agriculture field, waterbody, and settlements. Non-agricultural fields contain forest, shrubs, and grass appearances. Open land is land that does not have vegetation cover. The agriculture used is rice fields that can be identified. Rice fields and forests can be distinguished because of the different canopy cover conditions. Settlements contain buildings that are identified as residences.

Non-agricultural fields are the dominant land cover in Batang Regency. This is because the northern side of Batang Regency is part of the Dieng highlands, which has a lot of land cover in the form of forests. Agricultural fields are also found on the northern side of Batang Regency and tend to be in areas with flat morphology.

The trend from 2015 shows that agricultural and non-agriculture field cover tends to decrease. The area of land that has increased is open land and residential land. This can indicate that land conversion tends to occur in agricultural and non-agriculture fields. The need for residential land will continue to be suppressed due to the increasing population growth. The change in agricultural land into residential land is also due to the condition of agricultural land that can be more easily converted into residential land. Changes in land cover tend to occur on the north side of Batang Regency (Figure 2). The northern side of Batang Regency is an urban area, making more intensive land cover changes possible.

The accuracy test results show an overall accuracy of 96% and a kappa accuracy of 98%. These results will show the level of truth of the interpretation of the land cover classification that has been carried out. All values have met the minimum requirement of 85% related to the accuracy of the United States Geological Survey (USGS) (Wael & Siahaya, 2022). These land cover interpretation results are input for predicting land cover changes.

Predictions are made using data from 2021 and 2023 to determine conditions in 2031 and 2039. 2039 was chosen because it is the reference year in the Batang Regency spatial planning (RTRW) regulations. Predictions are also made in

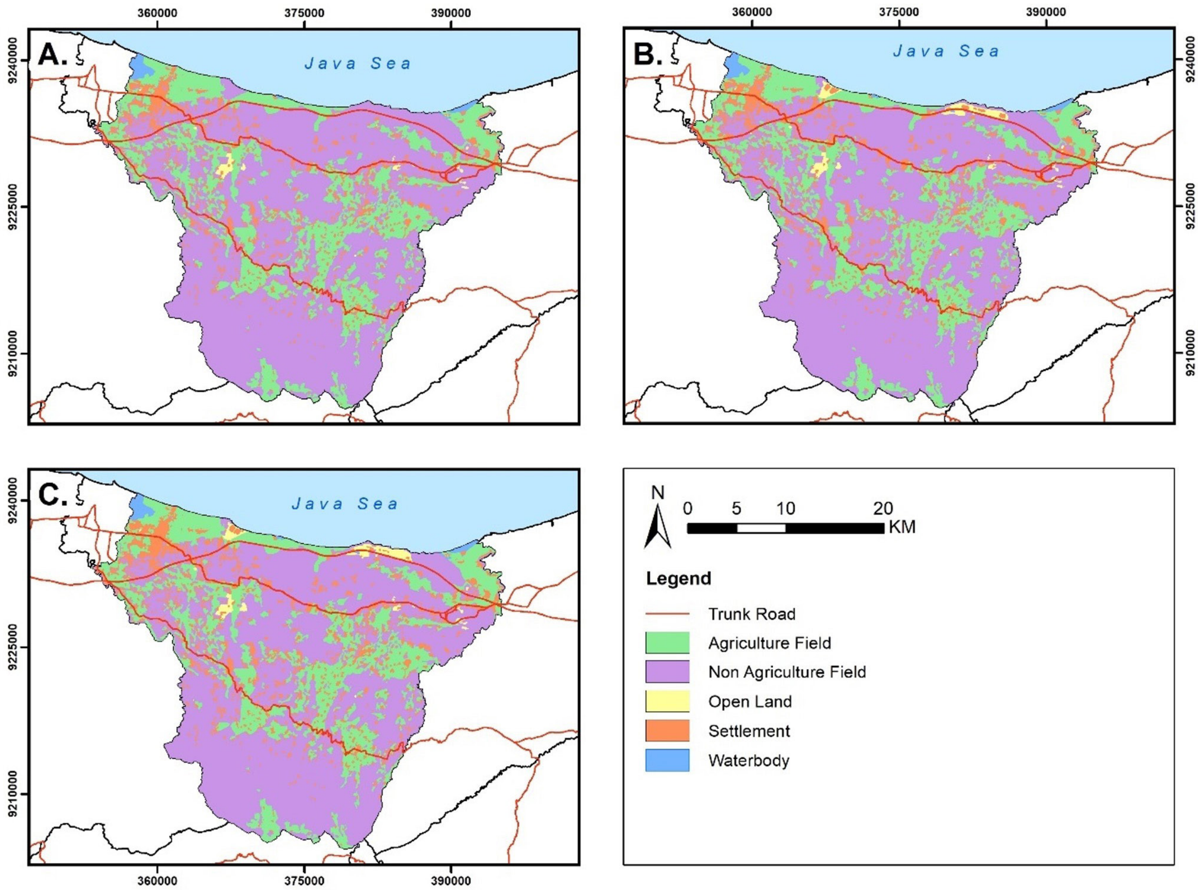

Figure 2. Land cover of Batang Regency: A) 2015, B) 2021, C) 2023

Table 1. Land cover dynamics of Batang Regency

No.	Land cover	Land cover area (ha)		
		2015	2021	2023
1	Agriculture field	21,867.34	21,819.87	21,808.98
2	Non-agriculture field	55,097.40	53,677.98	53,440.56
3	Open land	372.69	961.38	974.25
4	Settlement	7,960.36	8,841.15	9,037.98
5	Waterbody	564.04	563.76	566.37

2023 to determine the predictions' accuracy. Predictions in 2023 are made using data from 2015 and 2021 (Table 2). The prediction results in 2023 based on 2021 only show changes in the agricultural and non-agricultural Fields. This may be because there were a few changes in 2023.

The results of the prediction simulation in 2023 show results that are quite similar to actual conditions. Accuracy is calculated using the relative operation characteristics (ROC) method (Figure 3). The ROC concept uses the soft prediction results obtained through land cover prediction modelling. The ROC validation results obtained a figure of 0.86, which is included in the good category. This indicates that the land cover map in 2023 from the prediction and the land cover map in 2023 from the interpretation (existing) have good similarities. Then, the modelling is carried out using a similar algorithm for 2031 and 2039 (Figure 4 and Table 3).

The modelling results using CA show that land cover changes tend to be on non-agricultural fields and open land. This is shown in the probability matrix of change, which shows a number that is entirely from one in the same matrix. The value of the chance of change has a range of numbers 0–1, where the closer to 0, the chance of change is high; conversely, if it is close to 1, the chance of change is low (Ghosh et al., 2017).

Land cover changes in 2031 and 2039 are experienced by land cover in the form of open land (Table 4). This is because the condition of empty land tends to make it easy to experience changes in land cover function. The phenomenon of the

Table 2. Land cover probability change 2015–2023

Probability change in 2023					
Land cover	Agriculture field	Non-agriculture field	Open Land	Settlement	Waterbody
Agriculture field	0.99	-	-	0.01	-
Non-agriculture field	-	0.98	0.01	0.01	-
Open land	-		1.00		-
Settlement	-	-	-	1.00	-
Waterbody	-	-	-	-	1.00

Result of ROC**

AUC = 0.860472

The following section lists detailed statistics for each threshold.

With each threshold, the following 2x2 contingency table is calculated:

	Reality	(reference image)
Simulated by threshold	1	0
1	A (number of cells)	B (number of cells)
0	C (number of cells)	D (number of cells)
For the given reference image:	A+C=3274	B+D=2211836

No.	Exp. Thrhlds(%)	Act. Thrhlds(%)	Act. raw cuts	A	True posi.(%)	B	False posi.(%)
1	0	0	0	0	0	0	0
2	30	30.0000	0.0040	3138	98.6172	661246	29.9012
3	60	60.0000	0	3178	99.8743	1325592	59.9427
4	100	100	0	3274	100	2211836	100

Figure 3. Error calculation using ROC

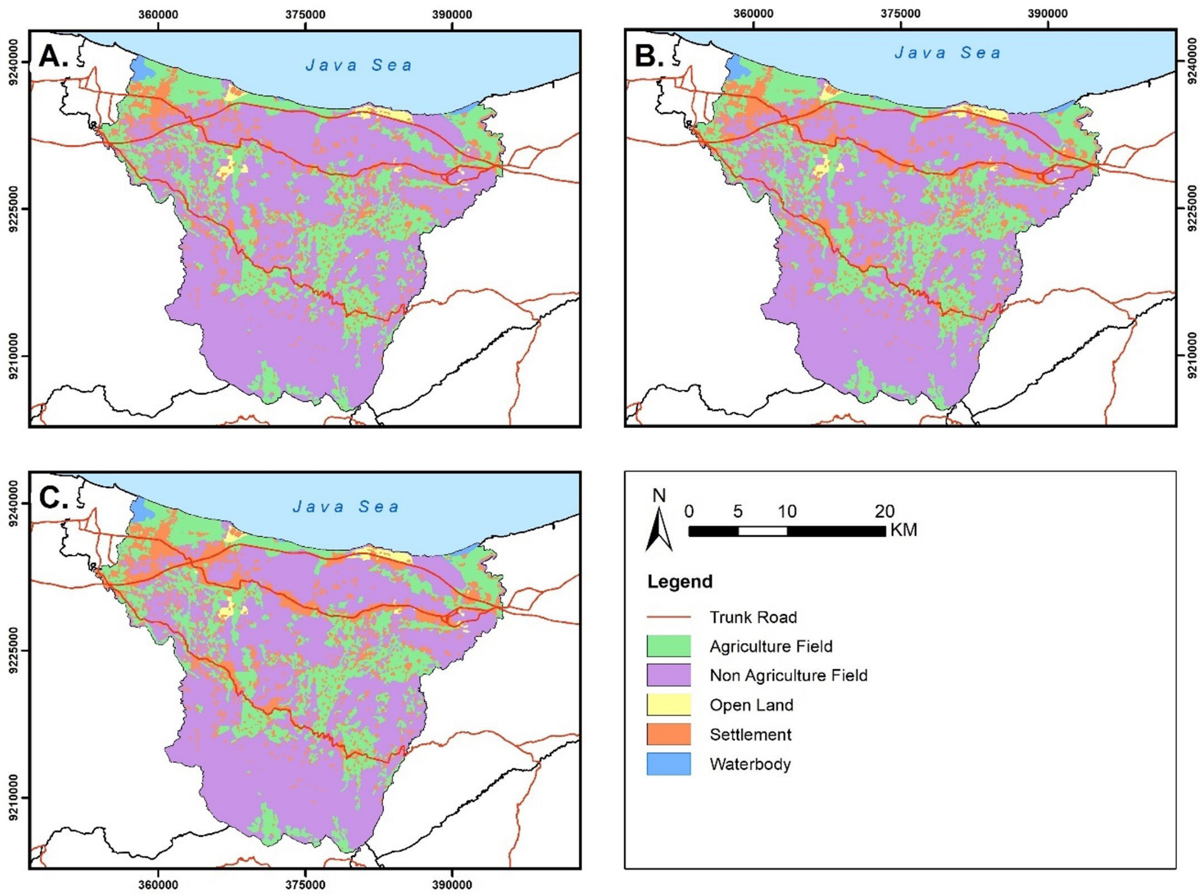

Figure 4. Simulation result of land cover prediction of Batang Regency: A) 2023, B) 2031, C) 2039

Table 3. Land cover probability change 2023–2031

Probability Change in 2023–2031					
Land cover	Agriculture field	Non-agriculture field	Open land	Settlement	Waterbody
Agriculture field	0.98	0.00	0.00	0.02	-
Non-agriculture field	-	0.87	0.01	0.12	-
Open land	-	0.18	0.73	0.09	-
Settlement	-	-	-	1.00	-
Waterbody	-	-	-	-	1.00

Table 4. Land cover probability change 2023–2039

Probability change in 2023–2039					
Land cover	Agriculture field	Non-agriculture field	Open land	Settlement	Waterbody
Agriculture field	0.97	0.01	0.00	0.02	-
Non-agriculture field	0.01	0.81	0.02	0.17	-
Open land	0.01	0.29	0.56	0.14	-
Settlement	-	-	-	1.00	-
Waterbody	-	-	-	-	1.00

addition of open land from 2015 to 2023 was due to the construction of several PSNs, such as the Batang industrial area and the Batang PLTU. This area is estimated to be completed in 2024 (Jateng-prov.go.id, 2020). The land conversion process tends to become settlements or Non-agriculture

Table 5. Comparison of land cover prediction and spatial regulation in Batang Regency in 2039

Land cover	Prediction (ha)	Regulation (ha)
Agriculture field	21,588.39	25,295.31
Non-agriculture field	48,949.92	42,267.71
Open land	1,044.00	521.11
Settlement	13,717.98	17,254.41
Waterbody	563.85	525.61

Fields, such as the construction of buildings and industrial areas for national strategic projects (PSN). Changes in the function of agricultural land are negligible due to the location of agriculture being quite far from economic centres and highways. Changes in land cover tend to occur in areas close to economic centres and highways. This phenomenon can be due to urban sprawl. and the presence of pressure that causes changes in land cover. This condition was also found by Beyene & Minale (2023) who stated that changes in land cover tend to occur in *urban areas* and areas close to community activity centers.

Roads are also an accessibility factor and significantly impact changes in land cover in Batang Regency. Changes in land cover that occur are generally close to the location of the highway and the existence of similar land cover. This factor is because roads are the leading indicator of accessibility and facilitate the movement of both humans and goods (Holl & Mariotti, 2018). This condition was also found by Neves et al. (2024) who stated that road factors are quite influential factors in changes in land cover.A comparison of results with RTRW was conducted in 2039 to identify differences in land cover mapping results obtained (Table 5). The general area results show that each land cover has a value that tends to vary. The agricultural area in the mapping results is lower than the planning, indicating that the program to maintain agricultural land has been considered in the RTRW. The area of non-agriculture fields shows a lower value. The land conversion that tends to be used as residential land is in the form of non-agriculture fields, such as forest and plantation areas. The development of residential areas tends to follow the form of existing settlements and tends to be close to road accessibility.

The modelling results can be used as a reference to anticipate changes in land cover outside the plan. Changes in land cover have been widely regulated in the RTRW of Batang Regency by anticipating extensive changes in agricultural land. Changes that occur in non-agriculture fields include changes to plantation areas. Open land is also an alternative that can be converted into residential areas. This difference can also be caused because the modelling does not consider population, or economic growth factors and only focuses on economic activities in Batang Regency. This was also found by Arfah (2024) who showed that economic growth factors would result in a settlement area that tends to be wider.

CONCLUSIONS

The conclusion from this study is that the modelling carried out can be used as a tool to predict changes in land cover. The growth of economic centres and accessibility also support changes in land cover. Land cover development tends to occur around growth centres such as PLTU and KITB, and around the main roads in Batang Regency. The modelling used was tested in 2023 and obtained quite good values, so the modelling can be run and used to identify changes in land cover using the cellular automata algorithm.

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