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Identification of Urban Expansion Driving Factors using CA-Markov model: a Case Study Demak and Jepara Regency, Indonesia

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ABSTRACT
Land cover changes are a critical concern in a developing country, where rapid urbanization and population growth intersect with environmental dynamics. Understanding the driving forces behind these changes is essential for sustainable development and effective land management. This study analyzes land cover changes in Demak-Jepara regency, Indonesia, over a 20 year period using Landsat data. The objective is to identify the dominant factors driving the increase in built-up areas, considering both natural and human-induced factors. Factors such as road distance, existing build area, and natural features are evaluated. Using ArcGIS and Idrisi Selva's Land Change Modeler, land cover data is processed, and Cellular Automata-Markov analysis is conducted. The analysis considers a cell size of 30 x 30 meters and a time step of 5 years from 2001 to 2009. Transition persistence analysis identifies significant factors, validated using 2020 land cover data through AUC (Area Under the Curve) and ROC (Relative Operating Characteristic) analysis. The combination of natural and human-induced factors (scenario-C) shows the highest AUC value of 0.9406, indicating better conformity with 2020 land cover. Dominant factors in scenario-C include roads, existing built-up area, river order, and slope gradient. Results reveal that road development and proximity to existing settlements are the primary drivers of land cover changes. Natural factors like river order and slope gradient have a lesser impact, while the coastline has minimal influence. These findings highlight the importance of considering both natural and human-induced factors in land use planning. They provide valuable insights for policymakers and land managers in making informed decisions for sustainable development and land use strategies.

INTRODUCTION

Land cover change is necessary for development (Hanafi et al., 2021). Land cover changes are always associated with population growth and land or space needs. Land cover variations are influenced by many factors, such as technological level, prosperity, spatial planning, and space availability (Akomolafe & Rosalina, 2022). However, the pattern and scales are dominantly driven by economic variables. Space or land is vital so that changes are dynamic and unavoidable.

Along with population growth and planning needs, Indonesia is also experiencing continuous land cover change. Indonesia's population growth in the last 20 years (2000-2020) has been very rapid, along with increased built-up land. In 20 years, Indonesia's population grew by more than 30.7 % and reached 269,603,400 people. The island of Java, one of Indonesia's most densely populated islands, is also experiencing the same thing, even faster. Java Island contributes 58.9 % of the Indonesian population, with the same growth rate (29.3 %). It is noted that the average deforestation in Indonesia is about 0.86 million Ha per year, so Java Island left only 16 % of the area of forest in 2020 of the whole island (Kehutanan, 2021).

More detailed, especially in the northern coastal areas of Java Island, have experienced an increase in built-up area. Several regencies are located on the north coast of Java Island and have experienced an increase in built-up land in the last ten years, such as Semarang City: 13% (Pamungkas et al., 2019), Pekalongan City: 24% (Suharini, E; Hanafi, F; Akhsin, 2017), Batang and Kendal Regencies: 14.08 %, including Jepara and Demak regencies (**Figure 1**.). Central Bureau of Statistics data showed that Jepara Regency has an average population growth per year from 2010 – 2017 of 1.79 percent. Along with the population increase, the level of population density also increases. In 2017, the population density of Jepara Regency was 1,218 people/km^2. The total population of Demak Regency is 1,117,901 people. This number comprises 553,876 males (49.55%) and 564,025 females (50.45%). This number has increased from 2014 to 5,681 people, or around 1.04%.

This research was conducted on Demak and Jepara regencies, which are directly adjacent to the north coast of Java, so most of their areas are affected by the coastline. The coastal area is generally known as the meeting area between land and sea, which is influenced by changes in the phenomena of land and sea (Islam et al., 2021). The potential of resources in coastal areas is excellent for the development and welfare of the community (Mardiatno, 2018). Coastal areas are also inseparable from problems caused by human activities, such as land use that is not following its function or due to natural factors such as natural disasters. Coastal regions are one of the most vulnerable areas to the effects of global warming, accompanied by an increase in mean sea level and changing shoreline configurations (Arjasakusuma et al., 2021). Development must always be balanced with planning, which plays a role in harmonizing development needs with the need to protect, preserve, and improve the quality of the landscape.

Remote sensing imageries are very diverse in type and characteristics. Commonly used examples include Landsat, Spot, Alos, and NOAA. Land cover change studies require continuous and broad temporal data. Remote sensing data has appropriate spectral, spatial, and temporal resolution and is suitable for land change studies. One type of remote sensing imagery that is suitable for land cover change studies is Landsat. Landsat is an image with the advantages of accurate calibration and a stable and consistent sensor (NASA, 2021). Landsat has been launched for nine generations. This research takes base date (2000-2020) 20-year study, it requires at least two Landsat generations, namely Landsat 7 (1999) and Landsat 8 (2013), with a spatial resolution of 15 m panchromatic sensor and a temporal resolution of 16 days.

Land cover change studies develop with the availability of varied data, representational techniques, and more flexible modeling. The contribution of geographic information systems (GIS) in spatial planning also follows technological advances. The interoperability of GIS to input a wide (various) data provides opportunities for dynamic modeling based on the past and the future more realistic. With GIS resources, it is easier to evaluate the results of past plans, including modifying plans that consider the results of several plans for urban planning and natural resources management (Ansari & Golabi, 2019). The accelerated use of GIS techniques and remote sensing data has made the geospatial processes faster, easier, and more complex (Rwanga & Ndambuki, 2017).

In regions like Indonesia, rapid population growth and urban expansion have driven significant land cover changes, particularly in the northern coastal areas of Java. Cities like Semarang and Pekalongan have seen substantial increases in built-up areas, reflecting broader trends of urbanization and deforestation (Hanafi & Pamungkas, 2021). GIS and remote sensing in these studies help understand and plan sustainable development (Gu & Zeng, 2024).

Markov Chain and Cellular automata (CA) are GIS products everyday for land cover change studies (Abdisa et al., 2023). CA is a matrix-based numerical model that is specific in space and time. The minimal structure of CA is cell size, initial cell condition, neighborhood template, and its transition function to time (Munthali et al., 2020). The integration of CA and geographic information systems (GIS) has the potential to simulate real-world urban development (Yeh et al., 2021) by considering various factors, including socioeconomic, policy, and geography/physical constraints (Liang et al., 2018). CA and statistical analyses can identify practical constraints or driving factors influencing land cover changes (Hamdy & Zhao, Shichen; A. et al.; Eid, 2017). Driving factors often used for CA-based land cover analysis include distance or type of road, spatial planning or policy, public service buildings or activity centers, and natural factors. Natural factors are given factors, such as stream or drainage pattern, slope, elevation, and shoreline.

The distinct features of Demak and Jepara Regency serve as both a coastal agglomeration and the hinterland for Semarang City (the capital of Central Java province), consequently forming particular constraints and driving factors for land cover change. An advanced study pioneering in identifying and analyzing these factors, encompassing anthropogenic and natural influences, using the Cellular Automata-Markov Land Cover prediction model as a basis for understanding and planning sustainable development is urgently required. Therefore, the research objectives are to (1) describe the Landcover transition of Demak and Jepara Regency over the last 20 years and (2) identify the constraints and driving factors that significantly influence the increase of built-up areas in Demak and Jepara Regency.

RESEARCH METHODS

Study Area

The study utilized land cover data at ten-year intervals (2000, 2010, and 2020) to analyze changes in the coastal areas of Demak and Jepara Regency. The research covered an area of approximately 1,959.37 km² across 30 districts. Demak Regency, situated in low-lying terrain, ranges from 0 to 100 meters above mean sea level (MSL). In contrast, Jepara Regency's topography is diverse—flat to undulating and steep—owing to the Muria Mountains in the east.

Landsat Data Collection For Landcover Extraction

Land cover data was selected with a time gap of approximately ten years (2001, 2009, 2020) to discover the contrast differences (Table 1.). The shorter time gap of Land cover change data will lead to misinterpretation and lack of contrast due to the slight change. The initial land cover change data is from 2001 to 2009, as simulation input to 2020. The 2020 data controls or tests the data accuracy results from the 2009 land cover data simulation. The primary data used are shown in Table 1.
The primary data used are shown in Table 1.

Table 1 Data Satellite Used

Satellite	Data Acquired	Path	Row
Landsat 5	2001-07-01	120	065
Landsat 5	2001-07-01	120	064
Landsat 7	2009-09-25	120	065
Landsat 7	2009-09-25	120	064
Landsat 8	2020-08-30	120	065
Landsat 8	2020-08-30	120	064

Source: USGS Data, 2023.

Landsat Data Preprocessing

All the geometric imagery was internally corrected with RMS 3,567-7,388, while the radiometric correction used the Top of Atmosphere method. Top of Atmosphere (ToA) is a satellite image correction to eliminate radiometric distortion because of the sun's position. In the ToA images, the changes in the sensor, variations in the sun-earth distance, solar geometry, and exo atmospheric solar radiation from the spectral band difference were minimized. Then, atmospheric correction on surface reflectance was performed to reduce atmospheric effects (Zhai et al., 2022). Atmospheric corrections were performed using the Quick Atmospheric Correction (QUAC) method (Niraj et al., 2022). (QUAC) is a visible infrared to near-infrared or visible to near-infrared (VNIR) atmospheric correction through short wave infrared (SWIR) for multispectral and hyperspectral images (Maviza & Ahmed, 2020). QUAC correction produces an image of the captured surface reflectance, which is then scaled to a two-byte signed integer using a reflectance scale factor of 10,000 (Kang et al., 2020).

Supervised Land Cover Classification

Multispectral classification is a technique of grouping spectral reflections against several bands. Uniformity of values between homogeneous, similar, or identical bands. Different objects identify differences in reflection values on the same band. Multispectral classification helps Earth monitor the planet's land surfaces (Clark, 2020). The multispectral classification consists of supervised and unsupervised. Supervised classification involves the classification of pixels with unknown identities through a classification algorithm using the spectral characteristics of pixels from a known information class (training area) (Zhang et al., 2023) identified by the analyst. The advantages of supervised classification are that the category, class, and criteria information is well controlled from start to finish; besides, the selection of training areas can bind the identity or class to an area whose type is known, so misclassifications are more accessible to detect.

Although there are some limitations to supervised classification, First is the character of supervised, i.e., imposing a classification structure upon the data regardless of spectral is the most relevant in the object (Kang et al., 2020). Second, because spectral is a secondary input, it often overlaps and is ambiguous. Third, sorting out categories based on analyst preferences takes local knowledge and time. Based on those advantages and disadvantages, land cover series data were obtained using Landsat 5, 7, and 8 data with supervised multispectral classification. The standard supervised classifications are the maximum likelihood (Abdullah et al., 2019) rather than others because the advantages are intuitive decision rule, a well-developed foundation such as normally distributed data, and the ability to accommodate various types of imagery. This research uses ArcGIS Image Classification with a supervised maximum Likelihood tool to process land cover data by considering it user-friendly and giving similar results to other software.

Accuracy Assessment

Previously, accuracy assessment was not a priority in image classification studies. However, accuracy assessment has become vital because of the accelerated chances for error digital imagery presents (Rwanga & Ndambuki, 2017). Land cover is the primary data in this research, so its quality is a priority. Therefore, quality control of land cover data becomes a primary concern. The accuracy test of the multispectral maximum likelihood classification was carried out using the confusion matrix method, with high-resolution (https://earth.google.com/) image data as a reference, through visual interpretation with a total of more than 500 samples with different locations in each data year. The sample is distributed as an equal grid on all research boundaries (administrative boundary of Demak-Jepara Regency). A Matrix Confusion was used to calculate the error with primary measures of each classification and overall, such as user's, producer's, and overall accuracy (Foody, 2020).

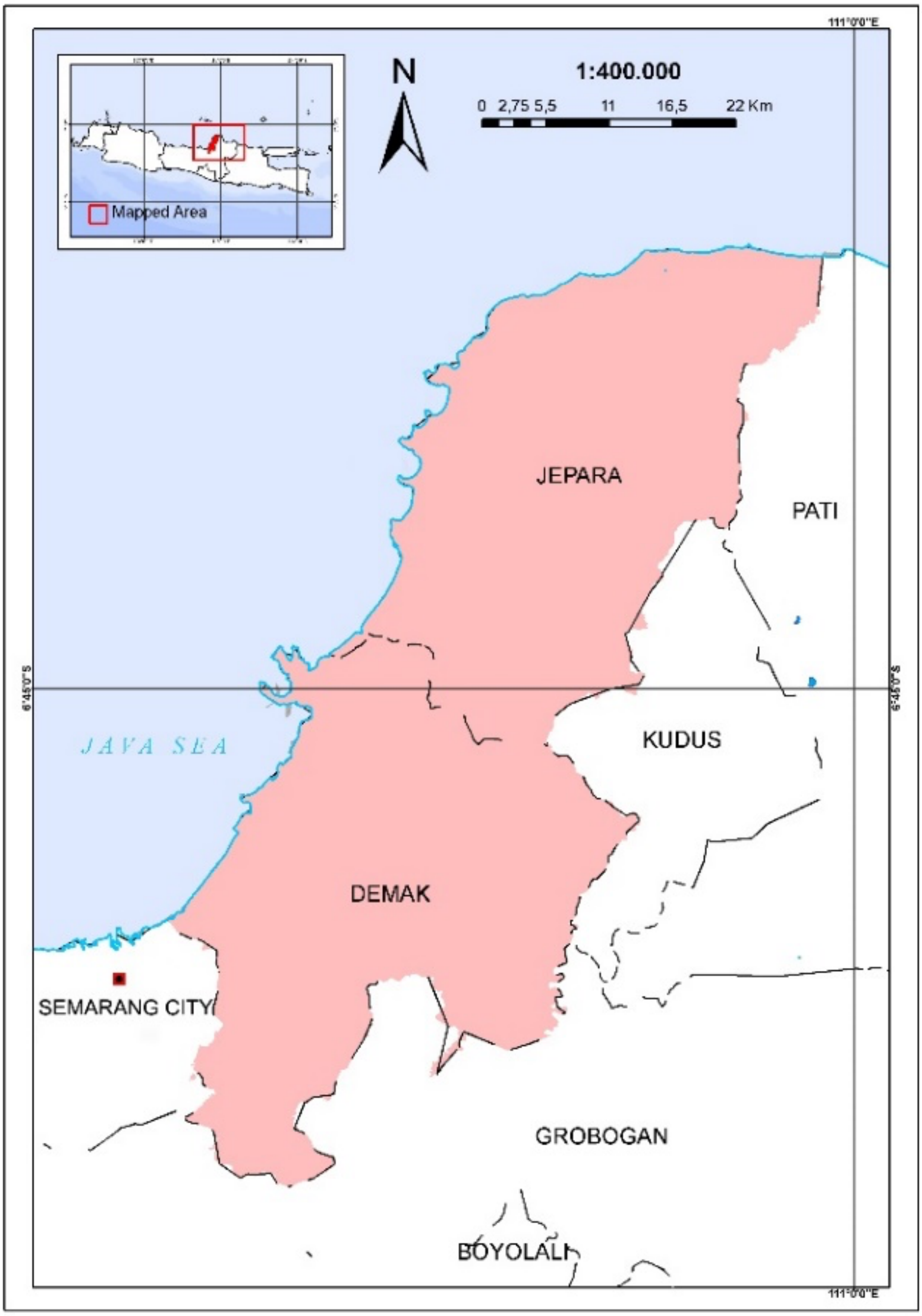

Figure 1. Research Location (Source: Research Results, 2023)

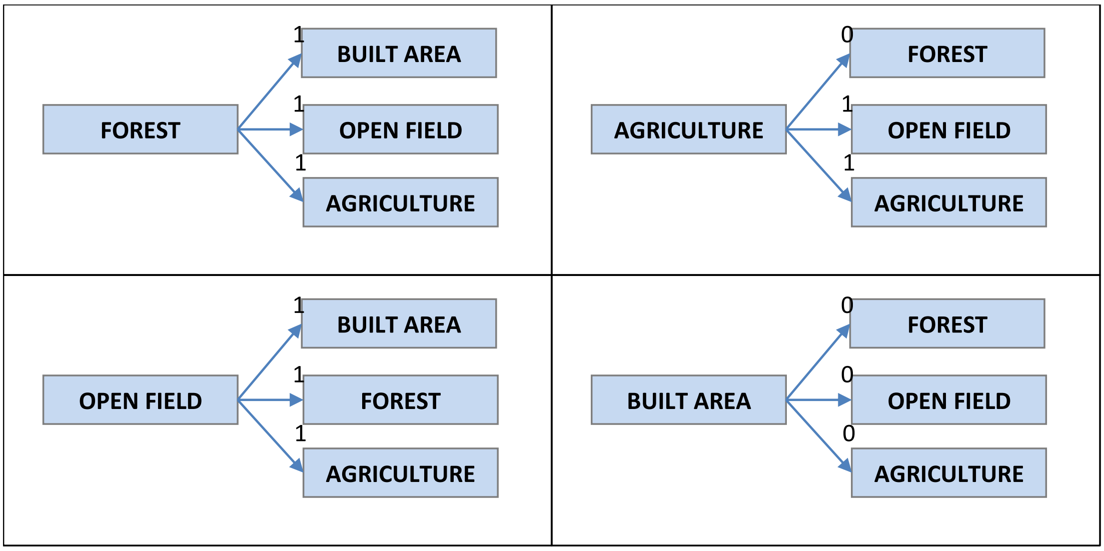

Figure 2. Research Transition Rule Potential (Source: Research Analysis, 2023)

Cellular Automata

Based on land cover raster data series, simulation and validation can proceed to cellular automata (CA) analysis. CA-Markov model is theory-based modeling based on random prediction (Janizadeh et al., 2021). The initial state (cell) is influenced by neighbors (matrix) surrounding. Matrix size can be 3x3, 4x4, or more (Abdisa et al., 2023). The changes movement can be influenced or limited with constraint factor, and the degree of changes ruled by time step.

This research uses ArcGIS software to process data land cover and Idrisi Selva (https://clarklabs.org/) to analyze the CA-Markov using Land Change Modeler (LCM)(Eastman, 2015). The condition is described as follows: the cell size is 30 x 30 m, the same as the output from the Landsat image; the state is 2001 landcover type with 2009 as the target; and the time step is set to five years.

Transition Rules

To generate a simulation that is close to reality, a transition (changes) rule is needed. The change rule is essential in developing a close and direct link between urban modeling and theories (Yeh et al., 2021). Transition rules in the Land Change Modeler refer to the rules that determine the possible transitions between land use/land cover classes in a particular area over time. The transition rules in Land Change Modeler are typically defined based on a combination of empirical data, expert knowledge, and theoretical considerations.

Some common factors that may be considered in developing transition rules include historical patterns of land use change, ecological processes, feedback, socioeconomic drivers of land use change, policy interventions, and potential climate change impacts. The transition rule in this research uses deterministic categories based on more deterministic models that specify the exact conditions under which particular transitions are likely to occur (Feng & Tong, 2018). Land cover that is possible to change is defined with a value of 1, while it is not possible to change with a value of 0. An example of a transition rule is shown in **Figure 2**. A controlling factor drives the outcomes through a transition rule to determine the optimal combination for improving the overall performance of urban Cellular Automata (CA) models. This results in the movement of available cells becoming more aligned with the actual development of urbanized cells (Xia & Zhang, 2021).

Driving and Limiting Factors

The changes on LCM changes in LCM can be influenced by driving or limiting (constraint) factors. Constraint or driven factors in the Land Change Modeler refer to the factors or conditions that limit or facilitate the occurrence of land use/land cover change in a particular area (Meneses et al., 2017). These factors can significantly impact land use change's direction, magnitude, and timing. They may be driven by various environmental, social, economic, and political factors. Driving factor control consistently gives empirical evaluation and limits the wild probability of each scenario (Kim et al., 2020). Examples of constraint or driven factors in the Land Change Modeler may include physical factors such as topography, soil characteristics, and climate, as well as human factors such as population growth, urbanization, land tenure systems, and land use policies.

These factors can act as barriers to land use change or as drivers of land use change. The contribution of constraint or driven factors into the Land Change Modeler can help improve the model simulations' accuracy and realism. This research uses constraint geographical factors such as coastline, stream order, and slope, meanwhile, the driving factors are existing built-up area and road network class. Those factors are simplified, as shown in Table 2, even though the process for validation and simulation will use different factors depending on the AUC analysis later.

Table 2 Driven/constraint factor treatment

Factor	Input	Data Description and Treatment
Coast Line (1)	Polyline	▪ Euclidian Distance for impact analysis based on proximity to the coastline ▪ Fuzzy Membership to generalize values from 0 - 1
Stream Order (2)	Polyline	▪ 3 Stream Order, Hack order ▪ Euclidian Distance and weight sum order 1 = 1, order 2 = 0,66, dan order 3 = 0,33 ▪ Fuzzy Membership to generalize values from 0 - 1
Slope (3)	Raster	▪ SRTM Data ▪ Percent Slope analysis and classify (I:0-8), (II:8-15),(III:15-25), (IV:25-45), (V:>45) ▪ Scoring using Euclidian allocation (2, 4, 6, 8, 10)
Road Network (4)	Polyline	▪ Classify of arterial, collector, local roads, and other roads ▪ Euclidian distance with Weight Sum with arterial: 1; collector: 0,8; local: 0,6; and other 0,4 ▪ Fuzzy Membership to generalize values from 0 - 1
Existing Built area (5)	Polygon	▪ Euclidian Distance for impact analysis based on proximity to the existing ▪ Fuzzy Membership to generalize values from 0 - 1

Source: Research Analysis, 2023.

The land cover change model from 2001 to 2009 is used as input to identify the influencing or constraint factors, with 2020 as the final simulation result. The final results of the 2020 simulation were tested with the existing 2020 land cover data using AUC and ROC analysis in the Idrisi Selva LCM Model.

AUC and ROC analysis are commonly used methods for evaluating the accuracy of classification models in remote sensing. Idrisi Selva offers a tool for performing these analyses on classification maps created using various algorithms. The ROC Analysis tool generates a plot of TPR (True Positive Rate) versus FPR (False et al.) for different classification thresholds. It calculates an AUC value to measure the classification model's accuracy overall.

If a predictor variable is categorical, the corresponding ROC curve will have one less than the number of categories as possible thresholds. However, if the predictor is binary, there will be only one threshold. Since the AUC value can inform decision-making when choosing the best model, it is essential to consider how it aligns with the insights gained from the ROC curve. ROC has proven helpful in assessing the quality of transition probability maps in

CA models (Tong & Feng, 2020). Therefore, it is essential to examine both the ROC curve and AUC value when evaluating the accuracy of a classification model (Muschelli, 2020). By using this tool, remote sensing analysts can assess the performance of their classification models and identify the best classification threshold for their specific needs. The research framework is shown in **Figure 3**.

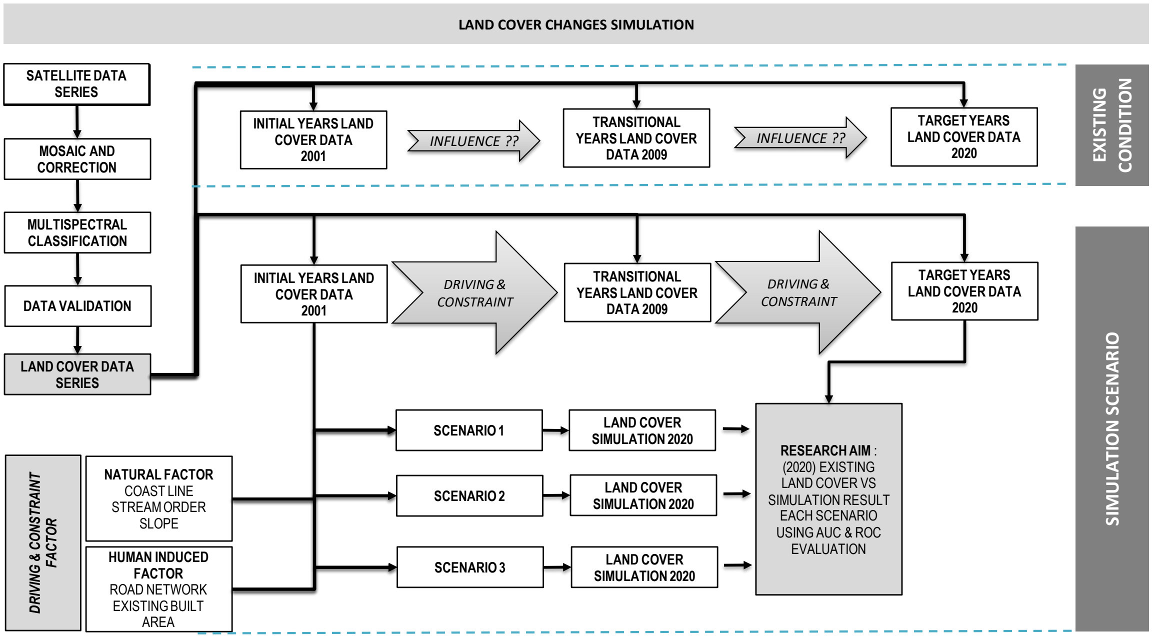

Figure 3. Research Framework (Source: Research Analysis, 2023)

RESULTS AND DISCUSSION

Time Series Land Cover From Landsat data

The land cover datasets for 2001, 2009, and 2020 were generated using supervised classification methods on remote sensing imagery, and their quality was assessed for further analysis. The results of the confusion (Table 3) matrix table, which was evaluated based on producer accuracy, demonstrate that the average accuracy of each land cover map is above 85%. This finding is consistent with the commonly used accuracy threshold of 85% for land cover analysis. Therefore, the land cover datasets are considered adequate quality for subsequent analysis.

The processed data reveals a gradual change in land cover in Demak and Jepara Districts from 2001 to 2020. Over 20 years, agricultural land has shown a consistent increase, although it has experienced fluctuations due to inconsistent data recording and shifting agricultural practices throughout the year. Conversely, there has been a significant rise in built-up areas, almost doubling in size, accompanied by a decline in forested regions. This trend aligns with the increased demand for space resulting from population growth during the same period, primarily for residential and commercial purposes. The changes in land cover, including open fields and water bodies, can be further examined in Table 4 and Figure 4.

Table 3 Confusion Matrices

Land Cover	Producer Accuracy		
	2001	2009	2020
Water Body	80%	86%	78%
Build Up Area	99%	93%	97%
Agriculture	100%	100%	99%
Forest	77%	79%	94%

Open Field	88%	84%	61%
Average	92 %	95 %	88%

Source: Research Results, 2023.

Table 4. Land cover Changes on Demak-Jepara Regency

Landcover	Years		
	2001	2009	2020
Agriculture	617,95 (32 %)	791,09 (40 %)	761,96 (39 %)
Built Area	270,21 (14 %)	519,52 (27 %)	662,99 (34 %)
Forest	633,95 (32 %)	267,63 (14 %)	195,78 (10 %)
Open Field	256,34 (13 %)	240,05 (7 %)	210,56 (11 %)
Water Body	180,55 (9 %)	140,71 (7 %)	127,71 (7 %)
Average	1.959,00 (100 %)	1.959,00 (100 %)	1.959,00 (100 %)

Source: Research Results, 2023

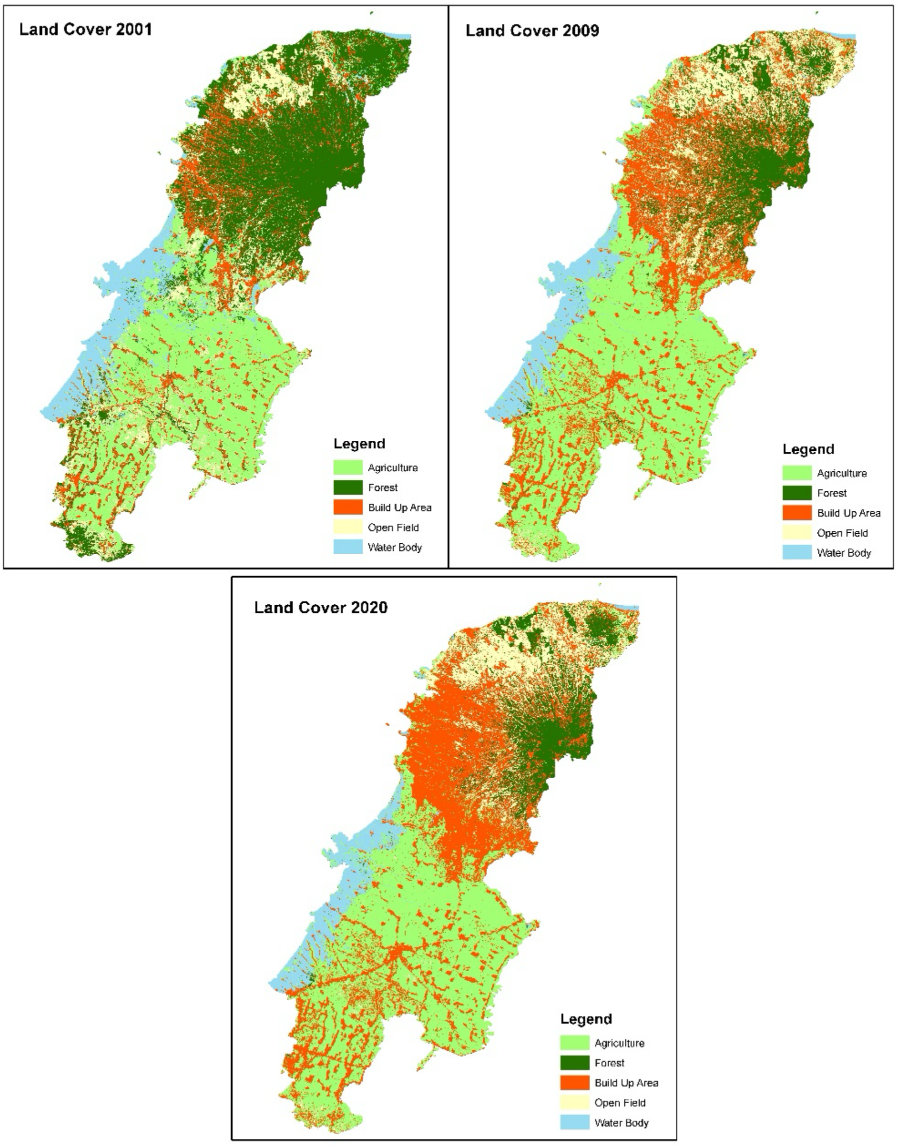

Figure 4. Existing Landcover of Demak-Jepara Regency (2001-2020)
Source: Research Results, 2023.

Driving and Limiting Factors for Built-Up Area

The analysis of transition persistence testing for each influencing variable was performed across multiple scenarios to investigate their effects (Li et al., 2020). The first scenario exclusively considered natural factors, namely (1) coastline, (2) river order, and (3) slope gradient. The second scenario focused solely on human-induced factors(Gupta & Sharma, 2020), including (4) roads and (5) existing built-up land. The third scenario encompassed a combination of both natural and human-induced factors.

Based on transition persistence analysis, we selected factors that were identified as significantly contributing to ensuring meaningful simulations for the year 2020. The influence of each variable was quantified on a scale from highest (approaching 0, indicating maximum influence) to lowest (approaching 1, indicating minimal influence). Notably, waterbody was excluded as a rule change, as depicted in Figure 2. Scoring and weighting are crucial in determining simulation outcomes, including selecting interval classes or continuous data. For instance, continuous data types can utilize distance analysis based on raster data, such as Euclidean distance and fuzzy membership functions (Mehra & Swain, 2024). The outcomes of implementing the transition rule across the three scenarios are delineated in Table 5.

Table 5 (Transition-Persistence) Forcing a Single Independent Variable Land Cover Changes to be Constant on Demak-Jepara Regency

Scenario	Land Cover Changes	Skill Measure				
		1	2	3	4	5
A	Agriculture To Built Area	0,0049	0,0026	0,0349	-	-
	Forest To Built Area	0,3202	0,3152	0,2427	-	-
	Open Field To Built Area	0,5220	0,0021	0,4715	-	-
B	Agriculture To Built Area	-	-	-	0,1073	0,0531
	Forest To Built Area	-	-	-	0,0391	0,0002
	Open Field To Built Area	-	-	-	0,0094	0,5810
C	Agriculture To Built Area	Failed	0,0428	0,1430	0,1352	0,1352
	Forest To Built Area	Failed	0,2889	0,3905	0,3911	0,2820
	Open Field To Built Area	Failed	0,5948	0,5942	0,0055	0,4590
	Average Best Scenario		0,3088	0,3759	0,1773	0,2921
	Influential Factor Rank		3	4	1	2

Source: Research Results, 2023.

Table 5 analyses land cover changes and their implications for coastal development. It focuses on the Root Mean Square of transitional potential iterations resulting under a sub-model structure involving testing and training (Raj & Sharma, 2022). (RMS) values in the context of a scenario, i.e.:

Scenario A. The first scenario is related to natural factors. The study investigates the challenges of evaluating these values, which display considerable variation. The findings reveal that all factors demonstrate favorable values during the transition from agricultural to built-up land. However, in the case of the transition from open fields to built-up areas, the coastline does not exhibit desirable RMS values.

Consequently, the coastline is excluded from the combination factor analysis due to its failure to meet the criteria in two out of three changes. The coastal region of Demak Jepara Regency is characterized by a predominantly flat and open field cover. However, considering potential tidal influences, extensive development as built-up land is only recommended if it is repurposed for activities such as fishponds. As a result, the coastline needs to be considered in the combined scenario analysis.

Scenario B. In the second scenario, which focuses on human-induced factors, land cover transitions influenced by road class consistently demonstrate values approaching 0. The presence of built-up areas has a substantial impact on these transitions. However, there are instances of low values observed during the transition from open field to built-up areas, resembling the findings observed along the coastline in the natural factor scenario. However, since it only fails to meet the criteria in 1 out of 3 transitions, it will still be included in the combined scenario analysis.

Scenario C. The results of the combined scenario demonstrate consistent RMS values for each rule and factor (natural and human-induced). However, two natural factors, namely river order, and slope, exhibit relatively low values (above 0,5), particularly during the transition from open field to build area. The simulation process provides valuable insights. Firstly, it indicates that the coastline has limited influence on the transition to a built-up area. This observation is prominent in coastal areas with flat terrain, where inconsistencies arise between land flatness and road accessibility.

The transition from open field to build area also shows suboptimal RMS values in multiple tests (Raj & Sharma, 2022). This pattern is evident in the combined scenario, where this transition yields low values for almost all factors except the road factor. The research findings highlight that the coastline factor has the most negligible impact (Rizzo & Anfuso, 2020), while the road factor exerts the most significant influence. This outcome is reasonable, considering that transportation access often plays a pivotal role in determining whether an area will undergo development or remain undeveloped.

Scenario D., The land cover results from the scenarios involving natural factors, human-induced factors, and their combination, were derived from land cover data from 2001 to 2009. These scenarios were subsequently evaluated for their conformity with the existing land cover data of 2020. Conformity was assessed using the ROC (Relative et al.) analysis, where a higher Area Under the Curve (AUC) value indicates a greater alignment with the existing conditions, thus signifying a more suitable scenario.

Scenario E. The AUC analysis for scenario A yielded a value of 0.7918, scenario B yielded 0.8156, and scenario C yielded 0.9406. These findings suggest that scenario C is the most optimal, approaching a value of 1. This particular scenario incorporates the following factors: (2) river order, (3) slope gradient, (4) roads, and (5) existing built-up land. By considering the average values of scenario C, as depicted in Table 5, it can be concluded that the development of Kab. Demak Jepara is primarily influenced by the expansion of road networks and built-up areas, while factors such as river order and slope gradient have a comparatively lesser impact. Locally, coastal morphodynamics has less influence due to the homogeneity of contour, tidal, or sedimentation (Rizzo & Anfuso, 2020).

Each tested scenario demonstrates that several factors influence land cover changes. First, the transition rule determines the degree of logical change for a given land cover type. Second, the variation and classification of driving and inhibiting factors influence the smoothness and accuracy of cell movement. Modeling these two aspects can enhance the accuracy of representing real-world changes, improving the precision of land cover change predictions.

Although this study has utilized several factors, namely (1) coastline, (2) river order, and (3) slope gradient, the second scenario focused exclusively on anthropogenic factors, including (4) roads and (5) existing built-up land. There remains substantial potential to incorporate additional factors such as disaster-prone areas, accessibility to public facilities, business location (Feng & Tong, 2020), hospitals, population distribution, industrial zones, and other relevant boundaries. Furthermore, the selection of scoring values and the weighting of each variable can be further refined to improve the quality of the scenarios.

CONCLUSION

Based on the analysis of transition persistence and ROC, it can be inferred that the 20-year development of Kabupaten Demak-Jepara is primarily driven by human-induced factors, particularly the expansion of different road classes and the proximity to existing settlements. Natural factors, such as river order and slope gradient, have a relatively minor influence on the changes in land cover. Interestingly, the coastline, which was anticipated to impact the coastal area significantly, demonstrates minimal influence. Among the five factors examined, the development and classification of roads emerge as the dominant factors shaping the land cover changes in the region.

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