

RESEARCH ARTICLE

Land Cover Changes Based on Cellular Automata for Land Surface Temperature in Semarang Regency

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Abstract

Land cover changes based on cellular automata for surface temperature in Semarang Regency has increased significantly due to the continuous rise in its population. Therefore, this study aims to identify, analyze and predict multitemporal land cover changes and surface temperature distribution in 2028. Data on the land cover map were obtained from Landsat 7 and 8 based on supervised classification, while Land Surface Temperature (LST) was calculated from its thermal bands. The collected data were analyzed for accuracy through observation, while Cellular Automata - Markov Chain was used to predict the associated changes in 2028. The result showed that there are 4 land cover maps with 5-year intervals from 2003 to 2018 at an accuracy of more than 85%. Furthermore, the existing land covers were dominated by forest with decreasing trend, while the built-up area continuously increased. The existing Land surface temperature range from 20.6°C to 36.6°C, at an average of 28.2°C and a yearly increase of 0.07°C. The temperature changes are positively correlated with the occurrence of land conversion. Land cover predictions for 2028 show similar forest dominance, with a 23,4% built-up area at a surface temperature of 28.9°C.

Keywords: Land cover change; Cellular Automata-Markov Chain; Land Surface Temperature

1. Introduction

According to the [United Nations \(2018\)](#), population increase is a global problem experienced in every country, with 55% of humans presently living in urban or regional areas, likely increasing by 68% in 2050. These changes tend to affect both local and global climate components, such as the land surface temperature (LST). For example, in Nigeria, there was an increase of 19,166.13 ha in urban built areas from 2002 to 2013, with a rise in LST by 6 °C ([Igum & Williams., 2018](#)).

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[Khandelwal et al. \(2018\)](#) stated that an increase in LST tends to disrupt the climate-energy balance, such as the heat wave phenomenon experienced in 7 major European countries, namely the United Kingdom (38.1 °C), Germany (41.7 °C), Belgium (41.8 °C), France (42.6°C), Luxembourg (40.8 °C), Scotland (31.6 °C), and the Netherlands (40.7 °C) recorded in July 2019. In Southeast Asia, several major cities also experienced similar conditions. An increase in hotspots was 20% greater than the average LST in Hanoi ([Tran et al., 2017](#)) and at a temperature of 2.9 ° C in Jakarta which is higher than in Bangkok ([Estoque et al., 2017](#)).

Land cover changes also occurred in Central Java Province. Moreover, 128 ha of rice fields were converted to settlements or used for other purposes from 2009 to 2010 ([BPS, 2015](#)). On the contrary, the average air temperature in Central Java Province from 2032 to 2040 was predicted to increase within the range of 0.81 to 0.85 ° C ([BMKG, 2019](#)).

Semarang Regency, Central Java Province, Indonesia, had a high population growth rate (8.74%) from 2010 to 2016 ([BPS, 2017a](#)). Based on statistical data, in 2016, 1.014 million people with a density of 1.081 people/km², was recorded. This figure is higher compared to the national average population density of 127 people/km². However, from 2011 to 2016, agricultural areas were reduced by 0.94% from 60,439.96 to 59,872.49 ha, while land used for other purposes was increased by 1.64%, which is equivalent to 35,148.18 ha ([BPS, 2017b](#)). This indicates that Semarang Regency is also susceptible to land and climate changes problems, specifically areas adjacent to the city, which has experienced rapid development and recorded an LST average of 1.32 ° C ([Nugraha et al., 2016](#)).

Analysis carried out using past and present spatial data is considered one of the requirements for geographic studies ([Dadras et al., 2015](#)). Cellular automata are the commonly used spatial model of land cover change. It is dynamic and composed of inter-related cells with discrete units ([Wang et al., 2012](#)). Cellular automata are used mainly to generate and predict potential changes ([Tran et al., 2017](#)).

[Fu & Weng \(2016\)](#) stated that temporal disparities of thermal characteristics due to land cover changes and responses need to be carried out comprehensively. One of the environmental parameters analyzed in this study is LST, estimated from the Single thermal Channel or Split Window Algorithm Method, dependent on the number of bands used ([Pu et al., 2006](#)). Both have a weakness in respect to the atmospheric profile uncertainty, which strongly affects the accuracy of the result ([Li et al., 2013](#)). However, this is anticipated by inputting the atmospheric profile data into the thermal band spectral radian correction made by the USGS (United States of Geological Surveys) ([Coll et al., 2010](#)).

Study carried out on the land cover change in Semarang regency is common for land suitability, flood (Susanti et al., 2012), landslide, sedimentation (Apriliyana, 2015), carbon stock, and spatial planning review (Pangi et al., 2017). These studies were specifically related to land and averaged surface temperatures (Kalinda & Bandi, 2018). Therefore, this study aims to model land cover changes based on raster data using cellular automata related to its surface temperatures in the future. In addition, it also intends to (1) analyze the surface temperature distribution and land cover changes of Semarang Regency in 2003, 2008, 2013, and 2018, (2) evaluate the relationship between land cover changes and LST, and (3) investigate the distribution of land cover for the following 10 years.

2. Methods

This field survey was conducted in Semarang Regency, Central Java Province, from April to June 2019. The area was considered due to the record time of the imagery data input. Furthermore, simulation data input only requires 2 land cover imageries, the initial and step year. However, for the sake of detailed information, this study used those acquired in 2003 (initial), 2008 (step 1), 2013 (Step 2) and 2018 (Step 3), which was compared using population growth and space needed, such as the assumption based on consistent population per built area on initial, and each step. The satellite image data used are (1) Landsat 7 path/row 120/65 imagery recorded on May 20, 2003; (2) Landsat 7 path/row 120/65 imagery recorded on June 18, 2008; (3) Landsat 8 path/row 120/65 imagery recorded on June 24, 2013; (4) Landsat 8 path/row 120/65 imagery recorded on August 25, 2018.

Unfortunately, Landsat 7 (2008) had some bad qualities due to the sensor stripping. However, USGS provided corrections using past imagery with a similar location. Secondary data used to support the population growth analysis were obtained from the (1) Population growth and built area of Semarang Regency from 2008 to 2018, then (2) Slope from AsterGDEM Radar Image data (USGS). Road networks, activity centers, and river patterns were obtained from BIG and Spatial Planning of Semarang Regency data and used as constraint input on land cover simulation.

Sampling calculation refers to the Technical Guidelines for collecting and processing Spatial Data from the Geospatial Information Agency (BIG). Meanwhile, the number of sample points for each land cover type is determined using the proportional stratified sampling method, as shown in Figure 1.

Field surveys are carried out to measure the temperature of the land surface and cover the ground check. This analysis was carried out from April to June 2019, synchronized with

the imagery record period. It was assumed that the weather condition, sun duration, and intensity are similar to the imagery and survey data. Also, the duration (on distribution sample) is customized from 08.00 to 11.00 AM to adjust the recorded time of the imagery.

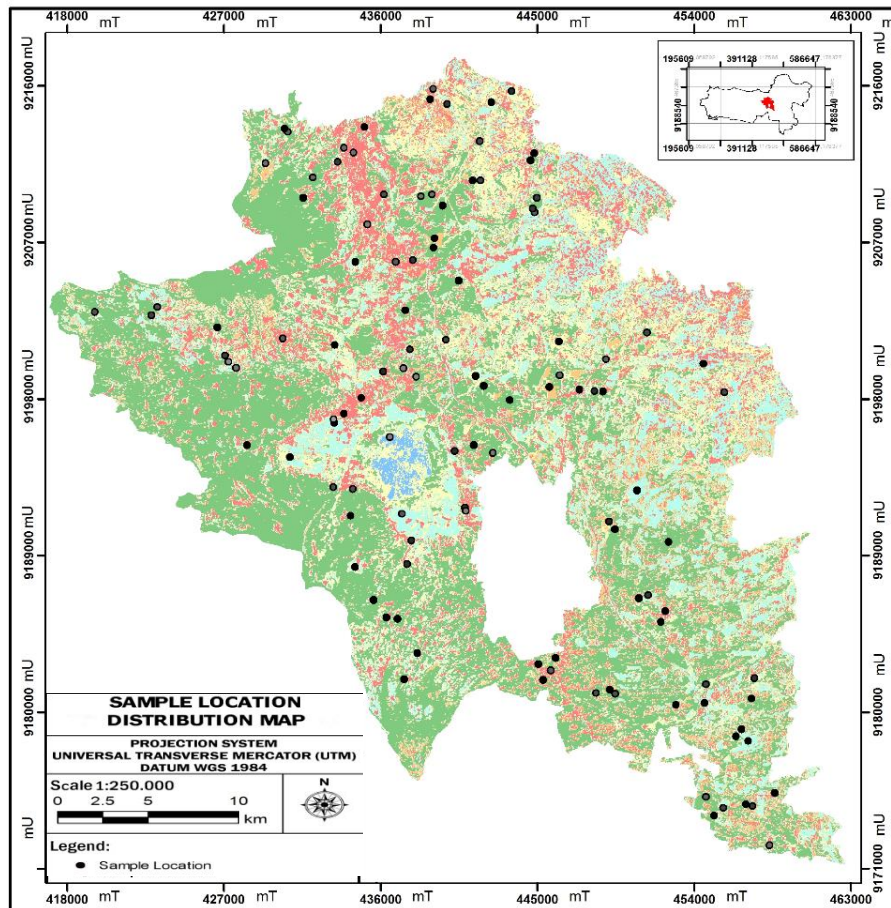


Figure 1. Location and Research Sample in Semarang Regency, Central Java

Land cover is classified (Maximum Likelihood) using ENVI 5.1 and differentiated according to the method proposed by [Danoedoro \(2006\)](#) concerning water, forest, shrub, agricultural, open, and built areas. The classification accuracy threshold used is 85%, thereby determining its mapping by comparing the 2018 image with field observations. Data from the previous year's image is compared with the temporal interpretation of Google Earth. Accuracy is determined using a confusion matrix involving the consideration of omission and commission. Overall, it indicates the probability that a pixel belongs to a certain class and its representation in the field ([Lillesand et al., 2004](#)).

Land cover prediction in 2028 was made with Selva's version of Idrisi software in accordance with the Markov Chain method based on Cellular Automata. Meanwhile, Markov Chain is used to analyze 2 land cover data realized in different years, namely past (2008) and

actual information (2019). The transition matrix is focused on the change of any land cover to build area using a 3x3 matrix. Built area conditions control this change from the forest, agriculture, or open field, besides the opposite. Agriculture is changed from the forest, or open field, besides the opposite including build area, etc.

LST is estimated by transforming pixel into spectral radian values using USGS equations to correct surface reflection errors and earth curvature. Meanwhile, errors due to atmospheric disturbances, specifically in terms of processing images of land surface temperatures, are determined with the equation proposed by Coll et al. (2010). It contains parameters that tend to affect LST, including emissivity, transmission, upwelling and downwelling (Kalinda & Bandi, 2018). The profile is obtained from the Atmospheric Correction Parameter Calculator, modeled according to data input's date, time, and location (Tran et al., 2017). The corrected spectral radian values are converted to brightness temperatures using the USGS formula for Landsat imagery. This is estimated as LST using the equation proposed by Artist & Carnahan (1982) and Amiri et al. (2009). It is also used to determine an accurate brightness temperature of 8-14 μm wave (Artis & Carnahan, 1982), while this study utilized bands 6 (10.4 to 12.5 μm) and 10 (10.60 to 11.19 μm).

The analysis technique is used to determine the effect of each land cover type on LST changes by comparing the t-count with the t-table. The t-test is carried out using a simple linear regression equation while the t-table size is calculated with the formula $t(a/2, n-2) = t(0.05/2, 116-2) = t(0.025, 114) = 1.98099$, based on the following criteria: (1) assuming the significance value is <0.05 and $t\text{-count} > t\text{-table}$, it means that there is an impact, and (2) assuming the significance value is > 0.05 and $t\text{-count} < t\text{-table}$, meaning there is no impact.

3. Results and Discussion

3.1 Land Cover Changes

Image classification performed with the supervised method produces land cover maps for 2003, 2008, 2013 and 2018. Confusion matrix analysis on Table 1 shows an accuracy of 91.38%, 92.24%, 88.79% and 86.21 %. According to Fariz (2016), misclassification is not only influenced by differences in recorded time as well as the misidentification of objects from residential land to the forest because tall trees cover their appearance. The accuracy test results obtained annually exceed 85%, therefore, the data is feasible and needs to be used for further analysis (Susanti et al., 2012).

Table 1. Producer and Overall Accuracies of Land Cover Matrix Confusion

Land Cover	Producer Accuracy			
	2003	2008	2013	2018
Water Body	100.00%	100.00%	100.00%	100.00%
Forest	98.31%	98.11%	100.00%	93.33%
Agriculture	61.90%	60.00%	56.25%	80.95%
Shrubs	100.00%	88.89%	66.67%	66.67%
Open Field	100.00%	100.00%	100.00%	77.78%
Built Area	91.67%	100.00%	95.45%	92.00%
Over All Accuracy	91.38%	92.24%	88.79%	86.21%

The results show that the dominated land covers are forest and agricultural areas because the Semarang Regency is near mountains and fertile, as shown in Figure 2. Table 2 shows the increased number of forests recorded in 2013, possible because “sengon” and teak plantations starts with land clearing and an approximately 5 years harvest period (Nuroniah & Putri, 2013) and 15 to 20 years for teak (Pudjiono, 2014). This result also corresponds with the Semarang Regency data by BPS (2017), which reported a critical land decrease of 26.2% in 2013 from the previous year a program on forestry services was held to boost its increase.

Agricultural areas experienced a significant increase of 75.50% from 2013 to 2018. This pattern is common in rural areas, specifically in reduced forest and open fields, thereby boosting agriculture. The reverse is the case in urban areas such as agricultural lands in the Nanjing region. China was converted to developed or built areas with 2.6% in 2009 (Wang et al., 2016).

Table 2. Land Cover Changes in Semarang Regency in 2003, 2008, 2013 and 2018

Land Cover	Years							
	2003		2008		2013		2018	
	(ha)	(%)	(ha)	(%)	(ha)	(%)	(ha)	(%)
Forest	52,696	51.7	45,742	44.9	49,183	48.3	39,452	38.7
Built Area	9,903	9.7	18,293	18.0	18,642	18.3	20,012	19.7
Shrubs	19,188	18.8	16,413	16.1	12,469	12.2	15,522	15.2
Agricultural	11,415	11.2	9,007	8.8	8,303	8.2	14,572	14.3
Waters Body	967	0.9	676	0.7	996	1.0	767	0.8
Open field	7,665	7.5	11,703	11.5	12,240	12.0	11,509	11.3
Amount	101,834	100	101,834	100	101,834	100	101,834	100

3.2 Land Cover Simulation 2028

Land cover simulation processed with Markov Chain on Cellular automata with population growth as a control. Furthermore, increase in population and built areas are linearly correlated to each step year to average growth. Therefore, the acquired data serves as an area of increased control when cellular automata are executed. The cell movement is constrained by slope, existent built area, road and river networks. Land cover changes are influenced by several attributes, from macro (policy) to micro (regional complex) factors (Figure 2). In the regional complex, Semarang Regency develops and changes the influence of roads, slopes, demographics, and land availability.

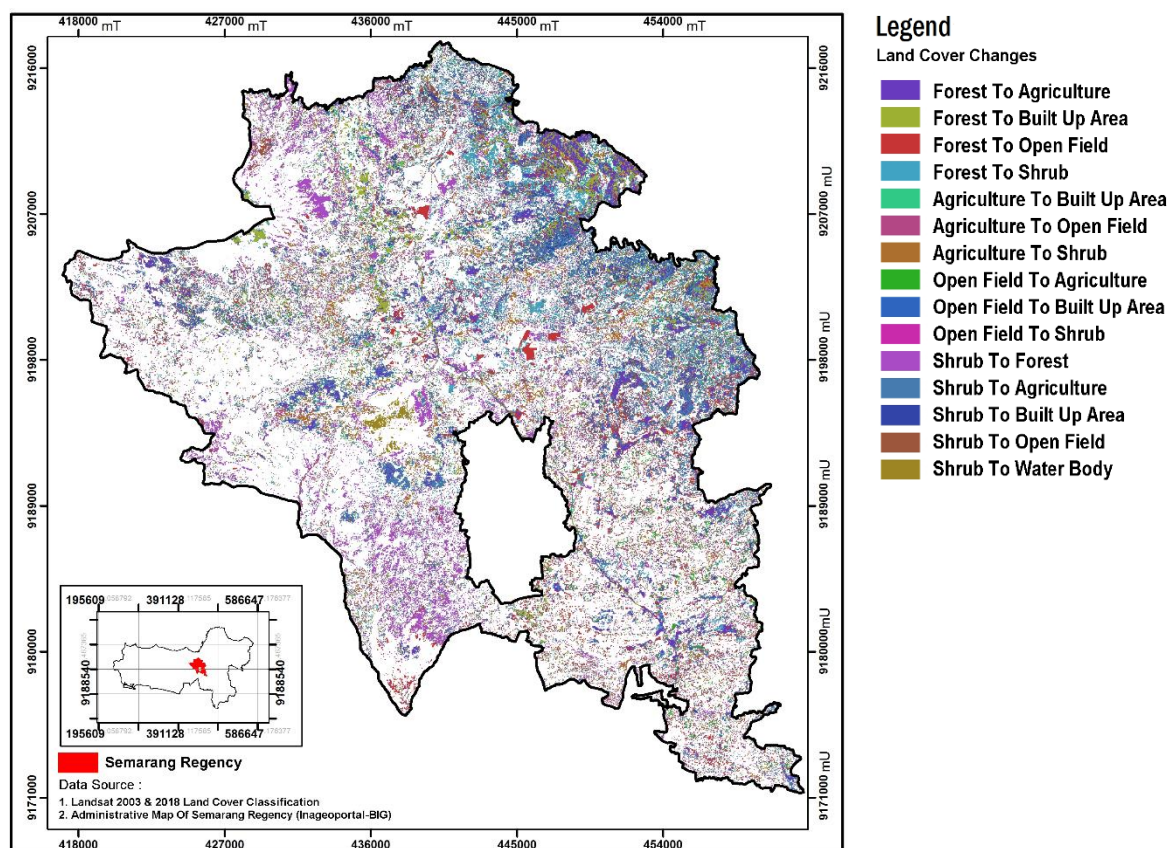


Figure 2. Land Cover Changes in 2003-2018

The road as a driving force for mobility affects the pattern of land development, which extends along with the northern and southern parts of Ungaran and Tengaran districts, respectively. Residents tend to build new settlements at a distance of <250 m from the main road. The slope affects development in the highlands, leading to the clustering of existing built areas.

Population affects human space requirements. The population density in Semarang Regency was 889 people per km² in 2003. However, it increased to 1,081 people per km² in 2017. This is presumed to influence the changing of forests and agricultural lands into built areas. Land availability along with its clearing increased from 2003 to 2013. This condition is also accompanied by a decrease in forests, shrubs and agricultural areas because the emergence of open land availability also promotes increased social facilities.

On the land cover simulation proposed by 2028, a decline in forests, shrubs and agricultural fields was recorded in the previous 10 years, except water bodies and built-up areas, as shown in [Table 3](#). The spatial distribution shows that the developmental pattern of regions built in 2018 is clustered at the regional and economic centers. This includes East, and West Ungaran, Bergas, Ambarawa, Bawen, Tengaran, Suruh, and Kaliwungu Districts, as indicated in [Figure 3](#). However, a difference of only 284.56 ha was realized in accordance with the conditions of built area development in the same location from 1991 to 2001 ([Pangi et al., 2017](#)).

Table 3. Land Cover Changes in Semarang Regency, 2018 - 2028

Land Cover	Years				Percent Changes
	2003		2028		
	(ha)	(%)	(ha)	(%)	
Forest	39,452	38.7	37,010	36.5	-5.68
Built Area	20,012	19.7	23,727	23.4	18.78
Shrubs	15,522	15.2	14,295	14.1	-7.24
Agricultural	14,572	14.3	14,096	13.9	-2.80
Waters Body	767	0.8	773	0.8	0.00
Open field	11,509	11.3	11,498	11.3	0.00
Amount	101,834	100	101,834	100	

Land cover simulation results in 2028 show an increase in built areas, a decrease in forest (6.19%), shrubs (7.90%), agricultural (3.27%), and open fields (0.09%). Waters bodies such as the Rawa Pening Lake increased by 0.88% in 2018 due to the influence of agricultural areas and shrubs. Similar conditions also occurred from 2001 to 2011 when an increase in agricultural lands (2,905.79 ha) was recorded ([Apriliyana, 2015](#)). The population and built area in the Semarang regency linearly correlate with the equation $y = 0.02x + 32.06$, where y is the built area and x is the total population, as shown in [Figure 4](#). This is also used to determine an estimate of 23,770.62 ha in 2028. Moreover, when compared with the predicted area determined by the Cellular Automata method, the 2 estimations are 43.59 ha or 0.18% deviation. This shows that the results of the Cellular Automata simulation of land cover and population linear regression do not contradict each other.

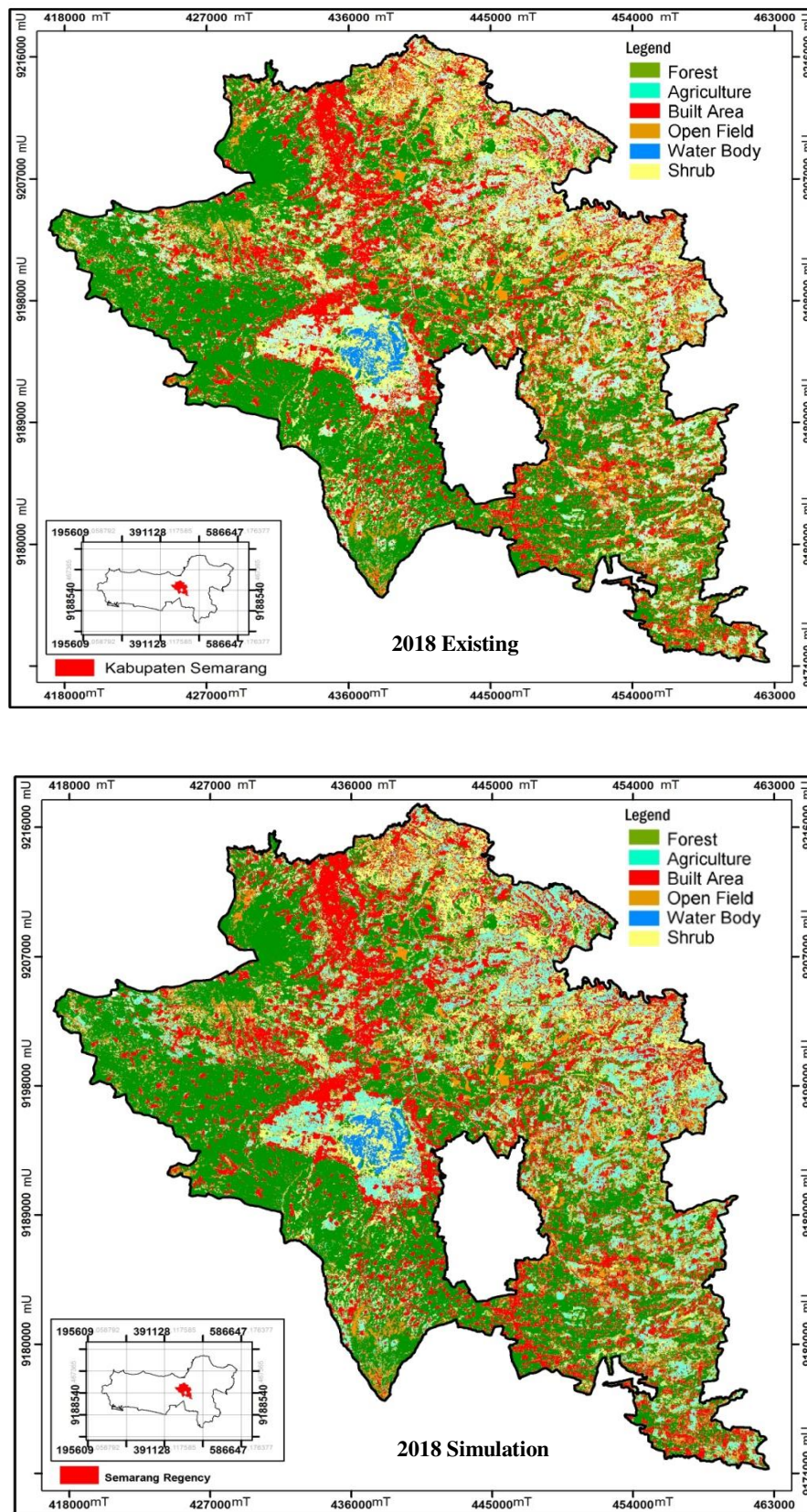


Figure 3. Land cover in 2018 and 2028 (modeling using the Cellular Automata)

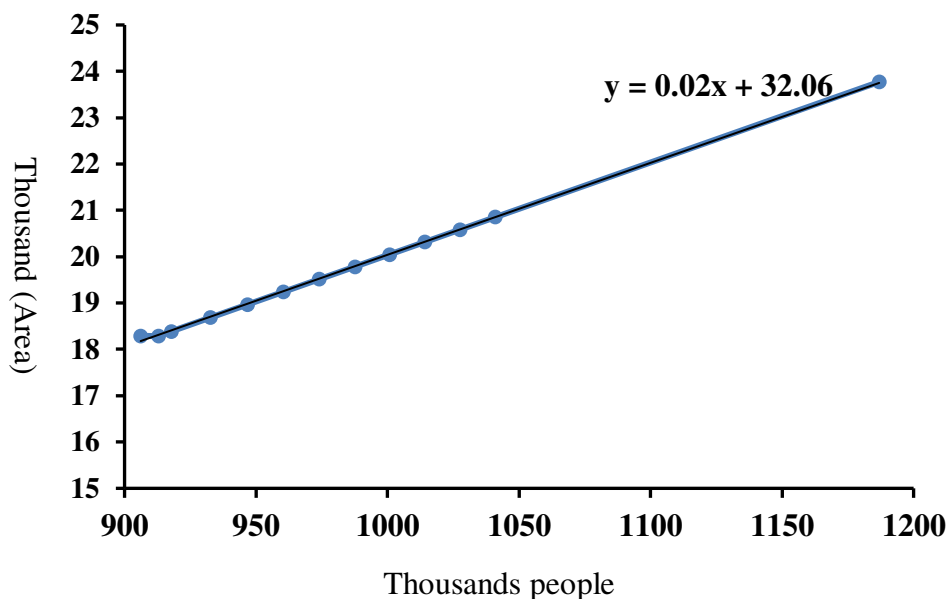


Figure 4. Linear equations for population and built-up area (prediction of built-in area in 2028)

3.3 Imagery Surface Temperature Vs Survey

The field survey led to the fluctuation of LST data every hour from 09:00 to 15:00 for different land covers, as shown in [Figure 5](#). This is used to ascertain the response of each land cover type to solar radiation. Besides, each has a different response rate, although they generally tend to reach the peak temperature at 13:00. It is clear that the built area has the highest LST, reaching 3.6 ° C, and decreases gradually after 13:00. Apart from land cover information, satellite imagery is also used to extract LST. This study produced 4 LST distributive maps in 2003, 2008, 2013 and 2018 ([Figure 6](#)).

Meanwhile, when compared with the estimated results of the image from the closest year, a positive relationship was determined with a correlation coefficient (R) of 0.637, coefficient of determination (R^2) is 0.45 with a degree of significance <0.005 (significant). According to the R-value, the relationship between LST imagery and field survey is positively correlated ([Fu & Weng, 2016](#)). [Figure 6](#) shows the image temperature is high, as well as the field, however, the coefficient is different due to dissimilarities in weather conditions.

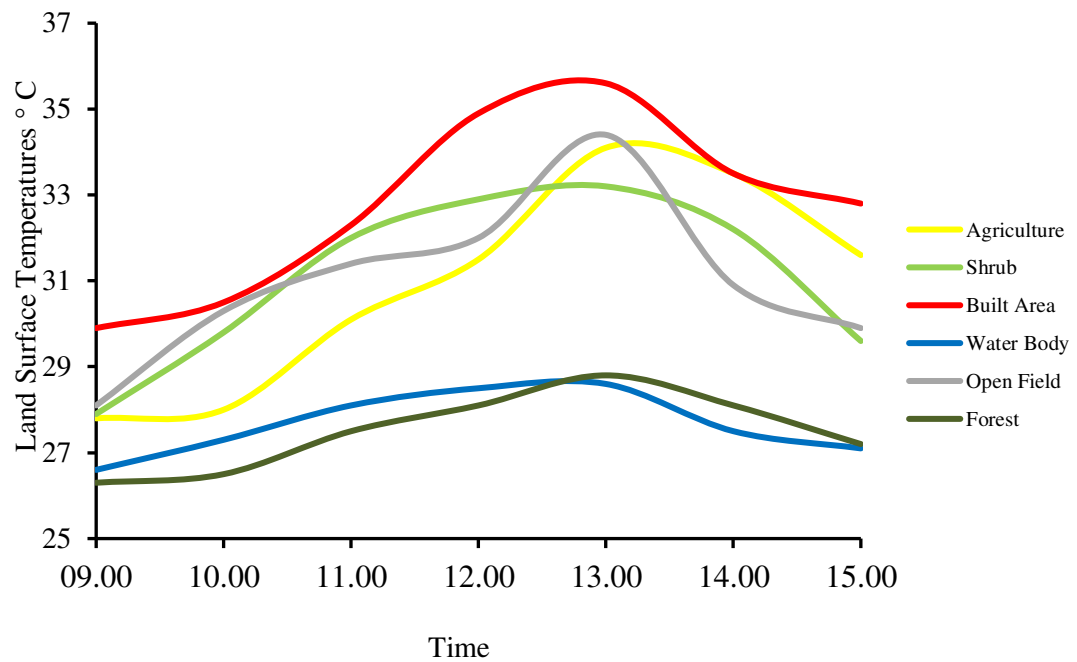


Figure 5. Changes in surface temperature on each land cover per hour

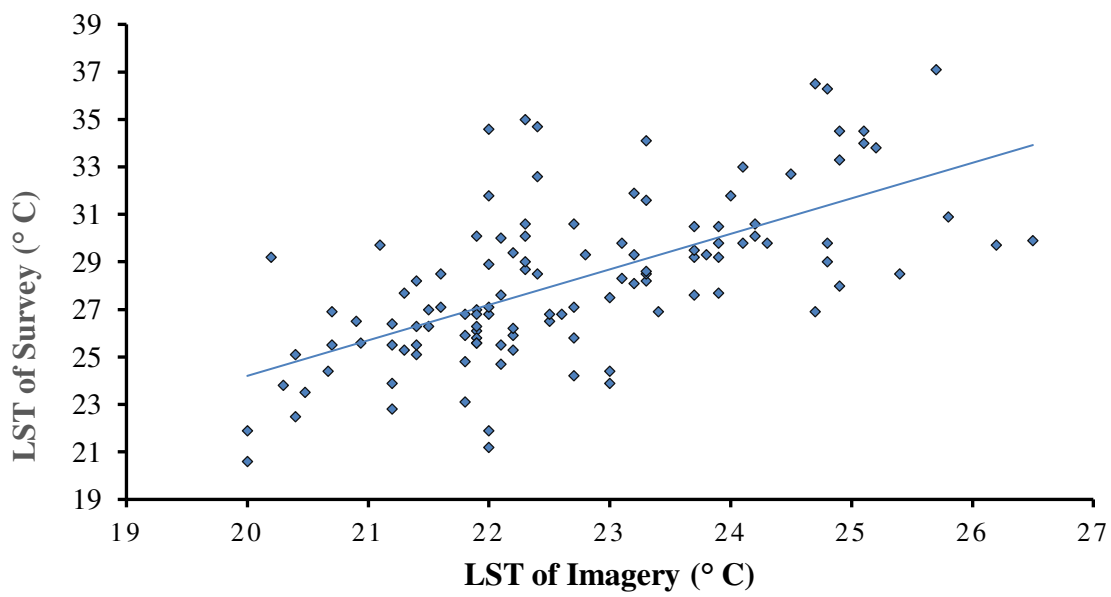


Figure 6. Linear graph of LST VS Land Cover Changes

3.4 Surface Temperature Changes

The results of the LST obtained using satellite imagery shows that the maximum and minimum temperatures reached were 37.6 ° C, and 20.6 ° C, respectively. The average LST and standard deviation values are 28.2 ° C and 3.39 ° C. Interestingly, the LST temperature from 2003 to 2018 tended to increase, while a decrease was detected in the data acquired in 2008. The decline in land surface temperature is influenced by low solar radiation of approximately 425.55 watts/m², accumulated over the years. This is caused by the position of the earth's aphelion to the sun, which usually occurs in June. The Australian Cold Munson phenomenon also affects the deviation, which blows cold and dry air from the Indonesian coast. It also causes upwelling followed by a decrease of not less than 3° C in the South Java Sea, besides this usually occurs from July to August ([Sukresno et al., 2018](#)).

The high-temperature area is regularly experienced in regional centers, as shown in Figure 6. This shows that LST is concentrated due to the urbanization influence caused by land cover changes ([Peng Fu, 2016](#)). However, it is different from the phenomenon that occurred in 2008 due to the concentration of newly built areas in Bancak District which has varying temperatures, depending on the various types ([Pal & Ziaul, 2017](#)).

3.5 Surface Temperature Vs Land Cover Changes

To compare continuous data from LST and land cover changes (ordinal), this study collected whole coverage and point samples using grid size as the location. The LST was generated as positive or negative changes compared to the land cover, which was converted to non-changes data. The results of correlation analysis ([Figure 7](#)) carried out on the land cover and LST from 2003 to 2018 was used to determine the strong relationship between the coefficient of determination (R^2 : 0.430) and the correlation coefficient (R : 0.655) ([Sarwono, 2006](#)). Meanwhile, from the t-test on each land cover, it is evident that agricultural areas, forests, and shrubs have a dominant influence ([Table 4](#)).

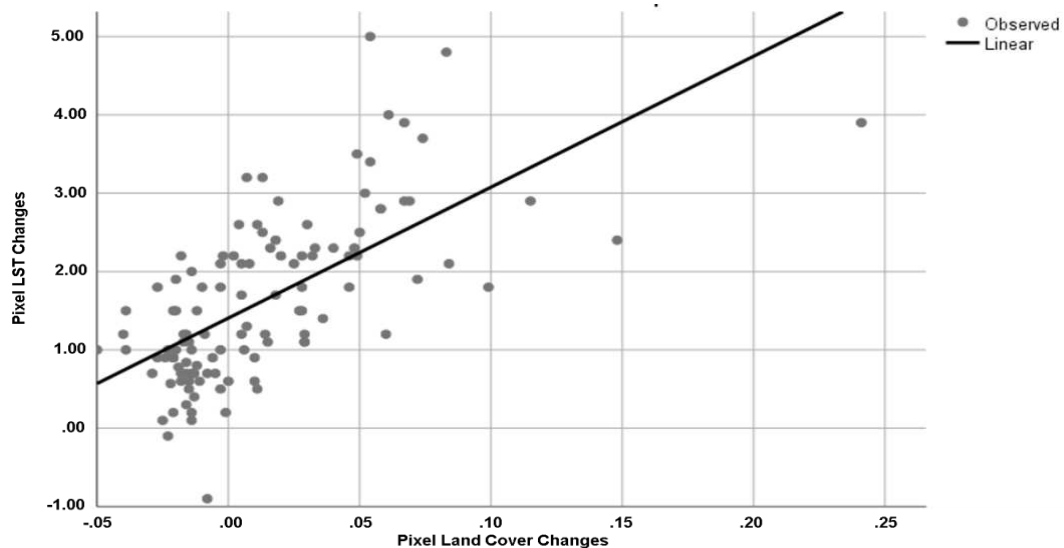


Figure 7. Linear Graph LST VS Land Cover Changes Data

Land cover is associated with temperature changes, it is evident that the dominant one is the conversion of forests to agricultural areas with a temperature (averaged area) increase of 0.31°C/ha , as shown in Figure 8 and Table 5. This led to an increase in the number of farmers from 144,369 (2013) to 167,044 (2018) in Semarang Regency (Yuliati, 2018). In addition, this condition was also experienced at the national level from 2000 to 2005, where plantations and agricultural areas were the dominant land cover types that replaced 44% of forests. The increase in average surface temperature of regional LST at the study site was raised to relatively 1.06°C with an average increase per decade of 0.7°C . Lin & Yu (2005) classified the LST increase in average surface temperature as being greater than the value obtained in Beijing and approximately within a range of 0.25 to 0.31°C . Based on this approach, it was estimated that the average LST in 2028 is expected to reach $28,9^{\circ}\text{C}$.

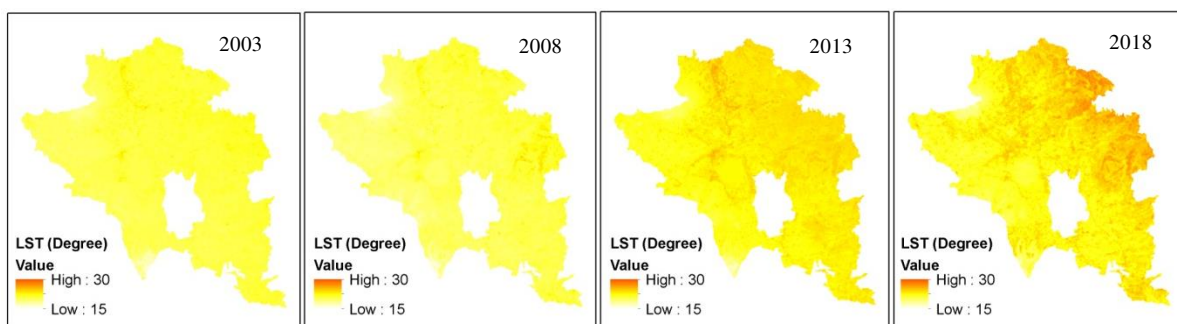


Figure 8. Land Surface Temperature Changes in 2003, 2008, 2013, and 2018

Table 4. Regression of Land Cover with Land Surface Temperature

Land Cover	R ²	t-Calculated	Significance
Forest	0.511	7.912	0.000
Agriculture	0.566	3.021	0.019
Open Field	0.331	2.537	0.025
Shrub	0.433	4.095	0.000
Water Body	0.078	-0.921	0.379
Built area	0.285	2.360	0.033

Table 5. Land Cover Area and Average Area LST

Land Cover		Area (Ha)	% Area	Changes (°C)	Averaged Area Changes
2003	2018				
Forest	Forest	5,825.07	61.41%	-0.09	-0.05
	Agriculture	734.58	7.74%	4.05	0.31
	Built Area	97.83	1.03%	2.78	0.03
	Open Field	123.84	1.31%	2.99	0.04
	Shrub	279.72	2.95%	2.70	0.08
Agriculture	Agriculture	1.53	0.02%	1.22	0.00
	Built Area	649.08	6.84%	2.62	0.18
	Open Field	26.01	0.27%	1.61	0.00
	Shrub	754.11	7.95%	1.34	0.11
Shrub	Forest	0.54	0.01%	-0.31	0.00
	Agriculture	137.38	1.45%	2.98	0.04
	Built Area	648.18	6.83%	3.90	0.27
	Open Field	2.97	0.03%	2.86	0.00
	Shrub	204.89	2.16%	2.53	0.05
Amount		9,485.73	100%		1.06

The differences in LST are not only influenced by the land cover type. The results obtained from this study differs from other studies due to regional complexes. This bias is caused by several factors such as solar radiation, topography, soil and vegetative types. The linear regression shows that the solar radiation value has a positive effect on LST. Every 1 watt/m² triggers the average LST area by 0.1 ° C from 2003 to 2018. The topography's response was slightly different from that of the LST. In addition, its sample distribution shows an inverse comparison. The regression equation is $y = -0.001x + 23.77$ with R² of 0.411. The minus sign (-) in the equation shows a negative relationship, therefore, an increase in height causes a decrease in the LST and vice versa.

Based on the map, the western and southern parts of the study location comprised mostly of andosols associated with brown and dark red Mediterranean lithosol, regosol, and brown latosol. Furthermore, soil type, texture and color affects the LST distribution. One of

the main ingredients of andosol soil, which is usually in the form of sand, is its ability to absorb high heat as well as to withstand low soil moisture within the range of 4 to 70% (Bavel et al., 1972). Meanwhile, hydromorphous alluvial soil types dominate the center, with clay as the parent material. It is also able to properly absorb a heat capacity of 0.279 calg-1 °C-1, although it is lower compared to sand (Lal & Shukla, 2004).

Vegetation is also considered to influence LST variation due to height, canopy character, and location of growth tendency. In accordance with the BPS data, cloves, rubber, coffee, sengon, teak, and mostly rice fields and shrubs are cultivated in the eastern part of Semarang Regency. Meanwhile, pine trees, fruits, bamboo, rubber, rice fields, and shrubs are cultivated in this regency at dense temperature fluctuations with high humidity and wind speed of 0.6 m/s. Conversely, the cone canopy has a speed of 0.4 m/s and a higher temperature (Fadlurrahman, 2018).

4. Conclusion

The dominant land cover in Semarang Regency from 2003 to 2018 was a forest with the tendency to be converted into agricultural areas. Land cover predictions for 2028 also show a similar change pattern. Furthermore, these changes had a positive relationship with LST and a significant effect with a correlation coefficient (R) of 0.655 (strong). Forest, agricultural areas, open fields, shrubs and built-up areas affect 51.1%, 56.6%, 33.1%, 43.3%, and 28.5% on LST. Land cover simulation shows that the built area is bound to increase by 18.56%, indicating dense growth in Tengaran, East Ungaran, Bank, and Kaliwungu Districts. Based on calculations, this caused an average increase of 28.9 ° C at a rate of 0.07 ° C/year.

Conflict of interest

The authors declare that there is no conflict of interest with any financial, personal, other people or organizations related to the material in this study.

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