The dynamics of land use/land cover change modeling and their implication for the flood damage assessment in the Tondano watershed, North Sulawesi, Indonesia

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Abstract The Markov Chain and Cellular Automata (Markov-CA) approach have been applied to create the dynamics of land use/land cover (LULC) change modeling in the Tondano watershed, North Sulawesi, Indonesia. The multi temporal of remotely sensed data, Landsat 5 TM in 1997, Landsat 7 TM in 2002 and Landsat 8 LDCM in 2015 were used to produce the LULC maps. Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) Global Digital Elevation Map (GDEM) data were used as input for the flood modeling created by the Monte Carlo algorithm. The LULC maps in 1997 and 2002 were used to create predictions and modeling LULC map with the Markov-CA approach in the next few years (for the year 2015, 2025, 2035 and 2050). Meanwhile, the LULC map in 2015 with an accuracy of 80.11 % based on the calculation of the Kappa index has been used as a reference map to determine the accuracy of the Markov-CA approach to produce a model of the LULC map in 2015. The result of the accuracy by using cross-correlation matrix between the LULC model in 2015 with the LULC reference in 2015 is 75.88 %. The dynamics of LULC changes showed that area-class forest, dry land, paddy fields and shrubbery would be expected to experience an area decreases in the extent from the year 2015 to 2050, with the rate of change in average: 10.52, 13.22, 14.49 and

1.15 ha/year, respectively. Meanwhile, the area-class bare soil, plantation, settlement and water body would be expected to experience an area increases, with the rate of change in average: 6.79, 11.14, 11.49 and 9.7 ha/year, respectively. Furthermore, flood damage assessment can be calculated by estimating LULC area affected by the flood, which is determined based on the overlay between LULC maps from the result of Markov-CA with flood maps from the result of Monte Carlo algorithm. Under current conditions, estimated flood damage exposure to extreme flood events with return periods of 100 years for the water level scenario $H_c = 3$ m and $H_c = 5$ m is more than €520 and €958 million, respectively.

Keywords Remote sensing · Flood damage assessment · Tondano watershed · North Sulawesi · Indonesia

Introduction

Land use/land cover (LULC) can be defined as part of the physical composition and characteristics of the land elements on the earth's surface. LULC systems have complex dynamics, which consists of natural, social and economic spatially. The availability and distribution of LULC change have significant impacts on climate, environmental issue and natural ecosystem conditions (Cihlar 2000; Wang et al. 2012; Yan et al. 2015). The management and good planning to LULC can provide an important role in the moderation of extreme events, climate change mitigation and land degradation. For example, its role can mitigate flood events, landslide and erosion through water retention in soils and water uptake by vegetation (Stürck et al. 2015). The LULC changes can be caused by several factors, such as human activities, e.g., urbanization, deforestation,

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agriculture intensification and others. In addition, natural factors also contributed to the change of LULC (Lambin 1997; Halmy et al. 2015).

The dynamics of LULC change can be monitored by using remotely sensed data. The availability of remotely sensed data have been provided a variety of temporal, spectral and spatial resolution, which can be used to detect changes on the earth's surface (Rogan and Chen 2004; Wu et al. 2006; Halmy et al. 2015). Furthermore, the utilizations of remotely sensed data were used as input in generating a LULC map. The monitoring of the LULC change dynamics can be done by comparing a LULC map at currently with the conditions in previous years as a multi-temporal (Behera et al. 2012). The use of remotely sensed data for mapping of the dynamics of LULC changes has been used extensively. Example include the use of Landsat MSS, Landsat TM, Landsat ETM+, Indian Remote sensing Satellite LISS-III (IRS), MODIS, NOAA/AVHRR, CBERS, among others (e.g., Sun et al. 2007; Gong et al. 2015; Wehmann and Liu 2015; Shooshtari and Gholamalifard 2015; Nejadi et al. 2012; Pouliot et al. 2014; Chen et al. 2013; Yang et al. 2011).

To determine the condition of the LULC in the next several years can be done with modeling of LULC predictions. The modeling can be done either by the model of Markov-CA (Guan et al. 2011; Yang et al. 2014; Gong et al. 2015). The use of Markov-CA is an interesting approach and it has advantages in the modeling of LULC change, spatially and temporally (Sylvertown et al. 1992; Wang and Zhang 2001; Behera et al. 2012). One of the implications of the use of monitoring the dynamics of LULC change and predictions can be used for the flood damage assessment (e.g., Marfai and King 2007; Ward et al. 2010; 2011; Joling 2013; Yulianto et al. 2015a). The flood damage assessment is required to estimate the impact of LULC in the next several years from the occurrence of floods. The existence of such information can then be used as input for flood risk mapping in a region (Su et al. 2005; Metzler 2011). Several other studies related to the implications of LULC for the flood damage assessment (e.g., Jonge et al. 1996; Herath 2003; Yen and Anh 2010; Jongman et al. 2012; Beckers et al. 2013).

The city of Manado is a downstream area of the Tondano watershed, and Fig. 1 shown the location of the

Fig. 1 a Indonesia map for inset location of Sulawesi island. b Inset location of the research area at North Sulawesi. c Digital elevation model (DEM) in the Tondano watershed, North Sulawesi, Indonesia (Source: ASTER GDEM in the year 2011)

research area. There are four major flood events in the city of Manado based on the historical record, namely: December 3, 2000; February 21, 2006; February 17, 2013 and January 15, 2014 (Dayantolis and Fitri 2014). Flooding that occurred on January 15, 2014 in the city of Manado, North Sulawesi, Indonesia is a flood of greatest impact. Rainfall with an intensity of more than 175 mm has become one of the causes of flooding in the research area. This condition during the flood event on January 15, 2014 can be shown based on the monitoring of rainfall accumulation from QMorph remotely sensed data on January 13–16, 2014 (Fig. 2). The existence of these conditions for

2 days with a relatively long duration of time has triggered flood in the research area.

The availability of information related to the impact of flood events in the research area is important to be done with the aim to quickly estimate of losses caused by flooding. One of the immediate measures that can be used to calculate the impact of flooding on LULC. In addition, the calculation of the impact of flooding from LULC change needs to be done in order to determine the potential loss to the effects of flooding in the future. That information can be used as input to government and several stakeholders to anticipate and minimize the impact of flood

Fig. 2 Rainfall accumulation based on the QMorph remotely sensed data in the research area (Tondano watershed), on January 13–16, 2014. **a** Rainfall accumulation on January 13, 2014, time: 00–23 UTC. **b** Rainfall accumulation on January 14, 2014, time: 00–23

UTC. **c** Rainfall accumulation on January 15, 2014, time: 00–23 UTC. **d** Rainfall accumulation on January 16, 2014, time: 00–23 UTC (Source: QMorph remotely sensed data, processed by: LAPAN 2014)

risk and it can also be used as a reference in environmental management policies in the research area. The objectives of this research are: (a) to analyze, modeling and predictions the dynamics of LULC change from multi-temporal remotely sensed data, (b) to implement the results of modeling the dynamics of LULC change and predictions for the flood assessment in the research area.

Table 1 The number of the population living at the Tondano watershed in the year 2014

Districts	Number of population in 2014
Manado	
Mapanget	51,259
Paal Dua	42,798
Singkil	47,963
Tikala	29,136
Tuminting	51,039
Wanea	22,768
Wenang	33,048
Minahasa	
Langowan Timur	12,475
Langowan Barat	15,308
Langowan Selatan	7539
Langowan Utara	8158
Tompaso	16,117
Kawangkoan	26,578
Sonder	18,064
Tombulu	16,196
Tondano Barat	19,513
Tondano Selatan	21,815
Remboken	11,175
Kakas	21,473
Eris	9819
Kombi	9874
Tondano Timur	14,130
Tondano Utara	12,525
Minahasa Utara	
Kauditan	24,263
Airmadidi	28,153
Kalawat	29,743
Dimembe	23,568
Talawaan	19,932
Tomohon	
Tomohon Selatan	21,682
Tomohon Tengah	21,329
Tomohon Timur	10,453
Total	697,893

Source: Indonesian of Central Agency Statistics (BPS) 2014a, b, c, d

Study area

The Tondano watershed in North Sulawesi, Indonesia, is located at the coordinates of about at 1°27'18.72" to 1°6'8.28"N and 125°1'38.64" to 124°45'57.24"E, and It is an include some district or city. For the upstream areas, the coverage area is an includes most of the Minahasa district, Minahasa Utara district and Tomohon city. Meanwhile, for the downstream areas, the coverage area is an includes most of the Manado city. The Tondano watershed area is about 54,108 Ha, which is divided into four (4) sub-watershed, namely: Tikala, Klabat, Tondano and Noongan (The Management Center of Tondano Watershed—Ministry of Forestry 2014). The number of people living in the Tondano watershed area for the year 2014 was more than 697,893 people and distributed in several districts. Table 1 shown the number of the population living in the Tondano watershed for the year 2014 (Indonesian of Central Agency Statistics (BPS) 2014a, b, c, d).

The geological conditions in North Sulawesi is dominated by limestone sedimentary basin as a unit Raratotok. Other rock types are breccias and sandstones, which consists of rough breccia-conglomerate, interspersed with smooth up rough sandstones, silt stone and clay stone, as well as pyroxene andesite breccia. The group of tuff Tondano has a Pliocene age and consists of fragments of andesitic volcanic rocks that contain pumice, tuff and ignimbrite breccia and andesite lava. In the Quaternary rocks are a group of young volcanic rocks, consisting of andesite-basalt lava, bombs, lapilli and ash. Meanwhile, the youngest rock group has a composition of limestone coral reefs, lakes and rivers and sediment deposition alluvium (Sompotan 2012). Figure 3 shown the geological conditions of the research area, which is part of Sulawesi island, Indonesia.

Method

Data availability

The availabilities of satellite image data were used in this research consists of Landsat 5 TM, Landsat 7 TM, Landsat 8 LDCM and ASTER GDEM, which have a spatial resolution of 30 m. Multi-temporal Landsat image data were used as input for LULC mapping, modeling and prediction of the dynamic LULC change. Meanwhile, the availability of ASTER GDEM data was used as input for flood modeling in the research area. Table 2 shown the availability of satellite image data were used in this research.

Fig. 3 Geological map of Sulawesi, Indonesia (Source: Hall and Wilson 2000; Sompotan 2012)

Table 2 The availability of satellite image data were used in this research

Date type	Spatial resolution (m)	Path and row	Acquisition date	Source
Landsat 5 TM	30	112, 059	June 04, 1997	USGS
Landsat 7 TM	30	112, 059	May 25, 2002	USGS
Landsat 7 TM	30	112, 059	July 28, 2002	USGS
Landsat 8 LDCM	30	112, 059	January 29, 2015	LAPAN
Landsat 8 LDCM	30	112, 059	April 03, 2015	LAPAN
Landsat 8 LDCM	30	112, 059	May 21, 2015	LAPAN
ASTER GDEM	30	N01, E124	October 17, 2011	Japan space systems

Data processing and analysis

Pre-processing satellite images

The pre-processing stages in this research were conducted by converting the value of Digital Number (DNs) into the reflectance values of Top of Atmosphere. In the standard product Landsat 5 TM and Landsat 7 TM imagery have DNs format 8-bit unsigned integer. Meanwhile, the standard product of Landsat 8 LDCM imagery has DNs format 16-bit unsigned integer. The pre-processing stage is done with the purpose to obtain the standard reflectance values, because there are differences in the DNs format of the image data. Thus, the results of the pre-processing data can be used for processing and analysis in the later stages. Landsat data processing in this research was done using the Semi-Automatic Classification Plugin contained on Open Source software Quantum GIS (QGIS) 2.12.2 Lyon and it was released on December 18, 2015 (<http://www.qgis.org/en/site/forusers/download.html>). According to Luca et al. (2013), this plugin is a free plugin for QGIS and it can be used for the semi-automatic supervised classification designed to expedite the processing of multispectral or hyperspectral remote sensing images, which provides a set of tools for pre-processing and post-processing.

In the pre-processing stage was required to change the range of values DNs in the image into reflectance values or radians using radiometric coefficients from the metadata file (MTL_file). The conversion process of DNs values into the reflectance values consists of two stages. The first stage is to convert the DNs values into radian values, and the second stage is to convert the radian values into the reflectance values. Formula to convert DNs values into radian values can be presented in Eq. (1). Meanwhile, the formula to convert the radian value into the reflectance values can be presented in Eq. (2) (Chavez 1988; NASA 2011; Luca et al. 2013; USGS 2013a, b).

$$L\lambda = \left(\frac{(LMAX_{\lambda} - LMIN_{\lambda})}{(Q_{Calmax} - Q_{Calmin})} \right) \times (Q_{Cal} - Q_{Calmin}) + LMIN_{\lambda} \quad (1)$$

where $L\lambda$ is the spectral radiance at the sensor's aperture. Q_{Cal} is the quantized calibrated pixel value. $LMIN_{\lambda}$ is the spectral radiance that is scaled to Q_{Calmin} . $LMAX_{\lambda}$ is the spectral radiance that is scaled to Q_{Calmax} . Q_{Calmin} is the minimum quantized calibrated pixel value. Q_{Calmax} is the maximum quantized calibrated pixel value.

$$\rho = [\pi \times (L_{\lambda} - L_p) \times d^2] / (ESUN_{\lambda} \times \cos\theta_s) \quad (2)$$

where ρ is the land surface reflectance for Landsat images. L_{λ} is the at satellite radiance. L_p is the path radiance. d is the earth to sun distance in astronomical units. $ESUN_{\lambda}$ is

the mean solar Exo-atmospheric irradiances. θ_s is the solar zenith angle.

The classification process for Land use/land cover mapping

At this stage, the multi-temporal of Landsat imagery were used as input for processing and classification of LULC mapping. The processing is done by the individual training areas. The maximum likelihood (ML) was used as a classification algorithm on the semi-automatic classification plugin, which is part of the supervised classifier categories.

According to Richards and Jia (2006), Huang et al. (2009), and Luca et al. (2013), the ML algorithm is used the Gaussian threshold stored in each class signature to assign every pixel class, which assumed that the probability distribution for the classes of the models form of multi-variate normal. ML algorithm can be presented in Eqs. (3) and (4).

$$G_i(x) = \ln p(\omega_i) - \frac{1}{2} \ln \left| \sum_i \right| - \frac{1}{2} (x - m_i)^t \sum_i^{-1} (x - m_i) \quad (3)$$

Therefore:

$$x \in \omega_i \text{ if } g_i(x) > g_j(x) \text{ for all } j \neq i \quad (4)$$

where $G_i(x)$ is the discriminant function in ML algorithm. ω_i is the class, where $i = 1, \dots, M$ and M is the total number of classes. x is the vector pixel in n -dimensional, where n is the number of bands. $p(\omega_i)$ is the probability that the correct class, in ω_i for a pixel at position x . $|\sum_i|$ is the determinant of the covariance matrix of the data in class ω_i . $\sum_i^{-1}$ is the inverse of the covariance matrix. m_i is the mean vector.

Modeling and prediction of the dynamic land use/land cover change

In this research, modeling and prediction of the dynamic LULC change has been carried out by using a Markov-CA. LULC maps in 1997 and 2002, which is the results of multi-temporal classification of Landsat imagery, were used as input data for the modeling and prediction LULC in the next years. Meanwhile, LULC map in 2015 that is the classification result of Landsat imagery in 2015 was used as a reference map to describe the condition LULC today. The reference of LULC map was used to perform the calculation of the accuracy assessment LULC in 2015 with Markov-CA approach.

Markov-CA approach is a combination model of Markov Chain and Cellular Automata approach, which can be used to predict and simulate LULC change in several next year (Behera et al. 2012; Yang et al. 2014). The Markov

Chain model is a stochastic process model that can describe the probability of a change from one object to another. The model is one of the recommended methods for modeling LULC based on the use of the time evolutionary trend. It means that the time ($t - 1$) to time (t) can be used as input probability LULC change, which is further used for LULC

prediction in the next year ($t + 1$) (Thomas and Laurence 2006; Behera et al. 2012). Cellular Automata is a part of the essential elements of geo-spatial, which focus on the variations in the dynamics of change and it is able to simulate the characteristics of the spatial-temporal complex system and it cannot be represented by a specific

Table 3 The parameter data were used for simulation of the probability of flood inundation using a Monte Carlo algorithm in the upper boundary Tondano river

Return periods (years)	Volume (m ³)	Maximum flow length (m)	Start iteration position (X; Y)	Height correction for water level (Hc)	The number of iterations	
					3 m	5 m
2	91,411,390	7435	711593; 163768	3 m, 5 m	33,800	20,300
5	107,900,660	7435	711593; 163768	3 m, 5 m	40,000	24,000
10	120,547,770	7435	711593; 163768	3 m, 5 m	44,800	26,800
20	133,995,330	7435	711593; 163768	3 m, 5 m	49,600	33,700
50	153,526,310	7435	711593; 163768	3 m, 5 m	57,000	38,200
100	169,695,400	7435	711593; 163768	3 m, 5 m	62,900	42,500

Source: summarized and modified data from Nanlohy et al. 2008

Fig. 4 The results of LULC map using maximum likelihood supervised classification on Landsat imagery. **a** LULC in the year 1997. **b** LULC in the year 2002

Fig. 5 Comparison between LULC classification was used as a reference map, with the LULC class was generated from the modeling Markov-CA approach. **a** LULC map in the year 2015 (reference map). **b** LULC map in the year 2015 (model map)

Table 4 The estimate area of LULC changes for the year 1997–2015 in the research area

LULC Class	Year		
	1997 Area (ha) ^a	2002 Area (ha) ^a	2015 Area (ha) ^a
Forest	16,498.44 (29.20)	15,617.37 (27.64)	14,305.65 (25.32)
Dry land	9390.15 (16.62)	10,181.44 (18.02)	10,596.88 (18.76)
Bare soil	587.61 (1.04)	810.01 (1.43)	946.36 (1.67)
Plantation	12,487.05 (22.10)	13,309.27 (23.56)	13,591.90 (24.06)
Settlement	2811.42 (4.98)	3270.47 (5.79)	3957.39 (7.00)
Paddy fields	6660.54 (11.79)	5095.80 (9.02)	4714.21 (8.34)
Shrubbery	3651.84 (6.46)	3721.96 (6.59)	3836.89 (6.69)
Water body	4413.96 (7.81)	4494.69 (7.96)	4551.74 (8.06)
Total	56,501.01 (100)	56,501.01 (100)	56,501.01 (100)

^a Percentage area

equation (Mousivand et al. 2007; Arsanjani et al. 2013; Yang et al. 2014). In this research, the modeling LULC have been processed by the tools of Markov-CA module contained in the IDRISI Andes software, which is developed by Clark Labs at Clark University.

Implication for the flood damage assessment

Their implication for flood damage assessment in the research area has been carried out by calculating the impact of flooding inundation of the LULC, which can scripted

Table 5 The estimate of the average rate area of LULC changes for the year 1997–2015 in the research area

LULC class	Change area (ha)		Average area (ha/year) 1991–2015
	1997–2002	2002–2015	
Forest	−881.07	−1311.73	−121.82
Dry land	+791.29	+415.44	+67.04
Bare soil	+222.40	+136.35	+19.93
Plantation	+822.22	+282.63	+61.38
Settlement	+459.05	+686.93	+63.67
Paddy fields	−1564.74	−381.60	−108.13
Shrubbery	+70.12	+114.93	+10.28
Water body	+80.73	+57.05	+7.65

‘−’ decrease; ‘+’ increase

Table 6 The accuracy of the Kappa index for the LULC map in 2015, which is the result of the maximum likelihood supervised classification and corrected by using high-resolution imagery from Google Earth

LULC Classes	Reference								Total
	Forest	Dry land	Bare soil	Plantation	Settlement	Paddy fields	Shrubbery	Water body	
Forest	151	3	−	16	−	−	−	−	170
Dry land	−	70	−	2	−	11	1	−	84
Bare soil	1	0	6	1	2	1	2	1	14
Plantation	3	1	1	55	1	4	1	−	66
Settlement	−	−	−	1	49	−	−	−	50
Paddy fields	−	8	2	7	1	62	4	1	85
Shrubbery	4	1	3	2	−	4	26	−	40
Water body	−	−	−	−	−	−	−	39	39
Total	159	83	12	84	53	82	34	41	548

and predictable for the next few years. In this research, flood inundation scenarios have been created by the Monte Carlo algorithm approach. Flood inundation modeling with the Monte Carlo algorithm approach does not require complex parameters and does not require long processing times, as it has been applied to some previous studies (e.g., Smemoe et al. 2007; Kalyanapu 2011; Yulianto et al. 2015b). The use of Monte Carlo algorithms previously were conducted by Felpeto et al. (2007) and Felpeto (2009) to simulate an inundation on the lava flows. The algorithm model is a probabilistic model, with the assumption that the topographic conditions have a dominant factor for determining the material flows.

In this research, topographic data can be represented by ASTER GDEM, with a spatial resolution of 30 m. In addition, several other parameters were used to run the Monte Carlo algorithm, e.g., maximum flow length, location to start iteration, height correction for water level scenario and the number of iterations. Table 3 shown the

parameter data were used for simulation of the flood probability using a Monte Carlo algorithm in the upper boundary Tondano river. The probability of flood inundation using a Monte Carlo algorithm can be presented in Eqs. (5)–(7) (Felpeto 2009; Yulianto et al. 2015b).

$$P_i = \frac{\Delta h_i}{\sum_{j=1}^8 \Delta h_j} \quad (5)$$

$$\Delta h_i = h_0 + h_c - h_i \quad \text{if } (h_0 + h_c - h_i) > 0 \quad (6)$$

$$\Delta h_i = 0 \quad \text{if } (h_0 + h_c - h_i) \leq 0 \quad (7)$$

where P_i is the probability of material flows. h_i is the topography represented by the value of the height (h) of a cell in the DEM data located in the cells $i = 0$ and $i = 1, 2, 3, \dots, 8$. Δh is the height difference between the cell with a cell-neighboring. h_c is the height correction.

The numbers of iteration were determined by the approximation formula. The formula was developed by Zhu (2010) and it has been applied by Seniarwan and

Gandasmita (2013) and Yulianto et al. (2015b) to simulate the inundation models. This formula can be presented in Eqs. (8) and (9).

$$f(H) = Q - V = Q - \sum_{i=1}^m Ax(H_i - E_i) \quad (8)$$

$$V = \sum_{i=1}^m Axhc \quad (9)$$

where $f(H)$ is the function of the equation to analyze the flood inundations height (H), which is based on the ratio between the volume grooves topography (V) and the volume of the flood source (Q). H_i is the accumulation of flood inundation height between the h_c and the DEM elevation E_i in unit pixels i and $i = (1, 2, 3, \dots, n)$. m is the number of units pixels or pixel iterations required. A is the area of the unit pixels.

The flood damage assessment can be created using overlaying the maps of flood inundation model under scenario return periods: 2, 5, 10, 20, 50 and 100 years with the maps of LULC modeling under scenario for the 2015, 2025, 2035 and 2050 years. Based on the results of the overlay can be estimated LULC affected by floods for several next year. The value of assets has been calculated with reference to the research conducted by Marfaei and King (2007) and Ward et al. (2011) and we have the same assumptions for asset values in the research area with the Semarang and Jakarta, Indonesia.

The value of assets for settlement was estimated to be ca. €1.2 million per hectare, for agriculture (e.g., paddy field, dry land and plantation) was estimated to be ca. €80,000 per hectare, and also for open area (e.g., bare soil and shrubbery) was estimated to be ca. €1700 per hectare. The absolute value of exposure damage estimated in this research are considered as an indication. Exposure damage was estimated based on the actual market value per hectare in each class LULC. However, these estimates give a good impression of exposure damage on LULC changes due to flooding.

Results

Land use/land cover mapping in the research area

In this research, the dynamics LULC change can be described using LULC maps in the year 1997, 2002 and 2015, which is the result of the maximum likelihood classification of Landsat imagery. Spatially, the dynamics LULC change from the year 1997 to 2015 can be presented in Figs. 4 and 5a. Meanwhile, the estimate area for LULC changes in the year 1997 to 2015 can be presented in

Fig. 6 LULC maps from the modeling using Markov-CA approach. **a** LULC map prediction for the year 2025. **b** LULC map prediction for the year 2035. **c** LULC map prediction for the year 2050

Tables 4 and 5. It can be shown that for LULC class on forest and paddy fields have experienced a decrease in the extent of 1997–2015, with an average change of area: 121.82 and 108.13 ha/year, respectively. Meanwhile, LULC class on dry land, bare soil, plantation, settlement, shrubbery and water body have experienced an increase with an average change of area: 67.04, 19.93, 61.38, 63.67, 10.28 and 7.65 ha/year, respectively.

Modeling and prediction of the dynamic land use and land cover change

Modeling and prediction of the dynamic LULC change have been created with Markov-CA approach. LULC maps in the year 1997 and 2002 were used as input data for LULC mapping in the next few years. Meanwhile, LULC map in the year 2015 was used as a reference map to determine the accuracy assessment of LULC model in the year 2015 from Markov-CA approach. The accuracy of the LULC reference in 2015 has been determined based on 548 sample location in the research area. At the sample location, LULC map in 2015 can be corrected by using high-resolution imagery from Google Earth. The results of calculation were performed by using the Kappa index obtained accuracy of 80.11 %, with the real similarity object of 83.57 % and inequality objects of 16.43 %. Table 6 shown the accuracy of the Kappa index on the LULC map in 2015, which is the result of the maximum likelihood supervised classification. Furthermore, the accuracy assessment of the LULC map from Markov-CA approach can be calculated using cross-confusion matrix between LULC reference in 2015 to LULC model in 2015 and it can be shown that the accuracy LULC model of 75.88 %. Figure 5 shown the comparison between LULC classification was used as a reference map, with the LULC class was generated from the modeling Markov-CA approach. Meanwhile, the result of the LULC prediction in 2025, 2035 and 2050 can be shown in Fig. 6.

Based on the results of modeling and prediction LULC using Markov-CA approach, the estimate area for LULC changes in the year 2015–2050 can be presented in Tables 7 and 8. It can be shown that for LULC class on the forest, dry land, paddy fields and shrubbery have predicted a decrease in the extent of 2015–2050, with an average change of area: 10.52, 13.22, 14.49 and 1.15 ha/year, respectively. Meanwhile, LULC class on bare soil, plantation, settlement and water body have predicted an

Table 7 The estimate area of LULC changes for the year 2015–2050 in the research area, which is the result of Markov-CA approach

LULC class	Year			
	2015 Area (ha) ^a	2025 Area (ha) ^a	2035 Area (ha) ^a	2050 Area (ha) ^a
Forest	14150.82 (25.05)	14012.89 (24.80)	13884.33 (24.57)	13782.46 (24.39)
Dry land	9567.41 (16.93)	9527.44 (16.86)	9432.80 (16.69)	9104.78 (16.11)
Bare soil	763.82 (1.35)	787.82 (1.39)	930.16 (1.65)	1025.41 (1.81)
Plantation	11461.22 (20.28)	11561.19 (20.46)	11667.34 (20.65)	11851.05 (20.97)
Settlement	5476.19 (9.69)	5546.91 (9.82)	5558.26 (9.84)	5878.28 (10.40)
Paddy fields	7138.69 (12.63)	6968.71 (12.33)	6842.73 (12.11)	6631.38 (11.74)
Shrubbery	3643.86 (6.45)	3615.60 (6.40)	3603.49 (6.38)	3603.28 (6.38)
Water body	4275.00 (7.57)	4504.47 (7.97)	4582.12 (8.11)	4624.16 (8.18)
Total	56,501.01 (100)	56,501.01 (100)	56,501.01 (100)	56,501.01 (100)

^a Percentage area**Table 8** The estimate of the average rate area of LULC changes for the year 2015–2050 in the research area, which is the result of Markov-CA approach

LULC class	Change area (ha)			Average area (ha/year)
	2015–2025	2025–2035	2035–2050	
Forest	–137.93	–128.56	–101.86	–10.52
Dry land	–39.97	–94.64	–328.02	–13.22
Bare soil	+24.00	+166.34	+95.25	+6.79
Plantation	+99.96	+106.15	+183.71	+11.14
Settlement	+70.71	+11.35	+320.02	+11.49
Paddy fields	–169.98	–125.98	–211.34	–14.49
Shrubbery	–28.26	–12.32	–0.21	–1.15
Water body	+229.47	+77.65	+42.04	+9.97

‘–’ decrease; ‘+’ increase

increase with an average change of area: 6.79, 11.14, 11.49 and 9.7 ha/year, respectively.

Implication for flood damage analysis

In this research, flood modeling has been performed by the Monte Carlo algorithm approach. Flood modeling scenario was created based on the annual flood for periods, namely: 2, 5, 10, 20, 50 and 100 years. The water level in the modeling has been created by scenarios $H_c = 3$ m and $H_c = 5$ m. Selection of the height flood inundation scenarios has been conducted based on observations of the real flood conditions in the field, which had occurred on January 15, 2014. The results showed that the height of the flood at the time of the incident almost reached the roof of the house settlements, which has a height of 3 m. One of these conditions can be shown in Fig. 7, which is heavily populated locations in Malendeng village. In addition, the height of the flood inundations has also reached about 5 m at the time of the flood event on January 15, 2014. These conditions can be shown in Fig. 8, which is one of the nearest settlement to the banks of the Tondano river. The results of the flood modeling

with the return periods and the height flood inundation scenarios can be shown in Figs. 9 and 10.

The implementation of flood inundation modeling can be used to determine the flood damage assessment on LULC affected by flooding in the research area. This result can be predicted on the impact of floods in each LULC class for year 2015, 2025, 2035 and 2050. Thus, the impact of floods in the future can be predicted. The results of overlay between the flood inundation maps with the LULC maps have produced LULC information affected by floods, which can be presented in Fig. 11. Meanwhile, the results of the damage exposure estimation at each flood scenario that is calculated based on the market value per hectare in each LULC class can be presented in Tables 9, 10, 11, 12, 13 and 14. It can be shown that the total of flood damage exposure for the water level scenario $H_c = 3$ m with the return periods 2, 5, 10, 20, 50 and 100 years are more than €424, €438, €499, €509, €511 and €520 million, respectively. Meanwhile, for the water level scenario $H_c = 5$ m with the return periods 2, 5, 10, 20, 50 and 100 years are more than €915, €922, €924, €947, €957 and €958 million, respectively.

Fig. 7 The height of flood inundation of 3 m at the time of the flood event on January 15, 2014. **a** During flood in Tikala river, Malendeng village. **b** Post flood in Tikala river, Malendeng village (photos from

The Management Center of Tondano Watershed—Ministry of Forestry 2014)

Fig. 8 The height of flood inundation of 5 m at the time of the flood event on January 15, 2014. **a** During flood in Tondano river, Kairagi village. **b** Post flood in Tondano river, Kairagi village (photos from The Management Center of Tondano Watershed—Ministry of Forestry 2014)

Discussion

This research has produced information related to the dynamics of LULC change modeling and their implication for the flood damage assessment. In this section, we will discuss related limitations, uncertainty and future direction for the use of methods that have been applied in the research area.

The results of LULC information that has been generated in this research, there are limitations. These limitations are related to the use of Markov-CA approach which does not include the parameters and factors that could affect or inhibit the occurrence of the LULC change in the research area. Thus, the resulting of LULC map updates in the next few years are assumed to be linear and the results are a scenario with a normally indication, without any triggering factor and inhibit the occurrence of the LULC change. This can be shown on difference in the average area change

between the results of LULC classification in 1997–2015 with the results of LULC modeling in 2015–2050. Where, the average area change of the LULC classification in 1997–2015 is tending to relatively large. Meanwhile, the average area change of the LULC modeling in 2015–2050 is tending to relatively small. As an example for class of forest and paddy fields, the LULC classification in 1997–2015 had a rate of change: 121.82 and 108.13 ha/year, respectively. Meanwhile, the LULC modeling in 2015–2050 had a rate of change: 10.52, 14.49 ha/year, respectively. It can be used as input for future research in the research area to add the factors and parameters that can trigger factor and inhibit the occurrence of the LULC change. Thus, the information on the prediction and modeling LULC maps that will be able to provide good accuracy and precision (note: the result of the accuracy by using cross-correlation matrix between the LULC models in 2015 with the LULC reference in 2015 is 75.88 %), as has

Fig. 9 The results of flood inundation modeling using the Monte Carlo algorithm with the height flood scenario $H_c = 3$ m. **a** Flood scenario return period 2 years. **b** Flood scenario return period 5 years.

c Flood scenario return period 10 years. **d** Flood scenario return period 20 years. **e** Flood scenario return period 50 year. **f** Flood scenario return period 100 years

been done by several previous studies (e.g., Guan et al. 2011; Halmy et al. 2015)

The limitations of the flood inundation models were used in this research, namely: (a) modeling was performed on the segment of the Tondano river with a range point of

downstream boundary to the point of the upper boundary Tondano river, (b) the Tikala river has been modeled as lateral inflow into Tondano river, (c) the existence of drainage, tributary and bridges in the segment of the Tondano river were ignored. These limitations have the same with the

Fig. 10 The results of flood inundation modeling using the Monte Carlo algorithm with the height flood scenario $H_c = 5$ m. **a** Flood scenario return period 2 years. **b** Flood scenario return period 5 years.

c Flood scenario return period 10 years. **d** Flood scenario return period 20 years. **e** Flood scenario return period 50 years. **f** Flood scenario return period 100 years

research created by Nanlohy et al. (2008). Map of flood inundation models that have been created by using the Monte Carlo approach presents a static and not dynamic modeling. In addition, the limitations of the resulting model can only present the distribution of flood inundation that is shown with

a probability value at each scenario in the running. Where, at a value of 0 indicates a low probability and value of 1 indicates a high probability. Thus, the depth of flood information is not available in this model. However, the modeling can provide relatively quick benefits of generating flood

Fig. 11 The results of overlay between the flood inundation maps with the LULC maps have produced LULC information affected by floods in the research area. **a** Flood scenario return period 2 years.

b Flood scenario return period 5 years. **c** Flood scenario return period 10 years. **d** Flood scenario return period 20 years. **e** Flood scenario return period 50 years. **f** Flood scenario return period 100 years

Table 9 The damage exposure estimation of the flood scenario return period 2 years and LULC model prediction in 2015, 2025, 2035 and 2050 (value in 1000 EUR)

LULC	Return period 2 years, Hc = 3 m				Return period 2 years, Hc = 5 m			
	2015	2025	2035	2050	2015	2025	2035	2050
Dry land	232	224	264	192	640	600	808	400
Bare soil	61	54	65	37	137	120	138	98
Plantation	2992	3472	3464	2784	6648	7528	7680	5896
Settlement	412,680	414,600	417,960	449,760	883,320	886,080	891,360	956,880
Paddy fields	8784	8520	7656	7720	24,240	23,896	22,000	22,080
Shrubbery	31	33	34	30	106	109	117	110
Total	424,780	426,903	429,443	460,523	915,091	918,334	922,103	985,464

inundation models. It is suitable for rapid mapping required during emergency response. The results of the flood inundation modeling have not been validated in this research.

Thus, the field of measurement and observation for model validation is required and recommended in the future research.

Table 10 The damage exposure estimation of the flood scenario return period 5 years and LULC model prediction in 2015, 2025, 2035 and 2050 (value in 1000 EUR)

LULC	Return period 5 years, Hc = 3 m				Return period 5 years, Hc = 5 m			
	2015	2025	2035	2050	2015	2025	2035	2050
Dry land	240	224	256	200	768	696	952	440
Bare soil	58	51	62	35	139	118	139	114
Plantation	3040	3520	3528	2816	6904	7936	8112	6136
Settlement	426,360	427,680	431,760	462,960	889,560	891,000	893,400	955,440
Paddy fields	8704	8432	7632	7640	25,384	25,096	23,280	23,312
Shrubbery	26	29	28	26	112	117	125	116
Total	438,428	439,936	443,266	473,677	922,867	924,963	926,008	985,558

Table 11 The damage exposure estimation of the flood scenario return period 10 years and LULC model prediction in 2015, 2025, 2035 and 2050 (value in 1000 EUR)

LULC	Return period 10 years, Hc = 3 m				Return period 10 years, Hc = 5 m			
	2015	2025	2035	2050	2015	2025	2035	2050
Dry land	296	264	320	200	648	624	856	344
Bare soil	70	62	73	43	133	116	134	103
Plantation	3112	3616	3584	2912	6400	7328	7544	5688
Settlement	485,880	488,520	492,360	525,000	892,920	893,400	897,120	960,720
Paddy fields	10,008	9688	8816	8936	24,672	24,392	22,536	22,624
Shrubbery	32	34	34	32	100	104	113	104
Total	499,398	502,184	505,187	537,123	924,873	925,964	928,303	989,583

Table 12 The damage exposure estimation of the flood scenario return period 20 years and LULC model prediction in 2015, 2025, 2035 and 2050 (value in 1,000 EUR)

LULC	Return period 20 years, Hc = 3 m				Return period 20 years, Hc = 5 m			
	2015	2025	2035	2050	2015	2025	2035	2050
Dry land	296	264	336	208	704	648	880	416
Bare soil	71	62	74	45	146	128	146	111
Plantation	3216	3712	3704	3000	6480	7400	7640	5712
Settlement	496,320	498,120	501,600	538,680	914,400	916,560	921,480	987,240
Paddy fields	9616	9408	8456	8336	25,424	25,024	23,080	23,192
Shrubbery	33	35	36	32	106	112	120	111
Total	509,551	511,601	514,206	550,301	947,260	949,872	953,345	1,016,783

Table 13 The damage exposure estimation of the flood scenario return period 50 years and LULC model prediction in 2015, 2025, 2035 and 2050 (value in 1000 EUR)

LULC	Return period 50 years, Hc = 3 m				Return period 50 years, Hc = 5 m			
	2015	2025	2035	2050	2015	2025	2035	2050
Dry land	328	304	360	208	712	696	928	416
Bare soil	69	61	73	43	138	120	140	110
Plantation	2992	3480	3480	2792	7024	8032	8176	6200
Settlement	498,600	499,560	504,120	538,680	923,520	925,680	927,720	992,760
Paddy fields	9880	9680	8728	8768	26,368	26,016	24,080	24,272
Shrubbery	28	30	30	27	116	118	130	120
Total	511,897	513,115	516,790	550,518	957,878	960,662	961,174	1,023,878

Implementation of the uses of LULC and flood inundation modeling was estimated flood damage assessment in the research area. The process is done in a simple, namely: overlay between the flood inundation model with the LULC model that has been calculated for the next few

years. Thus, the information of LULC affected by flooding can be determined in the research area. Estimates of flood damage exposure for the next few years has been calculated based on the asset value per hectare under current conditions in each LULC class. The results obtained by the

Table 14 The damage exposure estimation of the flood scenario return period 100 years and LULC model prediction in 2015, 2025, 2035 and 2050 (value in 1000 EUR)

LULC	Return period 100 years, Hc = 3 m				Return period 100 years, Hc = 5 m			
	2015	2025	2035	2050	2015	2025	2035	2050
Dry land	296	288	376	208	720	672	912	424
Bare soil	70	61	71	45	147	129	147	111
Plantation	3144	3608	3592	2896	6880	7872	7984	6032
Settlement	506,040	506,880	512,760	547,080	923,880	925,920	929,280	997,440
Paddy fields	10,472	10,320	9240	9184	26,512	26,160	24,192	24,416
Shrubbery	33	35	37	32	117	120	132	121
Total	520,054	521,191	526,075	559,446	958,256	960,873	962,647	1,028,544

flood scenario in extreme conditions for the return period of 100 year, the total of flood damage exposure can be estimated more than €520 million for the water level scenario Hc = 3 m and €958 million for the water level scenario Hc = 5 m. The market value of each class of LULC has not been done in detail. Thus, the limitations can be shown by the incorporation of market value in agricultural class (e.g., paddy fields, plantations and dry land) and the open area class (e.g., bare soil and shrubbery). It is necessary and recommended in the future research to focus in calculating the asset value for each LULC class in detail.

Conclusion

Markov-CA and Monte Carlo algorithm approaches have been successfully used in this research to create LULC and flood modelling, which can then be implemented to estimate the flood damage assessment for the next few years. The utilization of multi-temporal remotely sensed Landsat and ASTER GDEM have supported the acquisition of input data for modeling created by Markov-CA and Monte Carlo algorithm approaches. The results of LULC and flood modeling in this research could be used to support the mapping at a scale of 1:25,000–1:50,000. In the future research, it is advisable and recommended to use multi-temporal remotely sensed data with high resolution, such as Ikonos, Quickbird, Worldview, Pleiades and others. Thus, the need modeling for detailed mapping or less than scale 1:10,000 can be fulfilled. In addition, the use of stereo imagery from SPOT 6 and 7 with a spatial resolution of 6 m can be used for detailing topography information or DEM in the research area. The requirement of DEM data with a spatial resolution of less than 10 m is needed in flood modeling. Thus, the accuracy of the results of flood modeling can be improved and increased. The results of LULC modeling and their implication not only used for estimating the flood damage assessment, but also the results can be used to predict the flow discharge of flooding due to LULC changes for the next few years. Thus, in the future research can be suggested and recommended to

predict the flow discharge of flooding due to LULC changes, and the results can be used as one of the stages in the flood mitigation effort in the research area.

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