Conference Paper

Object Oriented Land Use Change Modelling Of Residential Areas (Case Study : Banyumanik Sub-District, Semarang City)

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Abstract

Land Use change marked by the shift of land usage to another. Banyumanik Sub-district is an administrative areas in southern part of Semarang City with higher elevation compared to City Center. The increase of tidal flood caused changes the land use of Banyumanik to residential. In this study we try to model the land use change of Banyumanik using Land Use and Land Cover Changes (LULCC) Packages in R. Using land use of 2011, 2013, and 2016 as input, elevation, slope, and distance to road as parameters, and population data for growth analysis. This study consists of firstly, study area extraction from input and rasterization. Secondly change probability model creation and comparison of population changes to residential changes, Lastly, obtaining actual change and the probability models in the form of maps and charts that describes the land use change in the future as probability model. The land use change to residential does not cope the population growth, and resulting a higher population density. We also found a temporal pattern of residential occurance over residential probability, where occurance slightly decreases as the probability rises, but jumps for the highest probability. Between 2011 and 2013, from area of $0.126km^2$ to $0.165km^2$. And between 2013 to 2016, it also shift from $0.177km^2$ to $0.286km^2$. It can be concluded that a general increment also took place to the existing pattern.

Keywords: land use change, remote sensing, Banyumanik Sub-district, r statistics, object oriented model, LULCC

1. Introduction

Land use change is generally caused by the increase of population which pushes requirements such as residential [1]. The dynamic aspect of the temporal phenomenas are residential shift caused by a difference between what residential occupants needs and what is available, and properties of its present housing condition [2]. How population increases relatively easy, but relating them to residential change are challenging. The observation of Land Use Changes are A fields of study that consist of spatial analysis [3]

How to cite this article: Andri Suprayogi and Sawitri Subiyanto, (2019), ``Object Oriented Land Use Change Modelling Of Residential Areas (Case Study : Banyumanik Sub-District, Semarang City)'' in *The 1st International Conference on Geodesy, Geomatics, and Land Administration 2019*, KnE Engineering, pages 303–312. DOI 10.18502/keg.v4i3.5870

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image analysis [4], software development and algorithm [4] that requires programming skills [5].

The Land Use and Land Cover Changes (LULCC) packages are developed for modelling the changes of Land Use based on Object oriented programming [5]. It is a library package that works as modules in the R Statistics, a freeware application generally use for data processing in a multiplatform environment such as Windows and Linux. The LULCC can process data to obtain change values, change probability models, and test the model [6]. This library have demo script for learning purposes with supplied data.

The Goal of this study is using LULCC to obtain Land Use Changes model from processable object data with the aim of several analytical parameters. One of them are as the process condition (data size, memory usage, and process performance) to obtain situational review of the implementation of LULCC. Aside from obtaining the figure of probability to actual residential changes, We also observe the residential changes corresponds to the population changes in the area study.

2. Methodology

2.1. Area Study

Semarang City is the capital of Centra Java Province, Indonesia, That Consist of Banyumanik District, that lies in the southern part of the city, next to Ungaran District. Recorded in **Semarang City In Figure**, there are rise of population [2] in this district for the year of 2016 and 2013 compared to 2011 [7]. The rise can be considered low between 2011 to 2013, but relatively higher between 2013 to 2016 as shown in Figure 1.
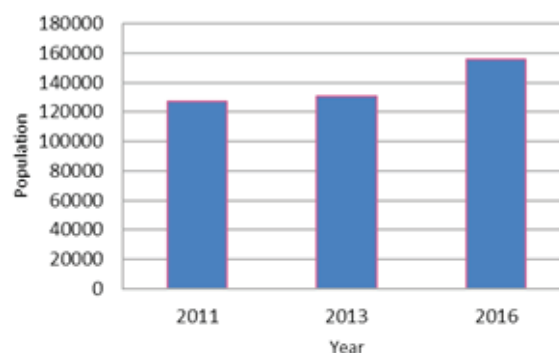
Figure 1: Population Increments in Banyumanik Sub-District.

The condition of Banyumanik District according to the DEMNAS elevation parameter being used are considered have high elevation relatively to Semarang City central areas, with mean elevation of 183.7 meters, minimum of 30.2 meters and maximum 360 meters.

It is one of the area of Semarang City that free from tidal waves. According to the slopes histogram, the Banyumanik consist of few flat areas shown as rapid increment of pixel count correspond to slope increments towards 4 and 5 degrees as slope with largest pixel count. Many parts of study areas have higher slope than the maxima, shown as steady decrease of pixel count of slope increments from mean to maximum slope as shown in Figure 2. In this figure, x-axis denote slopes in degrees, while y-axis denote pixels count.
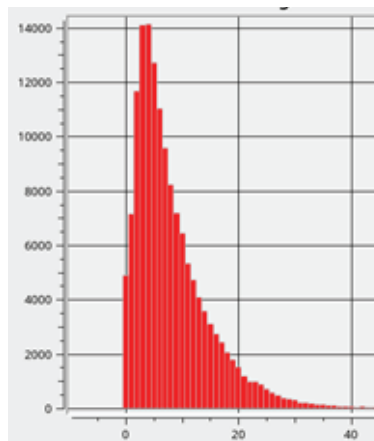
Figure 2: Banyumanik Sub-District Slope Histogram.

2.2. Study Environment

In this study, we use R version 3.6.1 executed in Rstudio version 1.2.13335 in Linux Mint 19.1 environment. The Rstudio makes the usage of R easier since the available GUI replaces some of the R script, especially functions of the applications such as installing and updating R packages. For the simplification and rasterization of Land Use data and parameters, we use QGIS 3.6.2 for Linux. The hardware we use are mainly a desktop with Intel Quad Core i7-3770 supported by 12 GB DDR4 RAM and connected to the internet, allowing us to install and update application from Linux and CRAN repository mirror. Using system monitor in this environment, we found that the process of LULCC were utilizing only a single core as shown in Figure 3. R and required packages can be seen having a single threaded execution

2.3. Processing and Modelling

In general, data processing consist of preparation and creating observation data. In the preparation we simplify each 2011, 2013, and 2016 land use data. Each records of the
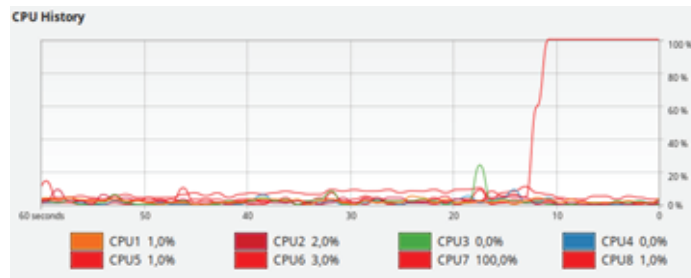
Figure 3: CPU Load percentage.

land use were reclassified into two categories, the residential as our primary focus, and non residential, a merged class of other land use. Meanwhile, from a DEMNAS elevation data, we calculate the slope of area study and from the road data, we create multiple 5 meter buffers with 5 class to create distance data. The elevation, slope, and distance data have a role as change parameters and required in formula creation stages later in the modelling process. As the data except elevation and slope are still in vector, we convert them to geotiff image in 16 bit with spatial resolution of 5 meter as shown in Figure 4.
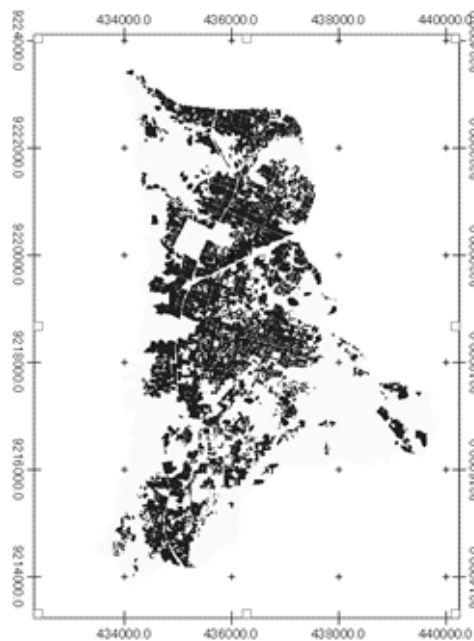

Figure 4: Residential Areas Of Banyumanik Sub-District in 2011.

The LULCC procedures guide can be found in [5]. In terms of processing stages, we change the demo data with our own to obtain observation data in Banyumanik Subdistrict. This approach consist of creating objects of layer stack and observation data. For the Layer Stack, we load all image data into R Workspace, then we create a layer stack Objects with properties that consist of both Land Use and change parameters with list commands

```
LU_201* <- raster("/media/gp-d18/Data/Penelitian2019/2.Rasterized/merged_201*_5m.tif")
ef_00** <-  raster("/media/gp-d18/Data/Penelitian2019/1.d.EF_Data/ef_001_5m.tif")
LUstack <-list(LU_2011,LU_2013,LU_2016,ef_001,ef_002,ef_003)
#* corresponding year, 1 for 2011, 3, for 2013, 6 for 2016
#** corresponding parameters, 1 for elevation, 2 for slopes, and 3 for the distance
```

The list command does not label the content of the LUstack object properly, we need to manually add names for each layer inside LUstack using Name commands, for example the Land Use layer of year 2011 below

```
names(LUstack)[1] <- "LU_2011"
```

Observation object data **obs** were generated from LUstack object. With additional options of that consist of pattern, categories, labels, and time. Firstly, the pattern for filtering only Land Use Layer, Secondly, the categories separate every Land Use layer values into class 0 or 1, identified with the labes of non residential and residential. Lastly, the t denotes time where first data always 0, and other time increment from the time 0, with unit in years.

```
obs<-ObsLulcRasterStack(LUstack, pattern = "LU", categories=c(0,1),labels = c("non_resident", "resident"),
t=c(0,2,5))
```

From the observation, we can observe the of land use changes using crosstab matrix. In this stage we count the crosstabs between the 2011 and 2013, and also 2011 to 2016. The crosstabs show Land use changes in pixel unit. From this crosstabs, we calculate the change that occurs within the corresponding duration as shown in Table 1. The number in the table indicate changes from a class to other. It can be seen that during the 2011 and 2013 there are 19443 pixel that changes class from non residential to residential. On the contrary, only 811 pixels are changes from residential to non residential. This indicates that more change are taken place towards resident class with difference of 18,632 pixels or 0,4658 km^2.

```
crossTabulate(x=obs, t=c(0,6))
```

The modelling of land use change are process of creating probability maps. It consist of training data creation from observation with a portion of 10 per cent Land Use data as sample partition in size option. In this stage we only change the formula as it specifically requires layer name to be stated and created from the entire parameter data. A Banyumanik change model were created similar to demo data change model creation

TABLE 1: Crosstab Matrix Of 2011, 2013, And 2016.

	2011-2013		2013-2016	
	non_residential	residential	non_residential	residential
non_residential	749936	19443	722121	28626
residential	811	451598	673	470368
Population changes	3207		25500	

[5]. In this study we use binary logistic regression available from base packages [5]. The formula we use are generically build by subtracting residential parameters, assuming that area with larger slope and longer distance to roads having less desirability for residential areas.

```
ef <- ExpVarRasterList(x=LUstack, pattern="ef")
ef <- resample(ef, obs)
part <- partition(x=obs[[1]], size=0.1, spatial=TRUE)
train.data <- getPredictiveModelInputData (obs=obs, ef=ef, cells=part[["train"]],t=0)
forms <- list(non_resident~ef_001-ef_002-ef_003,resident~ef_001-ef_002-ef_003)
rpart.models <- rpartModels(formula=forms,data=train.data,obs=obs)
probmaps <- predict(object=rpart.models,newdata=all.data,data.frame=TRUE)
```

In the last stages of change modelling, a probability map of areas that likely to change are created from available probability data. we transform the probability data to images in order to visualize it spatially as shown in Figure 5. The value of probability are transferred to a spatially registered points data, and reconstructed as image using rasterize commands. The raster of probability maps are then overlaid with existing land use data of 2013 and 2016 to look for its the closeness with actual changes.

```
points <- rasterToPoints(obs[[1]], spatial=TRUE)
probmaps <- SpatialPointsDataFrame (points, probmaps)
probmaps <- rasterize(x=probmaps, y=obs[[1]],field=names(probmaps))
plot(probmaps)
```

To obtain the correlation between model and actual changes using logical expressions, we first identify the location of changes. Each for the 2011 to 2013 and for the 2013 and 2016. These new residential probability are then extracted from the probability map, allowing us to observe the pixel frequency of actual occurance for each probability as shown in Table 2

```
change_11_13 <- raster(ncols = 1938, nrows = 1284)
change_11_13 <- (LU_2011[[1]] != LU_2013[[1]]) & LU_2013[[1]] == 1
match_13 <- raster(ncols = 1938, nrows = 128)
match_13 <- (change_11_13[[1]]== 1) * probmaps[[2]]
freq(match_13, digit = 2)
```
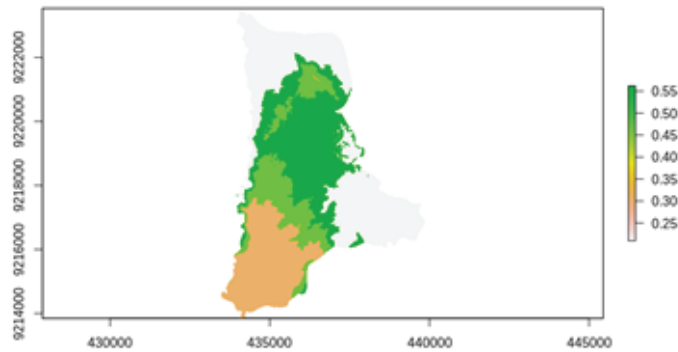
Figure 5: Probability Maps Of Residential Areas In Semarang City.

TABLE 2: Change Frequency Of Probability Class.

Probability Class Central	2011 -- 2013		2013 - 2016	
	Occurance	Change	Occurance	Change
0.21	4984		7068	
0.31	4629	-355	5925	-1143
0.47	3217	-1412	4176	-1749
0.56	6613	3396	11457	7281

3. Result and Discussion

We review the performance of open source application in our study as contribution to the software development. In using R that only single threaded, we found that when Rstudio executed, the memory rise to 2.4 GB from 1.8 GB. After we load our workspace, it is rise again to 2.6 G, and when the process of modelling finished, we found that 3.2 GB of memory were occupied. This memory usage comes from our raster data that have 5 meters spatial resolution and relatively small areas of 3,2 km^2 Processed only to the model creation and matching stages.

The relationship between population rise and Land Use changes to residential noted in Table 1. It can be presumed from Figure 6. that in Banyumanik Sub-District has phenomena where at first duration, larger residential units were made the changes, but occupied by a smaller number of population. Then although there are slight residential areas growth, it consist of new smaller residential units allowing to be occupied by a relatively large number of population. A possibility of older residential units reoccupation may also contribute to the population growth regadless the residential Land Use size.

The residential occurance probability are the result of data modelling determined by the formula and the selected samples in Banyumanik Sub-District. Table 2. Shows that new residentials were commonly built in relatively Low (<0.5) probability. This lead to
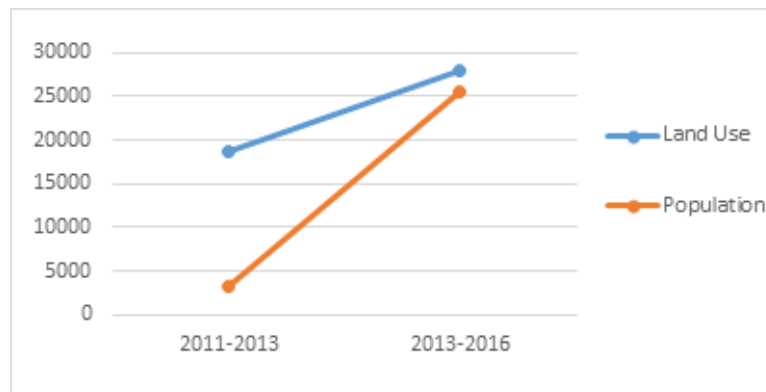
Figure 6: Land Use and Population Growth (x axis shows duration, y axis show pixel count of Residential Land use and number of people for population).

assumsion that many residential units were built with some effort to accomodate lands to be suitable as residential. However, as non residential in this study were consist of all other land use, there are possibility that many areas have a better potential to be use in another activity. In both Land Use change period, there is a trend of residential size to probability as shown in Figure 7.
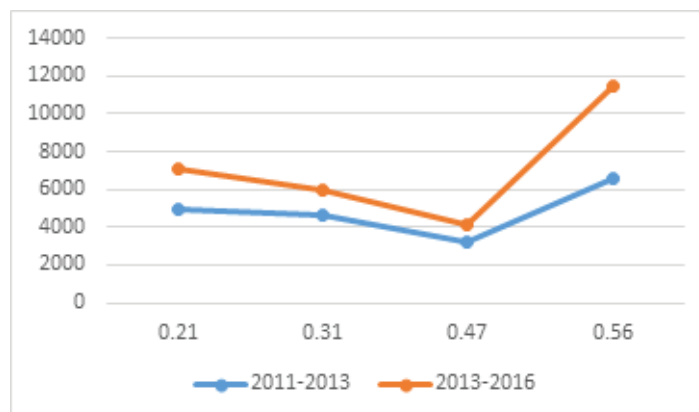
Figure 7: Residential Change Probability Distribution (x axis shows probability, y axis show pixel count of Land use, each with resolution of 5 meter).

4. Conclussion and Suggestion

Our study have a relatively small area study comparing to [1] so the process can be handled by LULCC in R as a single threaded application and high memory. Thus, demands of a system with high single processing power and large available memory. This also confirms that LULCC packages loads all data prior to the process [5]. In this study we also found that preparing the data for LULCC packages having major role as rasterization may lead to large raster spatial data, for this, in a larger area study. using lower spatial resolutions are recommended in order to maximize the package stability.

With 3 years of recorded land use and population only the Land Use change to residential does not cope the population growth, and resulting a higher population density as shown in Figure 6. A further identification of older and newer residential area are required to confirm this finding We also found a temporal pattern of residential occurance over residential probability, where occurance slightly decrease as the probability rises, but jumps in the highest probability. Between 2011 and 2013, from area of 0.126 km^2 to 0.165 km^2. And between 2013 to 2016, it shift from 0.177 km^2 to 0.286 km^2. It can be concluded that a general increment also took place to the existing pattern. This requires identification of the cause of existing phenomena, both internal or external aspects

The usage of additional observation year are recommended to obtain a better description. More over, we suggest a division to more than one Land Use type in order to obtain a more general change models. In this case, our attempt to constructing Object oriented data and for other modelling approach such as glm or randomforest in LULCC package resulted errors in the process. A more thorough study of LULCC usage is then required.

Acknowledgement

References

[1] Sodango, T. H., et al. (2017). Land Use/Land Cover Change (LULCC) in China, Review of Studies. *Int J Sci Eng Res,* vol. 8, no. 8, pp. 943-958.

[2] BPS kota Semarang, (2017), Semarang City In Figures 2017, Publication Number: 33740.1704, www. semarangkota.bps.go.id

[3] Feijten, P. and Van, H. M. (2009). Neighbourhood change...: Reason to leave?. *Urban Stud,* vol. 46, no. 10, pp. 2103-2122.

[4] Chen, G., et al. (2012). Object-based change detection. *International Journal of Remote Sensing,* vol. 33, no. 14, pp. 4434-4457.

[5] Moulds, S., et al. (2015). An open and extensible framework for spatially explicit land use change modelling: The lulcc R package. *Geosci Model Dev*, vol. 8, no. 10, pp.

3215-3229.

[6] Moulds S. Land Use Change Modelling in R: Package ``lulcc.'' https://cran.r-project.org/web/packages/lulcc/lulcc.pdf. https://cran.r-project.org/web/packages/lulcc/lulcc.pdf. Published 2019.

[7] BPS kota Semarang, (2016), Semarang City In Figures 2016, Publication Number: 33740.1619, www. semarangkota.bps.go.id

[8] Platt, R. V. and Rapoza, L. (2008). An evaluation of an object-oriented paradigm for land use/land cover classification. *Prof Geogr*, vol. 60, no. 1, pp. 87-100.