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Driving Factors Selection and Change Direction of a Land Use/Cover

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ABSTRACT

Many information on spatial data can be accessed freely. This information is useful for planners and people in predicting the proper locations of their particular land use, e.g. business office, school, hospital, and so on. This study proposed a method in finding driving factors based on the crowdsourcing application in Bekasi city, Indonesia. Driving factors was categorized as biophysical, infrastructure and economic. Driving factors gathered from the crowdsourcing application in the internet were converted into thematic map through the use of geographic information system tools. Another important parameter in land use/cover change is change direction that give important information about the location of land use/cover change and useful for anticipating its negative effects. Two date of satellite imagery from united states geological survey (USGS) was used. Result indicated that based on the change direction some driving factors were significant for land use/cover change model.

Key words: Satellite imagery, crowdsourcing, urban growth, image processing, unsupervised classification.

1. INTRODUCTION

Cities in developing country are experiencing a rapid urban growth. This phenomenon creates a lot of problems, e.g. slum areas, sprawl effect, health problems, and other negative effect because of improper land use allocation [1], [2]. United Nations suggests to every city in the world to follow the sustainable development goals (SDGs) since this type of region has been perceived as the main sources of environmental degradation [3], [4].

Many studies have been done by using geographic information system (GIS) technology in managing land use as well as remote sensing (RS) in the form of satellite imagery for analyzing the wide region [5]. These technologies have been combined with other artificial intelligent method, especially in land use optimization (genetic algorithm (GA), particle swarm optimization (PSO), and other hybrid method [6]) and simulation (neural network, Markov chain, cellular automata, and so on) for predicting land use/cover growth [7]. In land use/cover simulation, many factors are needed, e.g. driving factors [8]–[10], historical images, land use/cover map, constraints, etc. To provide these factors, a spatial manipulation has widely been implemented through the use of RS-GIS tools. Two main factors, i.e. driving factors and land use/cover change direction will be discussed in this study.

Many GIS applications are available in website or mobile environment with the characteristics of open source, open access, and crowdsourcing [11], [12]. These applications have been implemented to other system outside the RS-GIS, e.g. transportation, e-commerce, health, etc. In Big data era, the data from GIS application is dynamically changed because of the crowdsourcing characteristic in which people at a certain area can contribute to add and edit the geographic information.

Driving factors, which are useful for planners to predict urban growth, have to be prepared and validated before land use/cover growth simulation. One of current method, Cramer's V coefficient, has been widely used to validate the driving factor [10], [13]. This coefficient is difficult to understand for planners and other stakeholders without knowing about land use/cover change model. In this study, we proposed the method in selecting the best driving factors of land use/cover change by analyzing them with the change direction from two different date of land use/cover in the study area.

The study used some spatial data manipulation functions, especially in driving factors map creation, e.g. geoprocessing, Euclidean distance, polygon to raster, etc. Two software were used in this study, ArcGIS 10.1 and IDRISI Selva. Whereas ArcGIS 10.1 was used for driving factors manipulation, IDRISI Selva was used for change direction analysis of a land use/cover.

The rest of the paper is organized as follow. After basic term explanation, the method will be discussed. The change direction will be discussed with relation to driving factors before conclusions.

2. DATA AND METHODS

2.1 Data

Two kinds of data should be prepared for this study, i.e. vector data and raster data. Vector data is presented in point, line, and polygon with its attribute (id, name, etc.). In this study, vector data was gathered from Google Map, a crowdsourcing-based application. Crowdsourcing data is the data in which user participation is the main source of information [14], [15]. Users are able to not only insert the new data but also correct the wrong information from other users. The specific land use/cover locations were inserted into a map based on Google Map, e.g. commercial, industrial, educations, health facilities, sports, settlements, parks areas, etc. These classes of land use/cover can be used as potential driving factors of land use/cover change. Figure 1 shows Bekasi city, West Java, Indonesia as the study area in ArcGIS 10.1 with OpenStreetMap as the base-map to capture the infrastructures, e.g. house, office, business place, hospital, school, etc.

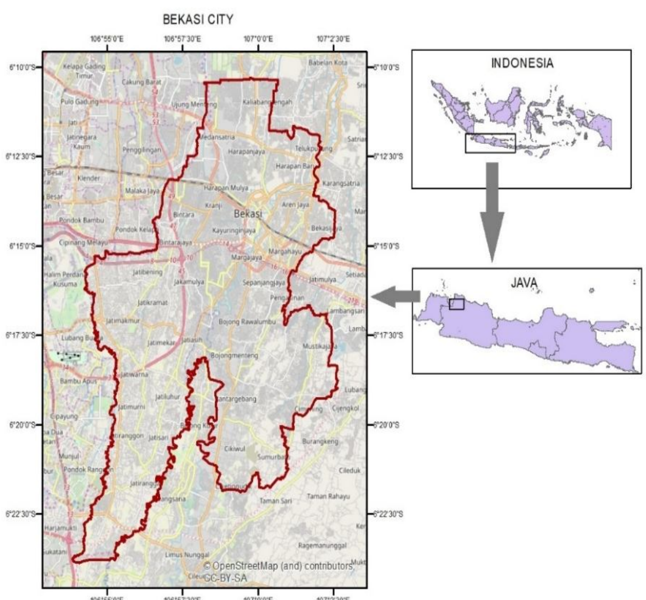

Figure 1: Bekasi City, West Java, Indonesia, with OpenStreetMap to Capture Infrastructure Location

Raster data is data in pixels, usually come from a satellite imagery. This study used satellite imageries from united states geological survey (USGS) [16]. One tile of images should be processed before image classification.

In order to calculate change direction of land use/cover, two dates should be prepared [17]. Table 1 shows the information of raster data from satellite imagery acquisition for land use/cover change analysis[18]–[21]. Two dates of cloud free images were used to predict the direction instead of current images, because the current image usually only for validation purposes before land use/cover prediction. The third date was also captured for the validation purpose.

Table 1: Satellite Imagery Acquisition

No.	Sensor	Date of acquisition (MM/DD/YY)
1	Thematic Mapper (TM)	July 31, 1998
2	Thematic Mapper (TM)	August 1, 2010
3	Enhanced Thematic Mapper Plus (ETM+)	August 31, 2015

2.2 Methods

The study proposed a new method in gathering driving factors through the use of crowdsourcing application, e.g. Google Map, street-directory, etc. and validated them with change direction. The crowdsourcing application has the ability for updating the data continuously, especially for land use that frequently change [22]. The same building might be converted, e.g. from education to commercial area. Table 2 shows the driving factors.

Figure 2 shows the framework of this study. Two types of data (raster and vector data) were simultaneously gathered and processed before analysis. Whereas the raster data was gathered from satellite imagery, the vector data was gathered through crowdsourcing-based GIS applications.Driving factors which initially used vector data, should be converted into raster data through polygon to raster function in ArcGIS 10.1 after creating the Euclidean distance map that showed the influence region of each driving factors in different color.

Table 2: Driving Factors

No.	Category	Notation	Driving Factors
1	Biophysical	Elev	Surface Elevation
2		PStr	Proximity to stream/canals/waters
3	Infrastructure	PHsc	Proximity to housing schemes
4		PRd	Proximity to roads
5		PCc	Proximity to city centre
6		PBu	Proximity to built-up
7		PR	Proximity to railways lines
8		PH	Proximity to hospitals
9		PS	Proximity to schools
10		PCwd	Proximity to central waste disposal
11	Socioeconomic	LPr	Land price
12		Pop	Population density

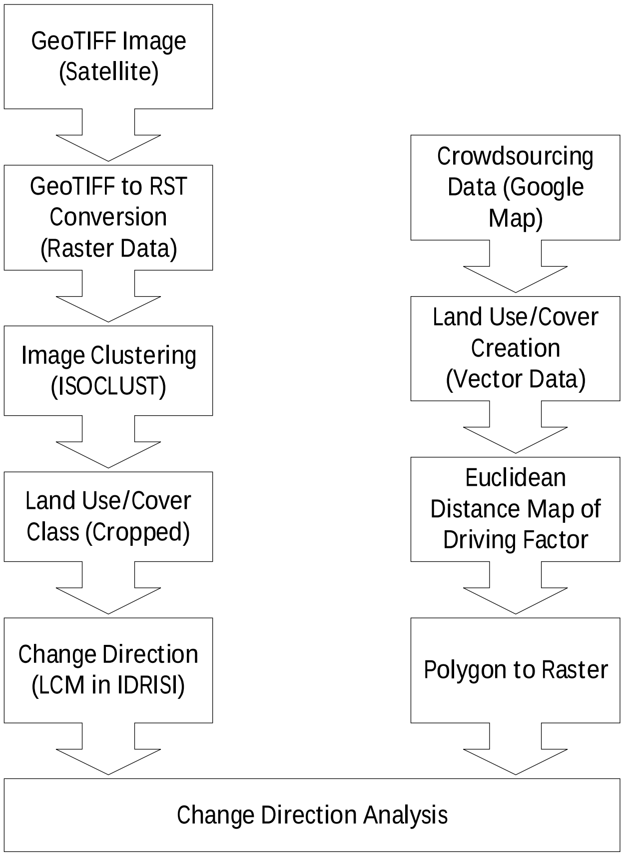

Figure 2: Research Framework

Satellite imageries, as raster data in this study, were gathered from United States Geological Survey (USGS). The Universal Transverse Mercator (UTM) Zone 48S was used as the projection system of the raster data. A GeoTIFF image (a default image format from satellite imagery) was converted into RST file in IDRISI. Seven band images were used for unsupervised classification using ISOCLUST function in IDRISI. Eighteen classes generated should be reclassified into proper land cover, i.e. agriculture, bare, built-up, vegetation, and water. The RECLASSIFY function in IDRISI was used [13]. The classified image should be cropped according to the study area through raster CLIP function.
Both two different date raster-images should be prepared in order to calculate the change direction of land use/cover growth. Land Change Modeler (LCM) module in IDRISI used to create change direction from two different date of classified images. Two and more degree can be chosen for the change direction model before analysis.

3. RESULT AND DISCUSSION

Geographic information both from crowdsourcing application and satellite imagery were collected for driving factors and change direction, respectively. The information was then compared to understand the driving factor influence to the change direction.

3.1 Driving Factors

Figure 3 shows all driving factors (biophysical, infrastructure, and economics) gathered from crowd sourcing application after spatial manipulation by a GIS tool (ArcGIS 10.1).

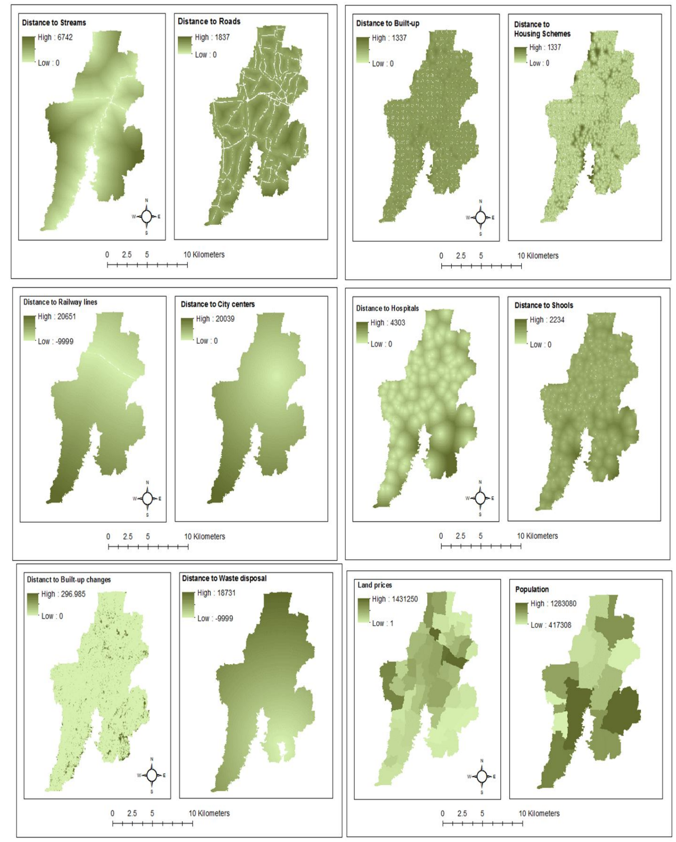

Figure 3: Driving Factors

3.2 Change Direction

LCM in IDRISI was used to analyze the change direction of Land use/cover change. Figure 4 shows the change direction for various of polynomial degrees. Higher the polynomial degree, the change direction showed more complex direction. Since the built-up areas were dominant as the land use/cover change, the "to-built-up" change was used for change direction.

Change direction was created by comparing two different date of land use/cover in LCM of IDRISI Selva. Figure 4a-4c shows the direction of land use/cover change where high probability is in the north-east and center of Bekasi city for the high degree polynomial and in the center for third order polynomial. The change direction was calculated from land use/cover conversion from bare-land to built-up.

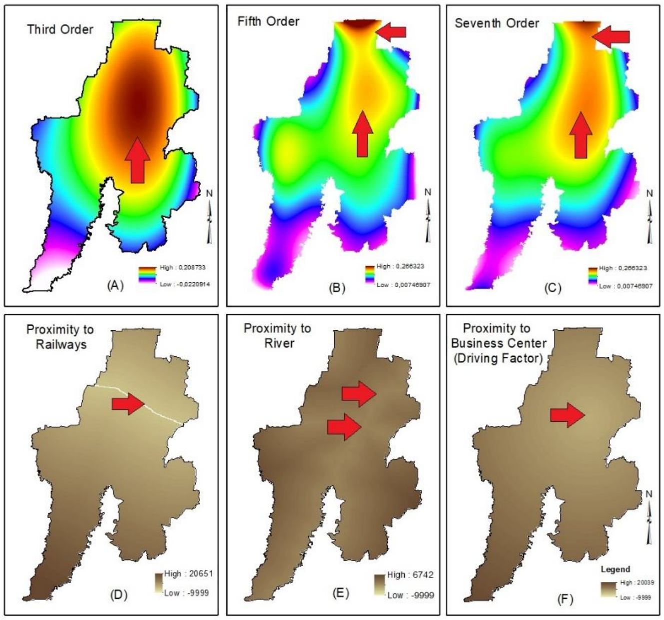

Figure 4: Change direction (bare-land to built-up) and driving factor: (a) Third Order, (b) Five Order, (c) Seven Order, (d) Proximity to railways, (e) Proximity to river, and (f) Proximity to city center

Figure 5 shows the change direction from vegetation to built-up. The direction was located in the center and west-south of Bekasi city. Three driving factors associated with the direction are shown in Figure 5d-5f, i.e. land price, population, and proximity to central waste disposal.

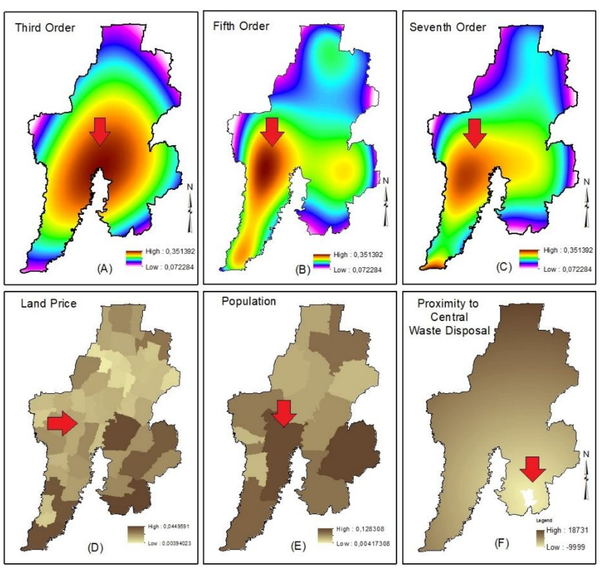

Figure 5: Change direction (vegetation to built-up) and driving factor: (a) Third Order, (b) Five Order, (c) Seven Order, (d) Land Price, (e) Population, and (f) Proximity to Central Waste Disposal

3.3 Driving Factors and Change Direction Relation

By comparing the driving factors (Figure 3) with change direction (Figure 4), the planners can understand the driving factors that significant to the land use/cover change. Proximity to railway, stream/river, and the city center were significant as the driver of land use/cover conversion from bare-land to built-up areas (Figure 4). The bright areas in those driving factors inline to the change direction (shown in brown areas). Bare-land areas located near the railway, rivers, and city center tended to convert into built-up areas.

Figure 5 shows that land price, population, and proximity to waste disposal were significant as the driving factors. Vegetations tended to convert into built-up areas where low land-price (light-brown in Figure 5d) and high population (dark-brown in Figure 5e), but far away from central west disposal in the south-east of Bekasi city (light area in Figure 5f).

Other driving factors, i.e. proximity to roads, existing built-up areas, hospitals, and schools could not be decided through change direction. However, the in-fill growth has proven from the existing built-up areas and the main facilities [23]. Surface elevation was excluded as driving factor since surface in Bekasi city is flat (maximum of 2% slope [24] [25] [26] [27] [28] [29]). Table 3 shows the driving factors' validity based on change direction analysis.

Table 3: Driving Factors Validity

No.	Driving Factors	Reason
1	Proximity to stream/canals/waters	Bare to Built-up Change
2	Proximity to housing schemes	Infill growth
3	Proximity to roads	Infill growth
4	Proximity to city center	Bare to Built-up Change
5	Proximity to built-up	Infill growth
6	Proximity to railways lines	Bare to Built-up Change
7	Proximity to hospitals	Infill growth
8	Proximity to schools	Infill growth
9	Proximity to central waste disposal	Vegetation to Built-up Change
10	Land price	Vegetation to Built-up Change
11	Population density	Vegetation to Built-up Change

4. CONCLUSION

Geographic information system in the form of crowdsourcing application and satellite imagery can be used to create the driving factors and change direction. Results indicated that some driving factors were significant to the change direction, i.e. bare-land to built-up and vegetation to built-up conversion. Therefore, it can be used for land use/cover growth prediction. In addition, the study can be used as a guidance for the city planners in land use management.

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