TRANSFERABILITY OF THE GENERIC AND LOCAL ONTOLOGY OF SLUM IN MULTI-TEMPORAL IMAGERY, CASE STUDY: JAKARTA

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March 2016

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ABSTRACT

The Generic Slum Ontology (GSO) was developed to assist the detection of slums in Geographic Object-based Image Analysis (GEOBIA). However, the GSO has three main challenges. The first challenge is due to local variations of slums, slums having their own unique spatial and temporal characteristics. The second challenge is the different conceptualizations of the term slum. Therefore, the GSO has to be adapted to each local context, by combining local expert knowledge and visual interpretation of the image. The third challenge is due to the dynamics of slum settlements, which require adaptation of the GSO to be able to perform properly in a multi-temporal data set. Therefore, as an effort to develop a more robust approach for slum detection, this study focuses on the transferability of the GSO across different conceptualizations of slums, spatial and temporal conditions. The case of the city of Jakarta, Indonesia was selected for several reasons. Firstly, approximately 60% of its residents, mostly low-income people, are living in informal settlements called *kampungs*. Secondly, several local definitions of slums are used in this area. Thirdly, the existence of *kampungs* blurs the line between slums and non-slums.

We developed two rulesets, one according to the definition of slums from the GSO and one based on the Local Slum Ontology (LSO) to analyse the different results of slums detection. The LSO was developed according to the definition of local experts. We applied both rulesets to multi-temporal Pleiades imagery (2012 to 2015) for two purposefully selected subsets. Two subsets were selected according to their spatial pattern to ensure the rulesets can work in various conditions. In the first subset, we chose an area where the slums are easy to distinct. In the second subset, we choose an area where the slums are difficult to identify. The transferability of the slum ontology to different spatiotemporal subsets was analysed using the quantitative and qualitative approach. For the quantitative approach, we employed three measurements, i.e., spatial comparison, temporal comparison and spatiotemporal pattern comparison. For the qualitative approach, we compared the applicability of the ruleset, which is measured by three indicators, i.e., utility, generality and reusability.

For the quantitative approach, the GSO ruleset performed better than LSO, in terms of spatial transferability. Meanwhile, the LSO showed better temporal transferability than GSO. The spatiotemporal comparison showed both ruleset only resulted in similarities in some measurements and time, which indicated the GSO and LSO result in a different interpretation of the spatiotemporal change of slums. Regarding qualitative measurement, the GSO is more transferable than LSO in terms of utility, according to the number of characteristics that can be used for slum extracting. Meanwhile, for the generality, the LSO is more transferable than GSO, according to the least number of adaptation needed. In the reusability measurement, we conclude some source of uncertainties has resulted in unexpected results. For instance, disagreement of slum boundary between local experts contributed to the low accuracy of classification quality.

This research has contributed to measure the transferability of the GSO and LSO across different conceptualization and spatiotemporal condition. However, further research needs to be done. Firstly, development of automated tools to estimate the appropriate smoothness and compactness parameter, in the multiresolution segmentation algorithm. Secondly, the application of fuzzy classification method, to overcome the uncertainties of the slum concept. Lastly, the incorporation of different data, e.g., the usage of active sensor, or testing the transferability for a multi-temporal image with a different sensor.

Keywords: Transferability, Spatiotemporal, Slums, GEOBIA, Ruleset

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Finally, I dedicate this thesis to my family. To my wife, kid and my parents, for the countless support that gives to me.

Enschede, February 2016

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LIST OF ABBREVIATIONS AND ACRONYMS

Bappeda	:	*Badan Perencanaan Pembangunan Daerah*/ Jakarta Planning Board
Bappenas	:	*Badan Perencanaan Pembangunan Nasional* / Indonesian National Planning Agency
BPS	:	*Badan Pusat Statistik* / Indonesian Central Board of Statistics
DKI	:	*Daerah Khusus Ibukota* / Capital City Region
ESP	:	Estimation of Scale Parameter
FN	:	False Negative
FP	:	False Positive
GEOBIA	:	Geographic Object-Based Image Analysis
GLCM	:	Grey Level Co-occurrence Matrix
GSO	:	Generic Slum Ontology
Kemen PU-Pera	:	*Kementerian Pekerjaan Umum dan Perumahan Rakyat* / Ministry of Public Works and Public Housing
LSO	:	Local Slum Ontology
MDG	:	Millennium Development Goals
MRS	:	Multi-resolution Segmentation
NIR	:	Near Infra-Red
NGO	:	Non-Government Organization
ROC-LV	:	Rate of Change of Local Variance
SDG	:	Sustainable Development Goals
TN	:	True Negative
TP	:	True Positive
USI	:	Unplanned Settlement Index

1. INTRODUCTION

This chapter describes the background of the study, including the review of previous studies that are related to the usage of remote sensing to monitor the dynamics of the slum settlements. It is then followed by the research problems, which shows the role of the Generic Slums Ontology for multi-temporal imagery. The final section provides the research objective and questions, and structure of this thesis.

1.1. Background

Slum reduction has been on the global agenda in the recent decade. According to the Millennium Development Goals (MDG), by 2020, at least, 100 million slum dwellers should achieve a significant improvement in their lives. Indeed, this target had been achieved during 2000 and 2012 (United Nations, 2014). By the end of the MDG in 2015, a new umbrella framework for global slum reduction is proposed under the Sustainable Development Goals (SDG). A slum reduction agenda is contained in goals 11: “Make cities and human settlements inclusive, safe, resilient and sustainable” (Open Working Group SDG, 2014, p. 17). The specific aim mentioned regarding slums is “by 2030, ensure access for all to adequate, safe and affordable housing and basic services and upgrade slums” (Open Working Group SDG, 2014, p. 17). We can notice that slums reduction remain a global concern after the end of the MDG. However, the number of slum dwellers remains growing. According to the United Nations (2014), the number of slum dwellers living in the urban area was 863 million in 2012, which increased from 2000 and 2010, which are 776 million and 827 million respectively. At 2010, 754 million people in Asia-Pacific lived in urban areas (United Nations ESCAP, 2013), and Asia had the greatest concentration of slums dwellers, with more than 60% of world’s slums (UN-Habitat, 2010).

The rapid growth of cities, as mentioned by the Centre on Housing Rights and Evictions (2008), is often beyond the capacity of local government to provide sufficient basic services. According to Ooi and Phua (2007), many cities in developing countries lack the ability to fulfil economic and societal needs of their citizens, including affordable housing, environmental and health infrastructure. Therefore, urbanisation has resulted in vast urban slums, where poor urban dwellers are living in sub-standard housing, with no access to essential services (Centre on Housing Rights and Evictions, 2008). Jakarta is the largest metropolitan area in South-East Asia and the second largest in the world (Demographia, 2015). It has more than 10 million inhabitants living in the inner city (Jakarta Planning Board [BAPPEDA], 2015), and more than 30 million in its metropolitan area (Demographia, 2015). Jakarta is facing problems to manage its rapid demographic and economic growth, including the rapid growth of slum settlements (New City Foundation & Government of DKI Province, 2015). Rakodi and Firman (2009) mentioned that approximately, 60% of the population, mostly low-income people, are living in settlements called *kampungs*. *Kampungs* are non-administrative entities, and it is hard to determine accurately how many inhabitants live in *kampungs* (UN-Habitat, 2003). Although a *kampung* is not necessarily an urban slum, they share characteristics of formal and informal settlements (Putranto, 2009).

Due to urbanisation, monitoring the dynamic change of slum settlements becomes crucial for policy makers to formulate appropriate policies. However, according to Shoko and Smit (2013), information regarding growth and expansion parameters of slum settlements is scarce. The survey-based methods of census data, as mentioned by Kohli, Sliuzas, Kerle, and Stein (2012), have limitations due to the long temporal gap and the degree of aggregation. Therefore, information collected from field surveys might be obsolete when it used (Hofmann, Strobl, Blaschke, & Kux, 2008). In the case of Jakarta, survey-based methods fail to capture the dynamics of slum settlements in many locations, e.g. slums at riverbanks, waste disposal site, or close to railways (Winayanti & Lang, 2004).

Satellite imagery gives the opportunity to bring an actual image of the spatial situation in almost real-time and is taken at constant time intervals (Hofmann et al., 2008). Therefore, it can capture the dynamics of slums settlements. Even though slums settlements have unique spatial, structural, and contextual characteristics, which distinguish them from other types of urban structures (Graesser et al., 2012), determining slum settlements from satellite imagery is somehow difficult. Kohli, Warwadekar, Kerle, Sliuzas, and Stein (2013) argued that slum and non-slum areas often share identical surface material composition that results in similar reflectance. Therefore, Jain (2007) recommended avoiding pixel-based classification using only spectral values. Furthermore, Kohli et al. (2013) suggested additional criteria, e.g. shape, texture and density, to avoid misclassification. As consequences, due to the limitation of pixel-based image analysis to detect slum settlements, it is crucial to promote methods that can deal with non-pixel classification, and can incorporate the knowledge of spatial feature characteristics.

Among various approaches that were developed by the remote sensing community, Hay and Castilla (2008) mentioned that Geographic Object-Based Image Analysis (GEOBIA), are developed to partition automatically remote sensing image into a useful image object. Furthermore, Blaschke et al. (2014) mentioned that GEOBIA bridges the concept of remote sensing, image and GIS analysis. GEOBIA is considering spatial, spectral and temporal scales. Hence, GEOBIA will generate new geographic information in a GIS-ready format. Therefore, GEOBIA has a good potential to determine slums settlements by following a hierarchical procedure and contextual information for objects and non-physical features (Ebert, Kerle, & Stein, 2009). To determine spatial characteristics of slums, Owen and Wong (2013) and Graesser et al. (2012), demonstrate how to distinguish its features by using spatially explicit indicators obtained from satellite imagery. The authors tested a large number of spatial indicators where they were useful to distinguish slum and non-slum settlements, and conclude that vegetations, road, texture and geomorphology are key indicators to distinct the slums from the formal settlements. Although GEOBIA is useful to determine slum location, Hofmann et al. (2008) stressed that results are very dependent on data, which is a limitation of GEOBIA. Hence, it is not flexible to be applied to another scene, specifically for complex slums area. Therefore, Hofmann et al. (2008) recommended considering the use of an ontology for GEOBIA.

Ontology, as described by Gruber (1993), is a specification of a conceptualization, which is developed to a specific standard and represented in specific languages. Nowadays, ontologies are becoming more common in representing knowledge from various fields (Kohli, Sliuzas et al., 2012). Also to develop a shared understanding of a particular domain, and to facilitate an exchange of information (e.g. in computer science, landscape studies, as well as in geographic information science and remote sensing) (Kohli, Sliuzas et al., 2012). Regarding the contribution of the ontology in GEOBIA, Arvor, Durieux, Andrés, and Laporte (2013) mentioned two general applications of ontology, which is data discovery and data processing and analysis, e.g. image interpretation.

Regarding slums, Hofmann et al. (2008) mentioned that an ontology of slums is the representation of the knowledge related to slums from various perception by using a defined language. Kohli et al. (2012) expanded on the result from Hofmann et al. (2008) and developed a generic slum ontology (GSO), by adopting durable housing indicator from UN-Habitat. As an effort to conceptualize the characteristics of slums, three spatial level (environs, settlement and object) are created by Kohli, Sliuzas et al. (2012) by adopting the taxonomy in an ontology development that was created by Devedzic, Djuric, and Gazevic (2009). Slums characteristics on environ level describe the location and neighbourhood, while, on settlement level, they describe the shape and density, and on object level they describe access network and building characteristics (Figure 2-2).

1.2. Research Problems

The GSO is developing as a generic concept of slums (Mathenge, 2011). However, applying the GSO has three challenges. Firstly, slums in a particular area have their unique spatial and temporal characteristics that are distinct from other places. Secondly, the different ways to conceptualize the slums. Therefore, Kohli, Kerle, and Sliuzas (2012) mentioned, to describe slum settlements in a particular study area, the GSO needs to be adapted to each local context, by combining knowledge gained from local experts, and visual interpretation of the image, to produce the Local Slum Ontology (LSO). Thirdly, the dynamics of slum settlements, which require adaptation of the GSO to be able to perform properly in a multi-temporal data set.

The development of an ontology to analyse spatiotemporal patterns of slum settlements is demonstrated by Dubovyk, Sliuzas, and Flacke (2011), who used the result obtained from the GEOBIA process, to develop a logistic regression model, to predict future locations of slum settlements. Another study from Sori (2012), incorporated socio-economic data to detect slum development stages. However, a study that focuses on transferability of the GSO to work with a multi-temporal imagery in a local context has not been done. Therefore, Mathenge (2011) stressed the need to analyse the transferability of the GSO for multi-temporal images. Transferability, as mentioned by Kohli et al. (2013), is the capability of a certain method to provide a comparable result for different imaging conditions, and it should require minimal adaptation for different imaging conditions. Therefore, to deal with various spatiotemporal data sets to determine the changes in slum settlements, it is crucial to analyse the transferability of the GSO.

This study contributes to analysing the transferability of the generic and local ontology of slums in different spatiotemporal imagery.

1.3. Research Objective and Question

1.3.1. Research Objective

The main objective of this research is to analyse the transferability of the Generic Slum Ontology (GSO) and Local Slum Ontology (LSO) to different spatiotemporal imagery employed in a Jakarta.

To fulfil this objective, several sub-objective need to be achieved as follow:

1. To identify characteristics of slums in the study area.
2. To develop a GEOBIA rule-set that allows detecting the occurrence of slums
3. To detect slums in the study area in different spatiotemporal imagery.
4. To measure the transferability of the GSO and LSO in different spatiotemporal imagery in the study area.

1.3.2. Research Question

In this study, we develop the research questions as follow:

1. Sub-Objective 1:
    a. Did the local experts have a common agreement regarding the characteristics of slums in the study area?
    b. Did the local experts have a common agreement regarding the locations of slums in the study area?
    c. Is the slum delineations from the local experts similar to results from the field observations?
    d. What are the characteristics of slums in the study area?

2. Sub-Objective 2:
   a. Which criteria allow detecting the occurrence of slum settlements?
3. Sub-Objective 3:
   a. How different are the results from GSO and LSO when it applied in different spatial conditions?
   b. How different are the results from GSO and LSO when it applied in different temporal conditions?
4. Sub-Objective 4:
   a. What is a suitable measurement of the transferability of the GSO and LSO?
   b. How transferable is the GSO and LSO to be applied to different spatiotemporal imagery?

1.4. Conceptual Framework

As mentioned in chapter 1.1, due to the dynamics of slums we argue for developing a transferable spatiotemporal approach. We also notice that the usage of the GSO in the GEOBIA domain might give a promising opportunity to tackle these obstacles. However, as mentioned in chapter 1.2, we can notice that there are three challenges in applying the GSO, which is temporal, spatial and conceptual issues. Therefore, we need an approach that is transferable and can be implemented in other conditions, with fewer adaptations. Hence, this research focuses on how the GSO can be transferred to other spatial and temporal conditions. Thus, this thesis measures the transferability of the GSO for different spatial, temporal and conceptualizations. We compare the slums mapped according to the definition based on the generic and local ontology of slums (LSO). The LSO were developed as a local adaptation from the GSO. We also compare the results of different spatial and temporal condition. In Figure 1-1, we can see the conceptual framework of this research.

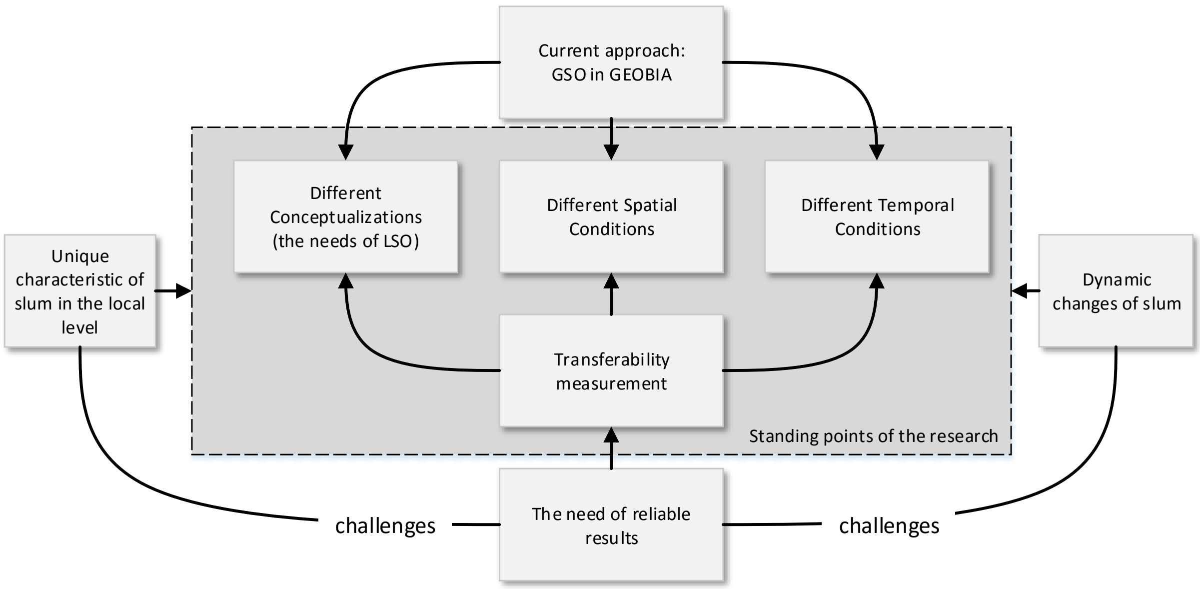


Figure 1-1 Conceptual Framework

1.5. Structure of the Thesis

This thesis is divided into six chapter, which are the introduction, literature review, study area, research methodology, result and discussion, and conclusion and recommendation. Description of the content of each chapter as follow:

1. **Chapter 1: Introduction**
   This chapter describes the background of the study, research problems, research objective and questions, and structure of this thesis.
2. **Chapter 2: Literature Review**
   This chapter describes the concepts that are related to this study. It starts with the description of the concept of slums. It then followed by a description of the methontology, GEOBIA, uncertainties in slum detection and transferability.
3. **Chapter 3: Study Area**
   This chapter describes the study area. It started with the discussion of the dynamics of slums in Jakarta. Second, it discusses the challenges in monitoring the dynamics of the slum.
4. **Chapter 4: Research Methodology**
   This section describes the methods that are used to identify characteristics of slums in the study area. The chapter provides the ontology development process, approach to conduct segmentation and classification and the methods that are used to measure the transferability.
5. **Chapter 5: Result and Discussion**
   This section gives the result and discussion of this thesis. It starts with the description and discussion of the characterization of slums, segmentation and classification, uncertainties analysis and transferability measurement.
6. **Chapter 6: Conclusion and Recommendation**
   This section describes the conclusion and proposes recommendations for further research.

2. LITERATURE REVIEW

This chapter describes the concepts related to this study. It started with the description of the ontology of slums, GEOBIA and transferability. For the conceptualization of slums, we use the concept of the ontology of slums to describe their characteristics. In the section on GEOBIA, we discuss two main aspects of the object-based analysis, which are segmentation and classification. Finally, in the section on transferability, we discuss the concept of transferability and its measurement, and how it is used in this thesis.

2.1. The Concept of Slums

Answering the question of what are slums is somehow difficult. There is various governmental and organization attempts to conceptualize the definition of slums. For instance, D. A. Smith (2013) indicated twelve definitions of slums, where some of them are highly dense, low-rise, substandard and unhealthy, self-built spontaneous community, and so on. Another definition from Merriam-Webster (2015) indicates that slums are areas in the city where the poor are living, and their buildings are in the bad conditions. Slums may also be conceptualized as an overcrowded urban street or district that is inhabited by poor people (Oxford University Press, 2015). Among different ways to conceptualize slums, the definition from UN-Habitat is the most widely used. A slum is an area that combines, to various extents, inadequate access to safe water, sanitation and other infrastructure, poor structural quality of housing, overcrowding and insecure residential status (UN-Habitat, 2003). According to the definition from UN-Habitat (2003), Kohli, Sliuzas et al. (2012) has developed the Generic Slum Ontology (GSO) as a bridging between the human conceptualization of slums and the image domain of slums.

2.2. Ontology of Slums

We can describe the concept of slums by an ontology. There are various definitions of the notion of ontology (Devedzic et al., 2009). However, the most widely used definition is "an explicit specification of a conceptualization" (Gruber, 1993, p.1). Ontologies consist of theories regarding a particular object, its properties and possible relationship between the object in a given domain (Chandrasekaran, Josephson, & Benjamins, 1999). Concerning the ontology of slums, the widely used definition is according to the UN-Habitat (2003). By following this definition, Kohli, Kerle et al. (2012) develop the Generic Slum Ontology (GSO).

2.2.1. Ontology Development Framework

The development of the ontology for slums, as suggested by Kohli, Sliuzas et al. (2012), are taken from the methontology by Fernández-López, Gómez-Pérez, and Juristo (1997). Methontology is a set of guidelines on how we should define activities to be considered for development of an ontology, and what techniques are the most appropriate for each activity (Fernández-López et al., 1997). The entire states and activities in ontology development can be seen in Figure 2-1. However, Kohli, Kerle et al. (2012) suggested three phases, which are specification, conceptualization and implementation. In the specification process, the aims are to gain clear coverage of the ontology (Kohli, Kerle et al., 2012). Meanwhile, the conceptualization seeks to organize and structure the knowledge that is acquired by a developed representation that can be understood (Fernández-López et al., 1997; Kohli, Kerle et al., 2012). On the implementation phase, the aims are to transform the conceptual model into an implemented model (Fernández-López et al., 1997). The study from Kohli, Kerle et al. (2012) described how the implementation phase is done by adopting GSO into local characteristics of slums. In this research, we follow the process that was suggested by Kohli, Kerle et al. (2012).

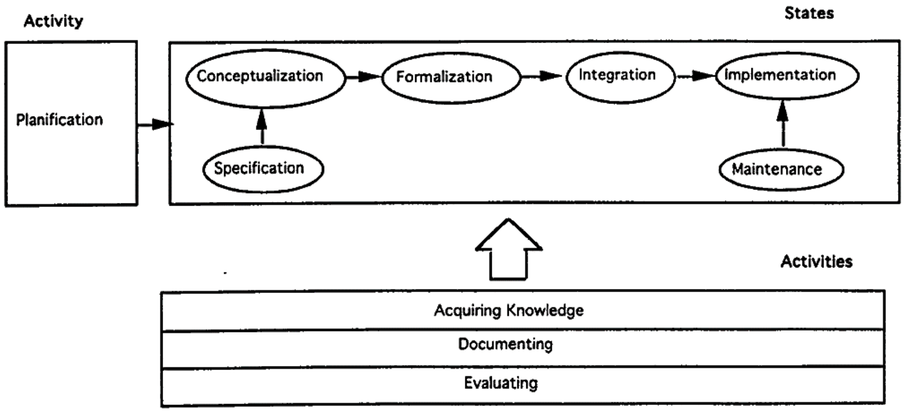


Figure 2-1 States and Activities in Ontology Development (Fernández-López et al., 1997)

2.2.2. Generic Slum Ontology

The GSO consists of three spatial level, which are the object, settlement, and environment (Figure 2-2). In the environment level, slums are characterized by location and neighbourhood characteristics (Kohli, Kerle et al., 2012). Slums are often located in hazardous areas, and its dwellers are dominantly unskilled or low skilled workers (Kohli, Kerle et al., 2012). On the settlements level, slums are characterized by its shape and density (Kohli, Kerle et al., 2012). Slums are often developed following the form of urban features, e.g. roads, railways or drainage, and have high roof coverage and no public space (Kohli, Kerle et al., 2012). However, Kohli, Kerle et al. (2012) mentioned that settlement density differs locally and depends on the development stages of the settlements. On the object level, slums are characterized by building characteristics and the access network (Kohli, Kerle et al., 2012). Even though building characteristics of slum settlements can be distinguished from formal settlements, not all characteristics can be determined by satellite imagery (Kohli, Kerle et al., 2012). However, Kohli, Kerle et al. (2012) recommended combining various attributes, such as roof type, building footprint, building shape and orientation. Regarding the access network, Kohli, Kerle et al. (2012) mentioned that slums could be characterized by its irregular network, its street types, surface, and widths.

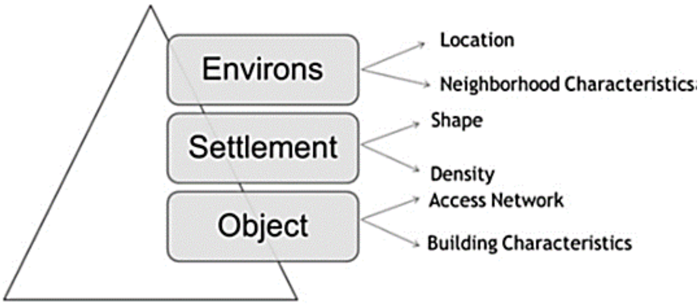
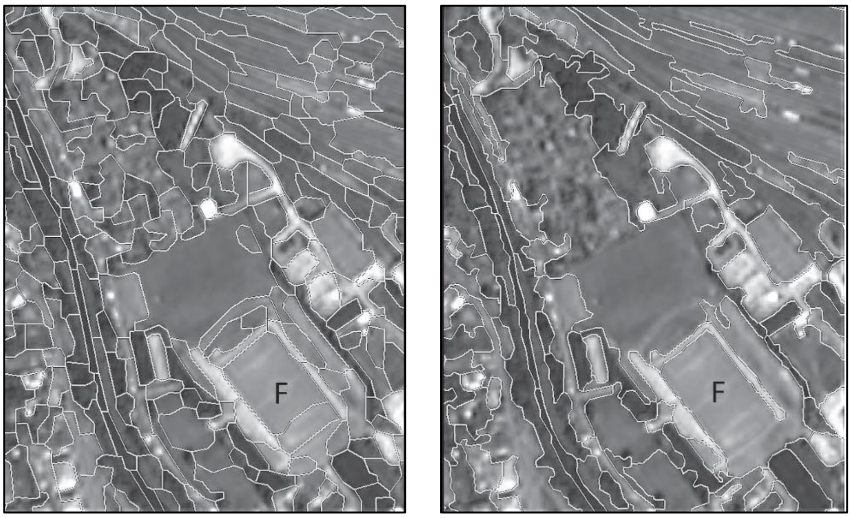


Figure 2-2 Three Spatial level at Generic Slum Ontology (Kohli, Sliuzas et al., 2012)

2.2.3. The Different Domain of Slums

Regarding the concept of slums in the GEOBIA field, we need to understand two distinct domains in GEOBIA, which are the image object and the geographic (or real world) object. We also need to understand how each domain is related. The image object is defined as "discrete region of a digital image that is internally coherent and different from its surroundings" (Castilla & Hay, 2008, p.94). Meanwhile, the geographic object can be defined as an object with is having a minimum size that allows being represented on the map, e.g. city, forest, lake, agricultural field and so on. (B. Smith & Mark, 1998). We can notice that an image object can be characterized due to its coherence and its difference to adjacent objects. Regarding the relationship between image and geographic object, Castilla and Hay (2008) mentioned that the image object has an opportunity to relate to specific geographic features. They also mentioned to be able to represent geographic features, the image object should achieve a substantial size. However, most of the initial image objects cannot be qualified as a significant object (Castilla & Hay, 2008). For instance, often the object are over segmented or under segmented. An over segmented object refers to a condition where the different among adjacent segments is unclear, and it should be merged into a larger object (Figure 2-3 (a)) (Castilla & Hay, 2008). Meanwhile, under segmented object refers to the conditions of the segment that lack of coherency, and it should be segmented into a smaller object (Figure 2-3 (b)) (Castilla & Hay, 2008).



a. Field (F) is over-segmented b. Field (F) is under segmented

Figure 2-3 Over and Under Segmented Object (Castilla & Hay, 2008)

Hofmann et al. (2008) mentioned that the real world domain is describing observable properties, such as what are the typical or unique characteristics of slums. Meanwhile, in the image domain, the slum characteristics have to be measurable, and it mostly can be understood by its signature or pattern (Hofmann et al., 2008). In Figure 2-4, we can see the distinction between the real world and image domain that can be used to characterize the slums.

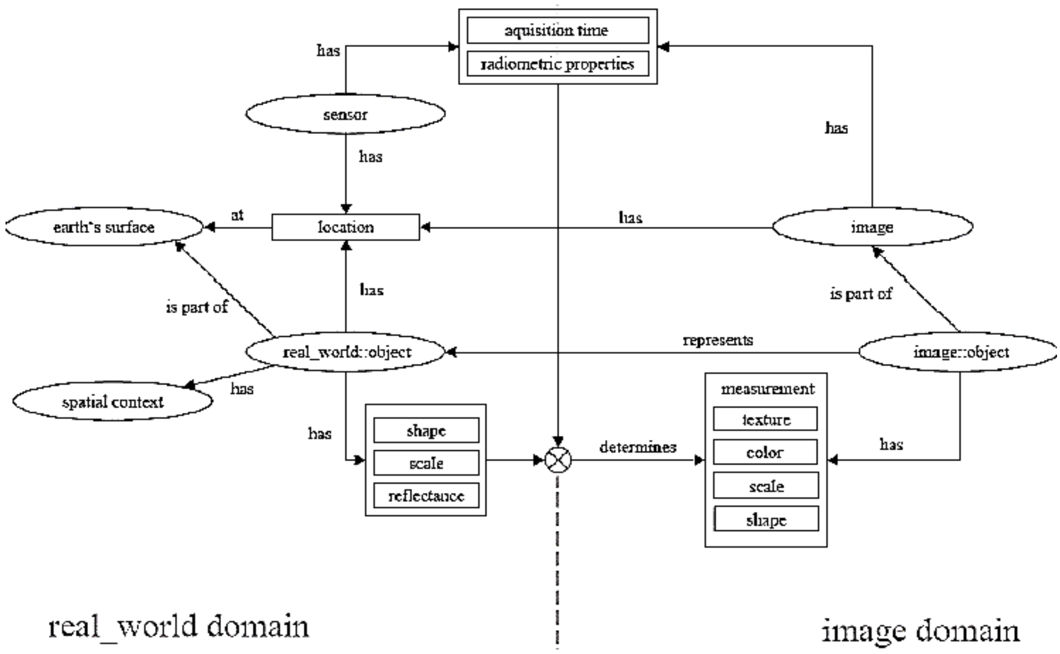


Figure 2-4 Real World and Image Domain of Slums (Hofmann et al., 2008)

To that end, to use the GEOBIA to detect slums, we need to understand the slum characteristics in the real world and to try to link its concept into a rule-set that is develop based on the image characteristics of slums. In Table 2-1, we can see how the slums can be characterized according to the real-world and image domain.

Table 2-1 Real World and Image Domain of Slums from the GSO

Level	Ontological Concept	Real World Characteristics	Image Characteristics
Environs	Location	Located in hazard-prone area	Located in high-slope
	Neighbourhood Characteristics	Dominated by low-skilled workers	Need to utilize socio-economic data
Settlement	Shape	Irregular building orientation	Irregular object geometry
	Density	High density	Texture-entropy, contrast geometry
Object	Building	Lack quality of building materials	Asymmetry geometry, roof spectral (corrugated galvanised iron, asbestos, plastics and so on.)
	Access Network	Poor road condition	Road width, road spectral (soil)

Source: Adapted from Kohli et al. (2013)

2.2.4. The Image Signature of Slums

After discussing the GSO in subchapter 2.1.2, and two ways to distinct slums and non-slums in subchapter 2.1.3, we discuss in this subchapter the signature of slums in the image domain. Various visual elements, e.g. tone, shape, size, association and texture can be used to differentiate an object from its background (Natural Resources Canada, 2013). An understanding of the slum characteristics in the image domain is crucial, to translate the description of slums from the real world, into something that known by computers.

Regarding the tone characteristics, slums can be characterized due to their roofs that are commonly made from corrugated galvanised iron, asbestos, plastics or any other sub-standard materials (Kohli, Sliuzas et al., 2012). These materials determine the spectral signature of slums since each of these materials have their colour that might be observed from the image. Tone characteristics are fundamental to distinguish geographical features, since the tone is allowing the development of other elements, such as shape, texture, and the pattern (Natural Resources Canada, 2013). Regarding the shape, it can be described as a form, structure, or outline of an object that can be used as a distinctive clue in image interpretation (Natural Resources Canada, 2013). As can be seen in Figure 2-2, the shape can be used to characterize the slums on the settlement levels. In the real world, slums can be characterized due to the building orientation. Meanwhile, in the image domain, slums can be characterized due to its irregular object geometry. Also, the size signature of slums is pretty straightforward since the size of slum buildings is smaller compared with non-slum buildings. The association describes the relationship between a recognized object and other spatial features in proximity to a target of interest (Natural Resources Canada, 2013). This information can be used to identify the object. For instance, we can recognize slums due to their location in or close to the hazard-prone areas, such as riverbanks.

The last image-domain characteristics that can be used to define the location of slums are the texture. The texture refers to the pattern and frequency of a variation of tone, in a particular area of the image (Natural Resources Canada, 2013). The analysis that can be used for image texture is, e.g., the Texton Theory, the Wavelet approach, or the Fourier approach (Gebejes & Huertas, 2013). Gebejes and Huertas (2013) argued that the easiest analysis is the Grey Level Co-occurrence Matrix (GLCM) that was defined by Haralick, Shanmugan, & Dinstein (1973). Several studies have demonstrated the usage of GLCM in the domain of slums. For instance, the study from Kohli, Sliuzas et al. (2012), Mathenge (2011), Owen and Wong (2013), Engstrom et al. (2015), Duque, Patino, Ruiz, and Pardo-pascual (2015).

GLCM depicts the spatial relationship of grey level of a neighbouring pixel (Gebejes & Huertas, 2013) by evaluating the correlation or similarity among neighbouring pixel inside fixed dimensions of the window (Stasolla & Gamba, 2009). Nine texture measures are commonly used, they can be grouped into three groups according to their similar properties (Stasolla & Gamba, 2009). Firstly, contrast group (contrast, dissimilarity and homogeneity), secondly orderliness group (angular second moment, max probability and entropy), lastly stats group (mean, variance and correlation)(Stasolla & Gamba, 2009).

2.3. Geographic Object-Based Image Analysis

Bhaskaran, Paramananda, and Ramnarayan (2010) mentioned that object-based classification is useful for extracting a feature from a high spatial, but low spectral resolution image since its characteristics are rather driven by an understanding of image object than the pixel. An image object, as mentioned by Bhaskaran et al. (2010), is a homogenous group of pixel or region, which have similarity in their spectral and/or spatial characteristics. Various studies have demonstrated the usefulness of GEOBIA for slum mapping. For instance, the study from Kohli, Sliuzas et al. (2012), which develop a semi-automatic approach for detecting slums from satellite imagery. Another study from Kohli et al. (2013) demonstrated the usefulness of GEOBIA to detect slum from very high-resolution imagery. A study from Sori (2012) demonstrated how slum development stages could be identified from satellite imagery using GEOBIA. In the field of GEOBIA, as mentioned by Arvor et al. (2013), the effort to relate geographic features and image objects depends on the segmentation and classification step.

2.3.1. Segmentation

Image objects, as mentioned by Bhaskaran et al. (2010), are extracted by using different segmentation parameters, according to the homogeneity or heterogeneity of spectral or shape criteria. Since the emphasis of GEOBIA is on the image object, the segmentation process is a crucial part. The aim of the segmentation process, as mentioned by Liu, Guo and Kelly (2008) is to delineate regions or segments of an image, which share common attributes. Similar with Blaschke (2010), segmentation are expected to divide the image in a relatively homogeneous and significant group of pixels. Hay and Castilla (2008) mentioned that the core of the segmentation process is the human conceptualization of landscape and its comprehension.

There are many image segmentation algorithms, and each algorithm is not equally suitable for a particular image (Dass, Priyanka, & Devi, 2012). Furthermore, Zhang, Fritts, and Goldman (2008) mentioned that, even though extensive research regarding the creation of different approaches and algorithms for image segmentation are done, it is still difficult to determine which algorithm produce the best segmentation accuracy. However, multi-resolution segmentation is the most widely used algorithm, due to its ability to produce an extremely homogeneous object from different types of data (Baatz & Schäpe, 2000). Various studies have demonstrated the capabilities of this algorithm in the domain of slums. For instance, the study from Kuffer, Barros, and Sliuzas (2014) that shows how multi-resolution segmentation resulted in the least degree of over and under-segmentation, compared to other algorithms. Another study from Kohli, Kerle et al. (2012) demonstrated how multi-resolution segmentation are used in the segmenting object in the domain of slums.

Multi-resolution segmentation depends on the scale parameter (SP) as a key control (Drǎguţ, Tiede, & Levick, 2010). The SP is described as a parameter that controls the heterogeneity of an image object, and the value is correlated with the size of the object (Baatz & Schäpe, 2000). However, selecting the value of an SP is commonly depending on a trial and error process, based on a visual assessment (Whiteside, Boggs, & Maier, 2011). Therefore, selecting the most appropriate SP is hard to justify, and became an important issue regarding the robustness of the approach (Arvor et al., 2013). Drǎguţ, Tiede, and Levick (2010) proposed an approach to estimate the SP for an image segmentation that is called estimation of scale parameter (ESP). ESP can be used to define appropriate SP by an optimization process with a various user-defined parameter. This method is developed according to the idea of Local Variance from Woodcook and Strahler (1987), which describes the object heterogeneity within image scene. To be able to represent the dynamic change of the Local Variance by an increased number of object sizes, Drǎguţ et al. (2010) proposed as a measurement the rate of change of local variance (ROC-LV), it shown in the Equation 1.

$$\mathrm{ROC} - \mathrm{LV} = \left[\frac{\left(\mathrm{L} - (\mathrm{L} - 1)\right)}{\mathrm{L} - 1}\right] * 100 \qquad \text{Eq. 1}$$

Where L is the local variance at the target level and L-1 is local variance at next lower level. The process to define an appropriate scale level can be seen in Figure 2-5.

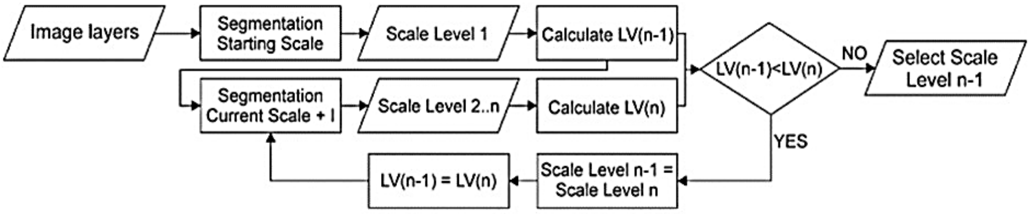


Figure 2-5 Selection of Scale Parameter using ESP (Csillik, Eisank, & Tiede, 2014)

The ESP tools is a rule set that can be run on the E-cognition software[1]. According to the calculation that is mentioned above, it results in a graph that shows the local variance and the rate of change. The peak of ROC-LV is indicating the object level where the image can be appropriate segmented, where the segment is characterized by the equal degree of homogeneity (Drăguţ et al., 2010). As the number of segment size increases LV, the ROC-LV will decrease (Drăguţ et al., 2010) (Figure 2-6).

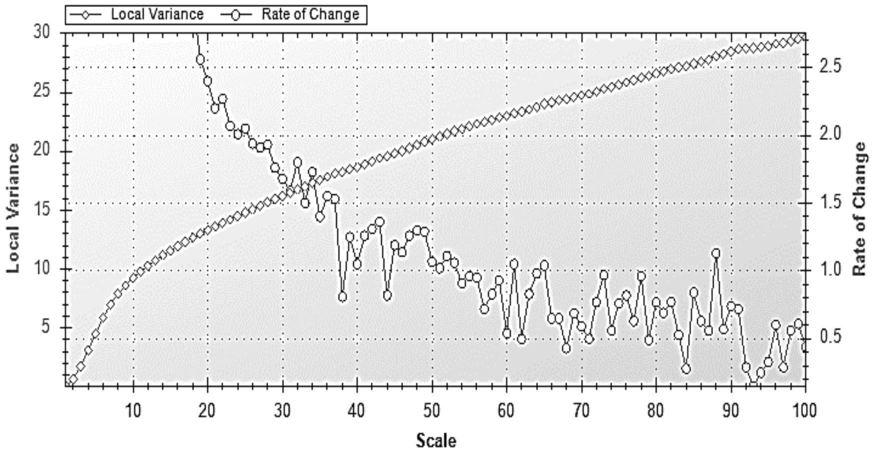


Figure 2-6 Graph of ESP

Since the quality of the classification results is related to the quality of the image object, determining the quality of a segmentation result is crucial. Two measurements can be used, which are area-based metrics and location-based metrics (Montaghi, Larsen, & Greve, 2013). The area-based metrics measures the quality of a segmented object according to the fitness of the object shape or size. Meanwhile, the location-based metrics measures the position of an object to the reference object. Various methods can be used in the area-based metrics. For instance, the relative area of the overlapped region to reference object (RA_{or}%), the relative area of the overlapped region of the segmented object (RA_{os}%), quality rate (QR), SimSize and Area Fit Index (AFI) (Montaghi et al., 2013). Meanwhile, the location-based metrics including the Discrepancy of a segmented object to reference object (D_{sr}) and relative position (RP_{sr}).

2.3.2. Classification

After selecting the most suitable parameter and algorithm in the segmentation process, selecting the appropriate classification is the next crucial step in GEOBIA. Several classification approaches can be used, namely, "assign class algorithm", "classification algorithm", "hierarchical classification algorithm" and "advanced classification algorithms" (Trimble Germany GmbH, 2015). The "assign class algorithm" is the simplest methods, where a class is assigned to an image object by using a certain threshold (Trimble Germany GmbH, 2015). Meanwhile, in the "classification algorithm", the class description is used to

[1] This tool is available at http://www.ecognition.com/community. However, we need to register as a member to be able to access the community forum.

determine an object whether it can be a member of a certain class or not (Trimble Germany GmbH, 2015). The advantage of this algorithm is the capability to apply fuzzy logic to the membership function, and it also combines various conditions in class description (Trimble Germany GmbH, 2015). The "hierarchical classification algorithm" is used by applying complex class hierarchy into the image object level (Trimble Germany GmbH, 2015). Lastly, an "advanced classification algorithm" is defined a classification setting similar to a "classification algorithm".

2.4. Uncertainties of Ontology and Slum Detections in GEOBIA

Although the application of ontology in GEOBIA is prominent[2], it is affected by specific issues relate to the geographic concept and the cognitive aspect of the image interpretation (Arvor et al., 2013). Firstly, the relationship between objects is the source of uncertainties and vagueness, and it also depends on the abilities of persons to describe an object from the real-world in the image perspective (Arvor et al., 2013). Secondly, the knowledge of particular features is often qualitative and subjective, but the information contained in the image is quantitative (Arvor et al., 2013). The third issue, as mentioned by Arvor et al. (2013) is the fact that the geographic features often have fuzzy boundaries and relationship between entities, which might result in multiple interpretations. In the fourth issue, Arvor et al. (2013) mentioned that the geographic features and their representation in the images is on the scale (spatial, spectral and temporal), whereas the description of the image object varies according to their scale. The difference between a real-world object that change over time and the description of an object that remains static in the ontology has caused the fifth issue (Arvor et al., 2013). The sixth issue (Arvor et al., 2013), is the discrepancy between open and closed world assumption. Arvor et al. (2013) mentioned that GEOBIA assumes that the world is a closed system (e.g. assuming that vegetation class have particular NDVI value) while the ontologies are developed according to the assumption of the open world system (it allows different description for particular geographic features). In the last issue, Arvor et al. (2013) mentioned the processing performance issue. The increased description of an object implicated on the demand for high-performance computing resource.

In many cases, the reference to accuracy assessment is often from manual image interpretation (Kohli, 2015). However, similar to Arvor et al. (2013), Kohli (2015) also mentioned that slums often have fuzzy boundaries, different way to conceptualize, lack of local knowledge, which causes uncertainties in delineation process. Kohli (2013) mentioned three different forms of uncertainties in the case of slums detection (Figure 2-7). The first picture (Figure 2-7) shows the slum boundary that is expanding beyond the actual slum area. Meanwhile, the second picture shows the slums boundary that is less than the real slums area. The last picture shows the slum boundary that fits with the real slums area.

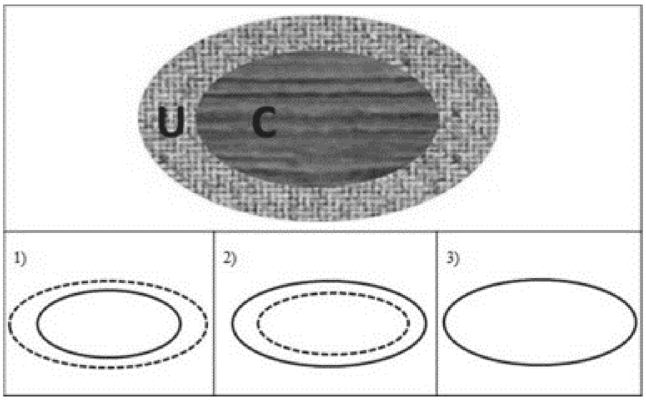


Figure 2-7 Uncertainties in Slums Detections (Kohli, 2015)[3]

[2] See Blaschke et al. (2014)

[3] C stand for core area, where it is certainly slums, U is area where slum is possibly appear

2.5. Transferability Measurement

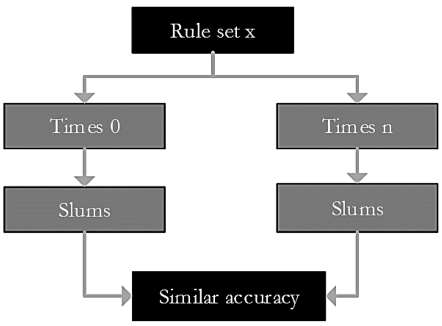
Transferability refers to the capability of a certain method to provide a comparable result for the different spatiotemporal condition, and it should require minimal adaptation (Kohli et al., 2013). Hofmann, Blaschke and Strobl (2011) used a different terminology called robustness. The ruleset can be considered as robust if it can deal with the variability of the object in different imaging conditions. However, to avoid ambiguities, we use transferability in our research.

Several studies have discussed the transferability in the domain of GEOBIA. For instance, the study by Foody, Boyd and Cutler (2003) analysed the transferability of models that were used to measure the biomass across different locations. Another study from Anders, Seijmonsbergen and Bouten (2015) discussed the rule set transferability of object-based feature extraction by combining LIDAR data and color infrared orthophotos. A study from Tuanmu et al. (2011) on the transferability of wildlife habitat model mentioned three parameters to measure transferability, which originated from the study of Randin et al. (2006).

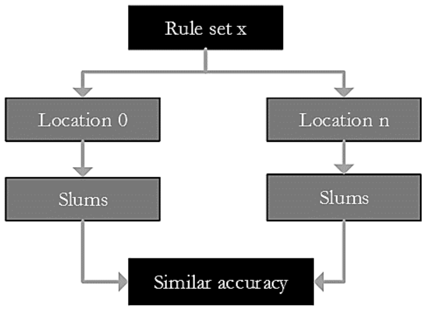
However, according to uncertainties mentioned above (Subchapter 2.4), finding a single evaluation methodology is difficult (Bamberger, 2012). Therefore, the combination of different evaluation framework is needed (Bamberger, 2012). The Mixed-method approaches to integrate the quantitative and qualitative approach, which combine the strength of both methods to overcome their weaknesses (Bamberger, 2012).

2.5.1. Quantitative Measurement of Transferability

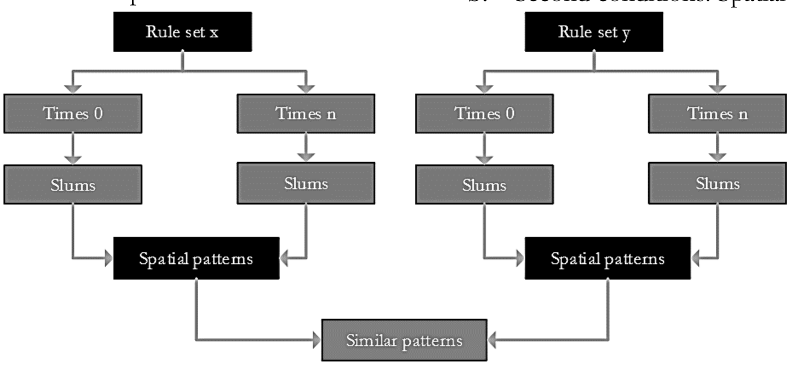
Quantitative measurement aimed to maximize objectivity, replicability and generality of findings (Harwell, 2011). The main characteristic of quantitative study is the used of some instrument, i.e., test or survey, and the dependency of a probability theory. Regarding the quantitative measurement of transferability, Tuanmu et al. (2011) mentioned three indicators of the transferable model. Firstly, they should result in similar accuracy within and beyond the time frame (Tuanmu et al., 2011). Thus, this measurement refers to temporal transferability (Figure 2-8 (a)). Secondly, the models should have similar performance in different places, whoever time frame that used (Tuanmu et al., 2011). Thus, this measurement refers to spatial transferability (Figure 2-8 (b)). Lastly, models should result in similar spatial patterns (Figure 2-8 (c)) (Tuanmu et al., 2011). This conceptual framework of transferability can be seen in Figure 2-8.



a. First conditions: Temporal Transferable



b. Second conditions: Spatial Transferable



c. Third conditions: Similar Spatial Patterns

Figure 2-8 Transferability Measurement Framework, Source: Adapted from Tuanmu et al. (2011)

Regarding the accuracy of the first two indicators (Figure 2-8 (a) and (b)), various measurements can be used, i.e., the overall proportion of area, correct classification of pixel or polygon, kappa and tau coefficient and user-producer accuracy (Stehman, 1997). However, Stehman (1997) argued that there is no common agreement regarding the most appropriate measurement, although the kappa coefficient is commonly accepted. Fitzgerald and Lees (1994) mentioned that the kappa test could be used to test the accuracy of classification result that is based on the error matrices. Furthermore, Fung and LeDrew (1988) mentioned that the kappa test gives a better measurement since this measurement is calculated based on every cell in the error matrix.

However, since the emphasis of our research is on object-based analysis, it is also important to consider the classification accuracy according to the object-based domain. Lee, Shan and Bethel (2003) assessed an automated building extraction by comparing the automated extracted buildings with manual delineations and categorized the results into four categories that were suggested by McKeown and Cochran (1999). These categories are True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). TP is the result when an automated and manual delineated object coincide, for TN, both the automated and manual methods label a pixel as a background (Lee et al., 2003). For FP, only the method of automated extraction labels a pixel as a building. Lastly, FN means only the method of manual extraction labels a pixel as a building. Hence, besides analysing transferability according to confusion matrix, we also have a quality assessment that fits with object-based analysis. As discussed by McKeown and Cochran (1999), the quality assessment can be conducted by measures percentage of TP with overall classification methods. It is clearly illustrated in following equations:

$$Quality = 100 * \frac{TP}{(TP + FP + FN)} \qquad \text{Eq. 2}$$

Where we bring the TP value as a size of slums that are detected by particular ontology, in a given place and time, which are matched with a manual delineation from the experts, as it discussed in Subchapter 5.1.2. The FP value is obtained from the automatics methods, and the FN value is obtained from manual delineations.

Regarding the third indicator (Figure 2-8 (c)), the spatiotemporal pattern measured by the spatial metrics. Spatial metrics measures the statistical attribute of thematic maps that shows spatial heterogeneity on the different scale and resolution (Herold, Couclelis, & Clarke, 2005). Spatial metrics has focused on the various application (Herold et al., 2005), i.e., Parker, Evans and Meretsky (2001) demonstrated the usefulness of spatial metrics in linking economic processes and land use patterns. Another study from Alberti and Waddell (2000) proposed a specific spatial metrics used to models the impact of the complex spatial pattern of the land use and land cover of the urban area.

About the slum domain, various studies have demonstrated the usage of spatial metrics. For instance, a study from Baud, Kuffer, Pfeffer, Sliuzas and Karuppannan (2010) used spatial metrics to understand the spatial diversity of different types of a slum settlement in the different electoral ward. A study from Sliuzas, Kerle and Kuffer, (2008) mentioned several usages of spatial metrics in the slum domain, including the ability to monitor changes in slums settlement over a period by analysing the changes in certain spatial metrics. Therefore, according to the usefulness of spatial metrics in the slum domains, we can conclude that spatial metrics can be used to monitor the multi-temporal pattern of slum settlements. Another study from Kuffer et al. (2014) demonstrates the usage of spatial metrics to develop an Unplanned Settlements Index (USI), which can distinguish slum and non-slum settlements in the urban area. USI is built by combining various dimension of deprived areas into one composite index (Kuffer et al., 2014). Key features of slums, as mention in this study consist of size, density and layout structure.

Among various spatial metrics that are analysed in Kuffer et al. (2014), in the case of Delhi, it shows that the Landscape Division Index (DIVISION) and the Effective Mesh Size (MESH) are the most significant metrics that can be used to distinct slums and non-slum according to the size characteristics. However, according to Mcgargial & Ene (2013) combining DIVISION and MESH is redundant, since they have perfectly inverse correlation. The difference is due to the units and interpretation, where DIVISION is interpreted as a probability while MESH as an area (Mcgargial & Ene, 2013). Regarding the metrics that related to the density, patch density (PD) is the most significant metrics (Kuffer et al., 2014). Meanwhile, regarding the pattern-related characteristics, the aggregation index (AI), Shannon's Evenness Index (SHEI) and Contagion Index (CONTAG) are the most significant metrics (Kuffer et al., 2014). The description of the metrics that used can be seen in Table 2-2.

Table 2-2 Selected Spatial Metrics

Metrics	Formulation	Description and Application in Slums Domain
1 Size-related		
Landscape Division Index (DIVISION)	$1 - \sum_{j=1}^{n} (\frac{a_{ij}}{A})^2$ Where a_{ij} = area (m^2) of patch ij, A = total landscape area (m^2)	The range is 0 ≤ DIVISION < 1, where 0 indicate that the landscape consists of a single patch. Meanwhile, the value 1 indicates that the patches size equal to pixel size. Regarding the application to slums, this metric indicate the domination of slums among the period of measurement (by comparing DIVISION value for each year) in the defined area.
2 Density-related		
Patch Density (PD)	$\frac{n_j}{A}$ (10,000)(100) Where N_j = the number of patches in the landscape of class i A = total landscape area (m^2)	The PD indicates the number of patches in 100 hectares. The higher the number of PD indicates that the patch is dispersed along 100 hectares area, vice versa. Regarding the application to slums, this metric indicate the number of slum pocket in the study area.
3 Pattern-related		
Aggregation Index (AI)	$\left[\frac{g_{ii}}{max - g_{ii}}\right](100)$ Where g_{ii} = some like joins between the pixel of class i, according to the single-count method. Max- g_{ii} = a maximum number of like joins between the pixel of class i, (single-count method).	The AI indicates the aggregation of patches. If the AI value equals to 0, indicate that the patch is maximally disaggregated. Meanwhile, the 100 indicate that the patch is aggregated into one single patch. Regarding the application to slums, this metric determine whether the slums is aggregated or disaggregated. By comparing these results in the defined period, we can see how the slums are more or less aggregated across years.
Shannon's Evenness Index (SHEI)	$\frac{-\sum_{i=1}^{m}(P_i \ln P_i)}{\ln m}$ Where P_i = proportion of the landscape that is occupied by the class i m = number of class in landscape	SHEI measured by comparing the observed Shannon's Diversity Index (SHDI) divided by the maximum SHDI for a particular class. The SHEI indicate 0 if the landscape only contains one patch. Meanwhile, it indicates one if the distribution of area among each class is perfectly even. Regarding the application to slums, this metric measure whether the slums are located exclusively in some parts of the cities, or it is distributed among other urban features.
Contagion Index (CONTAG)	$\left[1 + \frac{\sum_{i=1}^{m}\sum_{k=1}^{m}\left[P_i * \frac{g_{ik}}{\sum_{k=1}^{m} g_{ik}}\right] * \left[\ln\left(P_i * \frac{g_{ik}}{\sum_{k=1}^{m} g_{ik}}\right)\right]}{2 \ln m}\right] * (100)$ Where P_i = proportion of the landscape that is occupied by the class i g_{ik} = number of the join between the pixel of class i and k m = number of the class in the landscape	Contagion is related inversely to the edge density. The value is reaching 100 if a single class is occupied a large percentage of the landscape, vice versa. Regarding the application to slums, this metrics indicate the clumpiness of the slums among defined period

Source: Adapted from Mcgargial and Ene (2013) and Kuffer et al. (2014)

2.5.2. Qualitative Indicator of Transferability

While the quantitative measurement focused on objectivity and aside the experiences, perception and biases, qualitative measurement has not neglected those factors (Harwell, 2011). The aims of the qualitative method of measuring the transferability are to enhance, complement, also follow up with the unexpected result from the quantitative method (Harwell, 2011). Sori (2012) mentioned some qualitative indicators to measures the applicability of methods for slum detection, i.e., reliability, efficiency, utility and generality, and validity. A reliable method produces a similar result if repeated under similar conditions (Sori, 2012). Meanwhile, an efficient method refers to the precision of classification results in a particular time, equipment and expertise limitations (Sori, 2012). The utility refers to the effect and usefulness of the approach, whereas the generality refers to the degree of particular approach might be successfully applied with small adaptation (Sori, 2012). Lastly, validity refers to whether the output agrees with the real situation on the ground (Sori, 2012).

Another study from Lantow and Sandkuhl (2015) developed a quality metrics to measure the applicability of ontology according to some indicators, which are clarity, understandability, adaptability and reusability. Clarity refers to the recognition of all concepts, relationship and correspondences, whereas understandability refers to the comprehension of all concept, relationship, correspondences with their meaning (Lantow & Sandkuhl, 2015). Adaptability refers to the ability for adaptation while the reusability is the ability to be used in a different situation (Lantow & Sandkuhl, 2015).

2.5.3. Summary of Different Concept to Measure Transferability

Summary of a different concept to measure transferability that discussed in Subchapter 2.5.1 and 2.5.2 can be seen in Table 2-3.

Table 2-3 Different Concept to Measure Transferability

Indicator	Description	Sources
Quantitative Measurement		
Spatial Transferability	Transferable ruleset resulted in similar accuracy when it applied to the different area	Tuanmu et al. (2011)
Temporal Transferability	Transferable ruleset resulted in similar accuracy when it applied in the different period	Tuanmu et al. (2011)
Spatiotemporal pattern similarities	Transferability ruleset resulted in similar spatiotemporal pattern with ground change	Tuanmu et al. (2011), parameter: USI (Kuffer et al., 2014)
Qualitative Measurement		
Reliability	Transferable ruleset resulted in similar output when it repeated	Sori (2012)
Efficiency	Transferable ruleset produced a good result from limited resource	Sori (2012)
Utility	Transferable ruleset can be applied	Sori (2012)
Generality	Transferable ruleset needs a minimum adaptation to produce similar results	Sori (2012)
Validity	Transferable ruleset output is similar to the real situation	Sori (2012)
Clarity	Transferable ruleset should recognize all concept	Lantow and Sandkuhl (2015)
Understandability	Transferable ruleset described every relationship of their element	Lantow and Sandkuhl (2015)
Adaptability	Transferable ruleset can be adapted	Lantow and Sandkuhl (2015)
Reusability	Transferable ruleset can be applied to the different condition	Lantow and Sandkuhl (2015)

3. STUDY AREA

This chapter describes the study area. It starts with the discussion of the slum dynamics in Jakarta. Next, we discussed the challenge of monitoring the slum dynamic, which is due to the different terminology, the level of measurement, and the existence of urban village or *kampungs*.

3.1. The Dynamics of Slums in Jakarta

More than 10 million inhabitants live in the inner city of Jakarta (Jakarta Planning Board [BAPPEDA], 2015), and more than 30 million in its metropolitan area (Demographia, 2015). The existence of various public facilities and high economic opportunities has attracted more people to live in Jakarta. However, due to the lacking capacities of the local government to cope with the high rate of urbanization, e.g. providing public housing, many low-income people are living in sub-standard housing areas.

Since 1997, the government of Jakarta have established a survey to monitor the dynamics of slums by developing indices that are frequently updated through a survey. This measurement is done by neighbourhood[4] units, where all unit (2,538 neighbourhood) were surveyed (Department of Building and Settlements DKI, 2014). Ten indicators were used, i.e., population density, building orientation, building materials, air circulation, building density, road condition, drainage, clean water sources, sanitation and waste disposal (Department of Building and Settlements DKI, 2014). According to this survey results, the slums score are divided into four class (Figure 3-1), i.e., heavy slum, medium slum, light slum and very light slum. According to this measurement, we can see the slums dynamic in Jakarta between 1997 to 2013 (Figure 3-1 (a) to (f)).

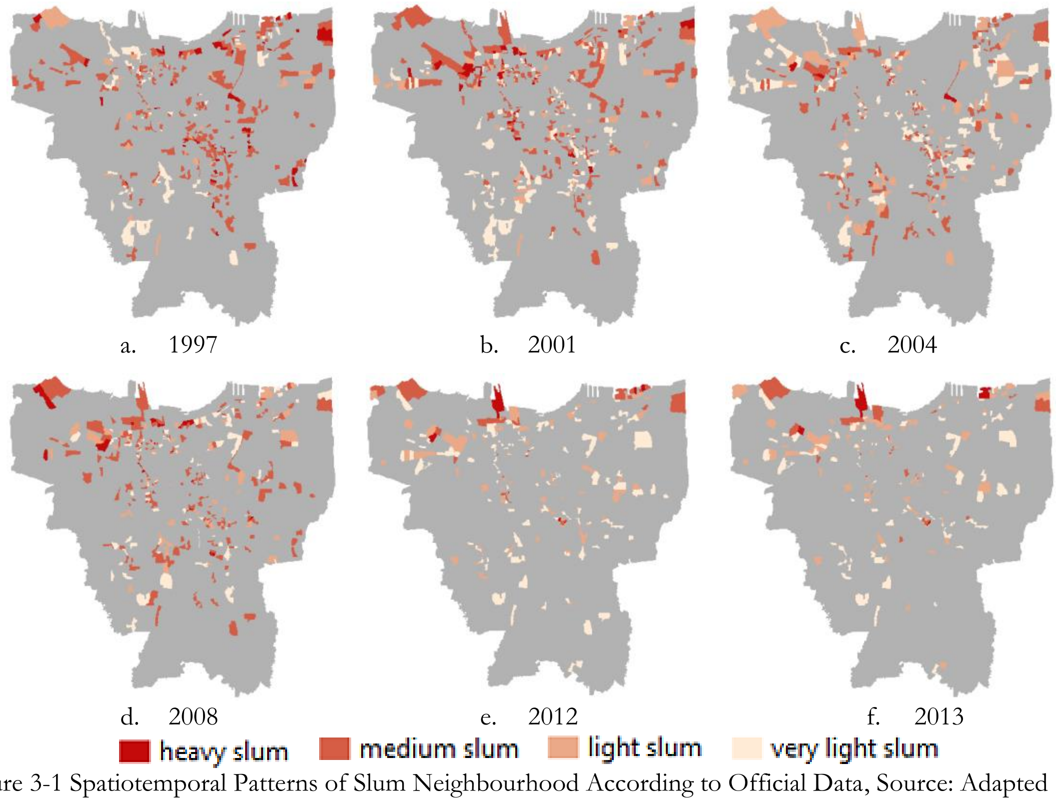


Figure 3-1 Spatiotemporal Patterns of Slum Neighbourhood According to Official Data, Source: Adapted from Department of Building and Settlements DKI (2014)

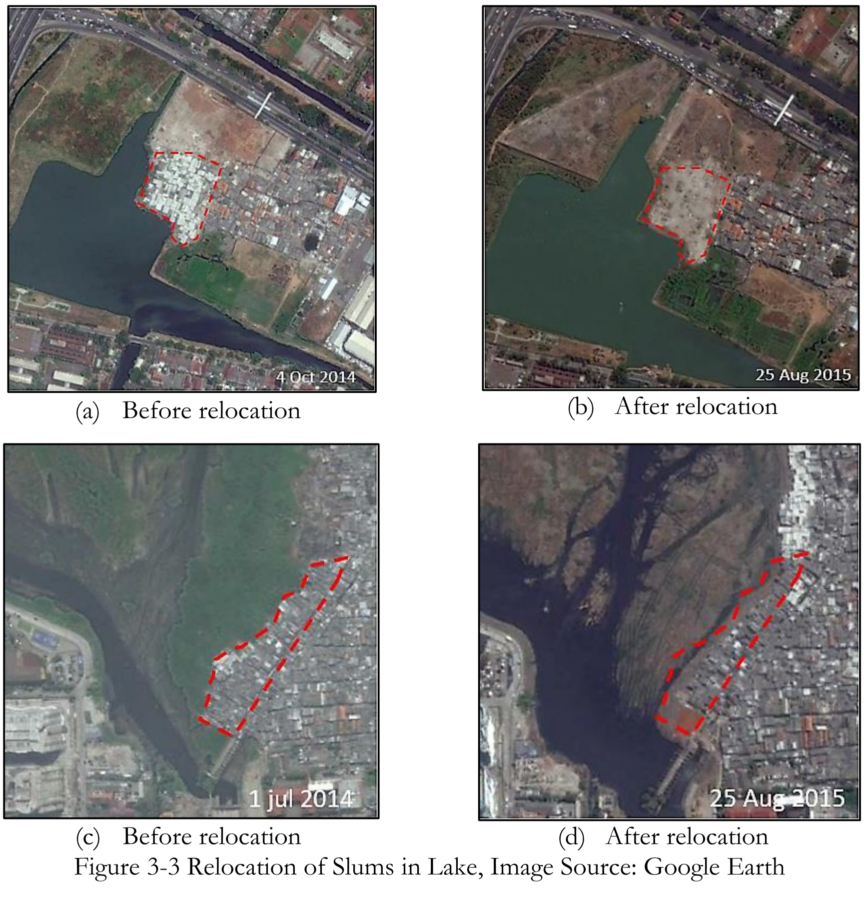
[4] A neighbourhood unit is a non-administrative division under sub-districts

According to the slum neighbourhood survey (Figure 3-1), the size of slums in Jakarta has greatly decreased from 2008 to 2012. However, there are no further studies that are analysing the cause of this phenomenon. Currently, the policies that are taken by the government of DKI Jakarta to reduce the slums are focusing on relocating the dwellers in a massive scale. It unarguably has contributed to the dynamics changes of slums. This impact is well illustrated in Figure 3-2.

(a) before relocation (b) relocation (c) after relocation

Figure 3-2 Relocation of Slums in Riverbank, Image Source: Google Earth

In Figure 3-2 (a), the slums exist (red-striped area). Suddenly, in the next three month the settlement was demolished (Figure 3-2 (b)). In 2015, the slums do not exist in this area (Figure 3-2 (c)). To that end, we can notice that within one year, a slums area might change in Jakarta. This phenomenon also occurs in various parts of the city, particularly in slums that are occupied the water body. For instance, Ria-rio Lake and Sunter Lake (Figure 3-3 (a) and (b) shows Lake Ria-rio before and after relocation respectively. Meanwhile Figure 3-3 (c) and (d) shows Lake Sunter). The Government of DKI takes this approach as an effort to counter the floods problems.



(a) Before relocation (b) After relocation

(c) Before relocation (d) After relocation

Figure 3-3 Relocation of Slums in Lake, Image Source: Google Earth

3.2. Problems in Monitor the Dynamics of Slums in Jakarta

Three issues made the monitoring of the slum dynamics in Jakarta is difficult. The first difficulty is the different terminology of slums that exist. The second difficulty is the various levels that are used to monitor slums; in some institution, they are using the settlement level. Meanwhile, other institutions use the housing level. Lastly, the third difficulty is the existence of urban village (*kampungs*), an area where the slums and non-slums are hard to differentiate. Further discussion of each issue as follow.

3.2.1. Different Definitions of Slums

The national government of Indonesia has set their target on the Medium Term National Development Plan (RPJMN) for improving the quality of housing and settlements in 100-0-100[5] policy by 2019 (UN-Habitat, 2014). 62 billion USD needed until 2019, where 9.5 billion USD are funded by the national government to achieve the 100-0-100 target (Ministry of Public Works and Public Housing, 2015). To monitor the progress of the slum reduction is the key factor to ensure the achievement of this program. However, the various definitions of slums have led to the question on what definition should be referred.

The normative definition is referred to National Law No 1/2011 on Housing and Settlements, where slum are differentiated in two levels, i.e., slum housing and slum neighbourhood (Government of The Republic of Indonesia, 2011). Slum housing refers to a housing with inadequate living space while slum neighbourhoods refer to settlements with under-served facilities (Government of The Republic of Indonesia, 2011). Several indicator were developed by a different institution to operationalize the definition from the national law. For instance, Indonesian Central Board of Statistics (BPS)(2013) developed four indicators of slums, i.e., lack of access to drinking water, a poor durability of housing, poor sanitation, and insufficient living area. Another definition from Ministry of Public Works and Public Housing (Kemen PU-Pera)(2014) indicated six indicators of the slum, i.e., poor quality of disposal, coverage and quality of road network, the area size of inundation, quality of water source, density and quality of settlement. Furthermore, the government of DKI Jakarta Province also developed their indicator (Figure 3-1). Comparison of different characteristics of slum settlements can be seen in Table 3-1.

Table 3-1 Comparison of the Characteristics of Slums

Criteria	International[6]	National Law[7]	Susenas[8]	National Institution[9]	Local Institution[10]
Lack of Access to safe water	√	√	√	√√	-
Lack of Access to sanitation & facilities	√	√	√	√√	√√
Lack Quality of Housing	√	√√	√	√	√√
Inadequate Living Space	√	√√	√	√√	√√
Insecurity of Tenure	√	-	-	-	-
Non-conformity with Spatial Plan	-	√	-	-	-
Poor Socio-economic Condition	-	√	-	-	-

Note: √ adopted √√ adopted by adding more criteria - not adopted
Source: Adapted from Indonesia National Planning Agency (2014)

Therefore, the difference of indicators might result in different interpretations of slums condition. Among different approaches to determine slums, the Indonesia National Planning Agency (2014) mentioned that slums could be categorized due to the ownership status of their property, recognition of its right by the government, the condition of basic infrastructure, and compliance with spatial planning. The different typology of slums that exist can be seen in Table 3-2.

[5] 100-0-100 refer to 100% access to clean water, zero slums and 100% access to sanitation
[6] UN-Habitat (2003)
[7] Government of The Republic of Indonesia (2011)
[8] Indonesian Central Board of Statistics (BPS) (2013)
[9] Ministry of Public Works and Public Housing (2014)
[10] Department of Building and Settlements DKI (2014)

Table 3-2 Typology of Slums in Study Area

No	Ownership	Recognition by government	Infrastructure condition	Compliance with Spatial Plan	Slums Category
1	Self-owned	Recognized	Ageing	Comply	Legal slum
2	Not self-owned	Recognized	Ageing/Not exist	Comply	Legal slum
3	Not self-owned	Not recognized	Not exist	Comply	Illegal slum
4	Not self-owned	Not recognized	Not exist	Not comply	Illegal slum

Source: Adapted from Indonesia National Planning Agency (2014)

3.2.2. Different Level of Measure Slums

According to the discussion in previous parts, the National Law on Housing and Settlements mentioned two distinct levels on measuring slum, which is household and settlements. A slum household refers to a household that is living in sub-standard housing, where a slum settlement is an area with sub-standard infrastructure.

Due to the different level to measure slums, defining the scale of a slum in the study area is difficult. On Figure 3-4, we can notice how different level of measurement has caused a different interpretation.

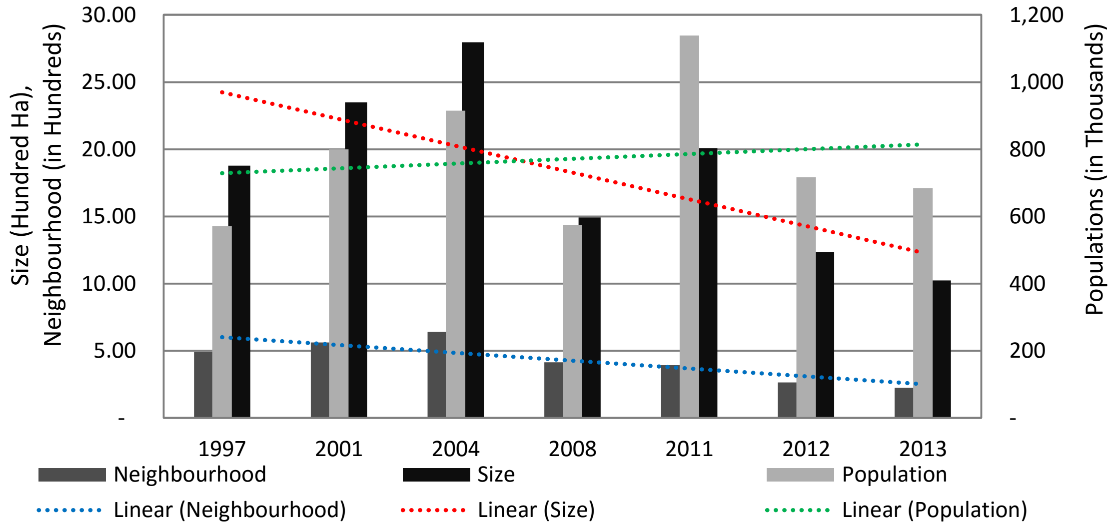


Figure 3-4 Trend of Slums in Jakarta, Source: Adapted from Department of Building and Settlements DKI (2014)

If we focus on using the neighbourhood or size as the level of measurement, we could conclude that the slums in Jakarta reduced between the periods of 1997 to 2013. This result is similar to the Figure 3-1 that shows rapid decreasing of slums in Jakarta between periods 2008 to 2012. However, if we measure according to the slum population, it shows an increasing trend. Therefore, to claim whether slum reduction policies properly work, the policy makers should be aware of their level of measurement.

3.2.3. Existence of Urban Villages

Slums in Jakarta are characterized by overcrowding, physically deteriorated, and limited amenities, including open space (Zhu, Bunnell, & Yeo, 2010). Discussing settlement problems in Jakarta are closely relate with discussing the concept of the urban *kampungs*. When discussing the context of a *kampung* in Jakarta, we need to trace back into 1950, when Jakarta was experiencing rapid urbanization, just after the end of the colonial era (Putranto, 2009). During this time, the planning institution did not exist as a part of the government system in Jakarta (Rukmana, 2008). Together with the rapid development of the city centre, many vacant lands and rice fields changed into built-up, and some of them are the housing areas for low-income people, called *kampung*. Due to the continued growth of Jakarta, more people occupied land and forming new *kampungs* or increasing the size of existing ones. This growing not only made the *kampungs* bigger, but also more heterogeneous. Nowadays, many high-skilled workers are living in a *kampung*, in particular in enclaves located nearby the Central Business Districts. Many *kampungs* have been provided with basic infrastructure, although their high-density characteristics are not changed. However, in particular, the low-income people remain in *kampungs* with sub-standard housing. Regarding tenures, some *kampungs'* dwellers have their rights on their land and properties (Putranto, 2009), and in some not, especially in location nearby riverbank.

Kampungs can be characterised due to the high density and unorganized layout, but having different characteristics on the ground (Figure 3-5). In Figure 3-5 (a) we can see a *kampung* with electricity and clean water. Asphalt paves the road, and a car is parked on it. Meanwhile, in Figure 3-5 (b) we can see a different type of *kampungs,* where dwellers lack access to sanitations. This *kampung* is located on the riverbank.

(a) Kampung with basic infrastructure (location: -6.2171456; 106.8465643,270)
Source : Google Map (left), Google Streetmap (right)

(b) Kampung without basic infrastructure (location: -6.2209576,106.8607349,315)
Source: Google Map (left); Fieldwork data (right)
Figure 3-5 Different Typology of *Kampungs*

Although all *kampungs* share, at least, one of the characteristics of slums (Table 3-1), some evidence mentioned above indicated that we cannot easily categorize all *kampungs* as a slum. Furthermore, by comparing different characteristics of *kampungs* with the GSO, we can notice that some global characteristics of slums are not applicable in the study area, e.g. high density of the built-up area. Therefore, we need to have a better understanding of the various typology of slums in Jakarta, to be able to define the location of slums.

4. RESEARCH METHODOLOGY

This section describes the methods to address the questions of this study. It starts with the description of the general approach, followed by the description of the specification, conceptualization and implementation phase. In the last part, we discuss the methods to measure the transferability of the GSO and LSO in different spatial and temporal condition.

4.1. General Approach

Four phases are employed in our research. In the first three phases, we follow the methontology that is discussed in chapter 2.2.1. Meanwhile, at the fourth phase, we employ the transferability measurement. During specification phase, the local characteristics of slums are identified according to local experts' perception from the expert interview and field observation. Local experts were asked to indicate the location of slums in the image (Figure 4-4 (b)), and the result was compared with the ground data. During the conceptualization phase, we developed two rulesets, i.e., GSO and the LSO. In the third phase, we execute both rulesets for different spatial and temporal conditions. We use the radiometrically corrected image as test set data. This phase resulted in the several maps of slum locations. In the last parts, we analyse the transferability of both rulesets across different conceptualization, spatial, and temporal conditions. Figure 4-1 shows the stages that are taken to achieve the objective of this research.

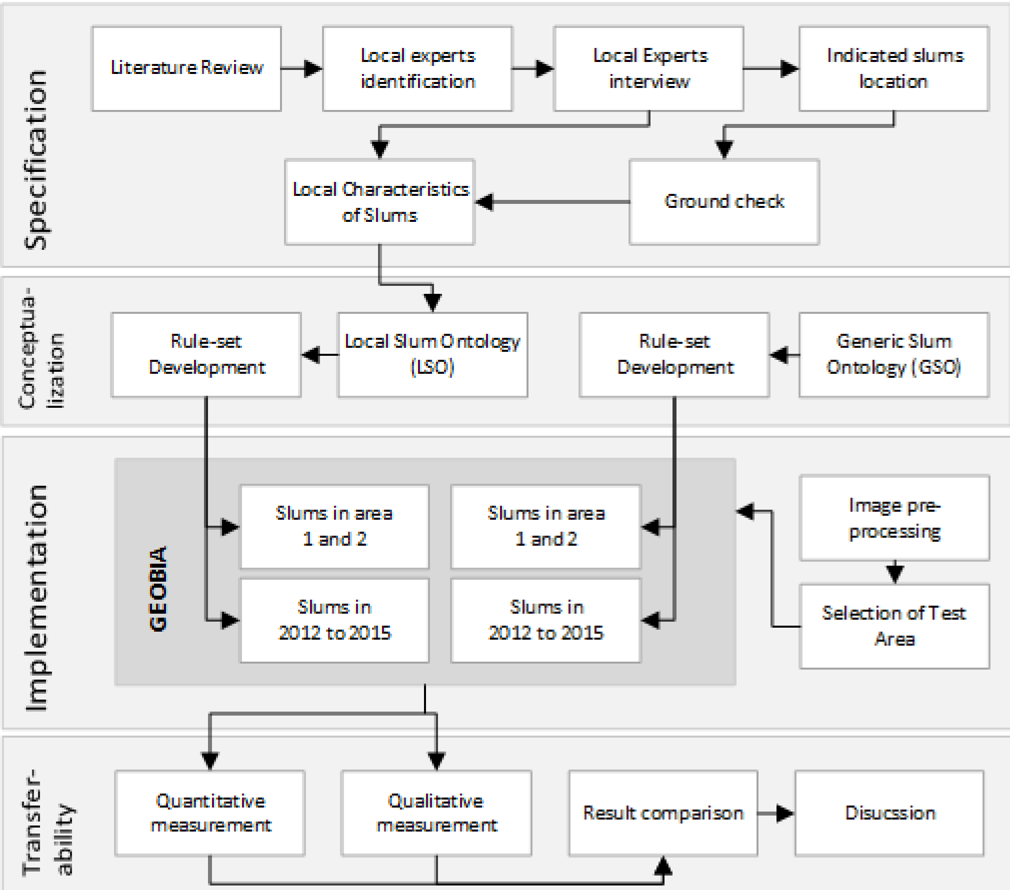


Figure 4-1 Research Framework

4.2. Specification Phase

The aims of this area are to determine the characteristic of slum settlements in the real world and image domain in Jakarta. This process is crucial since the following steps use the result of this step. The approaches used are a literature review, interview with the local experts and field observations.

We use various sources of the literature review to identify the local experts that relate to the slums issues in the study area, e.g., the role of the stakeholder related to slums alleviation in Indonesia (Indonesia National Planning Agency [Bappenas], 2014). Another report from Ministry of Public Works and Public Housing (2014) indicate the role of the central and local government in settlements programs. We also used the search engines, e.g. http://google.co.id, to identify the NGO that related to slums, by using the keywords of "NGO", "slums", and "Jakarta". Furthermore, we used snowballing sampling to define the appropriate expert. Snowballing sampling is a method to select sample, where a few individual asked to identify other people and the people that selected become the sample (Kumar, 2011).

According to the sources mentioned above, two different groups of experts existed, i.e., government and non-government groups. The government institutions focused on developing a minimum standard of settlements, i.e., the Guideline for Urban Settlement and Infrastructure Development (Ministry of Public Works and Public Housing, 2014). They can be categorized into two sub-groups, central and local government. We interviewed experts from Ministry of Public Works and Public Housing (to represent the central government), and Department of Spatial Planning Jakarta (to represent the local government). Meanwhile, the non-government group consists of various institutions, i.e., NGO, consultants and the private sector. However, to understand the character of slums, we focused on interviewing NGO and consultants that are intensively involved in the slum mapping in Jakarta. Similar to the government institutions, we selected institutions that are involved in slums issues in Jakarta. We interviewed one expert from NGO (Kemitraan Habitat[11]) and two consultants (SAPOLA[12] and BSPS[13]). The role of institutions mentioned above can be seen in Table 4-1.

Table 4-1 Local Experts Related to Slums and Its Role

Groups	Institutions' Role
Central Government: 1. Directorate General of Cipta Karya, Ministry of Public Works and Public Housing	1. Develop policies/standards on housing and settlements 2. Facilitate the local government to tackle the issues related to housing and settlements
Local Government: 1. Department of Spatial Planning of the Government of DKI Jakarta Province 2. Department of Building and Settlement of the Government of DKI Jakarta Province[14]	1. Develop spatial planning, including monitoring and evaluation stages[15] 2. Manage public housing, improve quality of settlements, conducting survey to measure slums[16]
Non-government Organization: Kemitraan Habitat	1. Tackle issues that formal institutions cannot handle, i.e., community empowerment is a long-term programme that needs continues funding. 2. Give a different view regarding the slums problems

[11] They focused to facilitate central government, local government and society in strengthen the governance of settlement programs. Detailed description (in Bahasa) in http://kemitraanhabitat.org/

[12] They were responsible to manage the project titled "Slum Alleviation Policy and Action Plan", where the aims is to develop a national policy on slum alleviation program. Detailed description (date accessed: 5 February 2016) in https://sapola.wordpress.com/

[13] They were responsible to conduct survey for determining the dweller whom eligible to obtain the stimulus fund from the government (BSPS) to increase the quality of their house. Detailed description (date accessed: 5 February 2016) in http://bsps2015.com/

[14] We failed to arrange an interview with this institution. However, we had access to some report regarding slum mapping as mentioned in chapter 3.1

[15] Slums in Jakarta are related to the spatial planning aspect, e.g., tenure issues. Therefore, we argue that the Department of Spatial Plan is the appropriate institutions.

[16] According to the official website of this department (http://dpgpjakarta.com)

Groups	Institutions' Role
Consultant: 1. Slum Alleviation Policy and Action Plan (SAPOLA) Consultant 2. Housing Stimuli (BSPS) Consultant	1. Assist in the primary task of the government, such as providing policy advice or providing human resources. 2. As a bridging between academician to involve with government program (according to the Indonesian Procurement Regulations)

We arranged to meet (in Jakarta, on September 2015) and asked them for an appropriate time for an interview. We conducted five interviews with five different experts. The aims of these interviews were to determine the characteristics of slums in Jakarta. We used topic-focused interview methods. This method is carried out with respondents that have been involved in certain experience (Groenendijk & Dopheide, 2003). There are several advantage in a topic-focused interview, it is flexible, responsive to new data from the respondent, an interview guide ensures every required information are collected, and the topic can be explored (Groenendijk & Dopheide, 2003). However, this method also has several limitations, which is the requirement of a skilled interviewer, inability to process the result statistically, bias from the interviewer and it consumes time (Groenendijk & Dopheide, 2003). Therefore, some action needs to be prepared, for instance by developing an interview guide and finding interviewee in the earliest step. During the interview process, the respondents are asked question and activity, which are:

1. Please indicate where are the slums located in this image![17]
2. Why do you indicate this area as slum?

After the interviews had been done, we conducted ground observations. The selected locations were based on the slum delineation by the experts (point 2 above). However, we applied two more criteria for the selection of the locations. The first criteria are the locations should represent the different degree of agreement among experts[18]. The second criteria were the safety of the locations, to allow accessed during the fieldwork time, and had to fit into the available resources (e.g. mode of transportations to access particular locations). According to the criteria mentioned above, fifteen locations were chosen (Figure 5-3). Since the cars cannot access many areas, we conducted the survey by a motorcycle. While the motorcycle is passing through the defined location, we took a picture with a GPS camera.

4.3. Conceptualization Phase

The main activity in the conceptualization phase is to develop a rule set that allows detecting the slums in the study area. Rule set development is a crucial part of this research since its role as a bridge between local knowledge obtained and GEOBIA process. We structure the knowledge obtained from specification phase to develop the Local Slum Ontology (LSO). Hence, we have developed two rulesets, GSO and the LSO. The GSO ruleset was developed according to the definition from Kohli, Sliuzas et al. (2012), and the LSO ruleset was developed according to the local experts.

4.4. Implementation Phase

Various stages have to be taken in the implementation process. It started with selecting the satellite imagery, image pre-processing, and selection of subset and test area, lastly segmentation and classification. Description of each stage is given below.

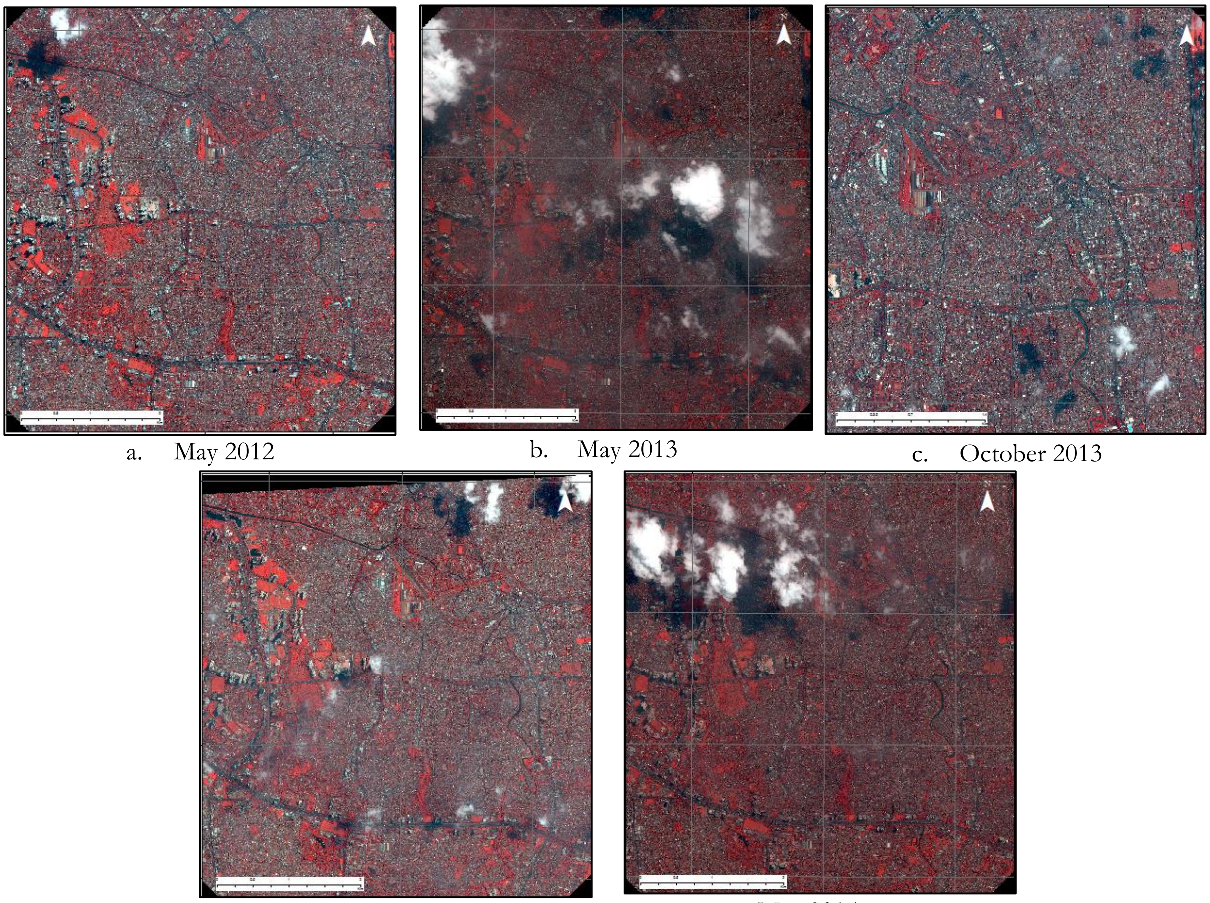
4.4.1. Selection of the Satellite Imagery

Since the object of interest is relatively small (if we consider the building as the object), thus the images need to have a resolution that is smaller than the object size. Additionally, since slums are often associated with the lacks vegetation (Kohli, Sliuzas et al., 2012), the usage of near infrared (NIR) band gave a benefit. For

[17] To support this activity, we provide an image of the study area, which we presented in Figure 4-4 (b)
[18] See Kohli (2015)

this study, we selected Pleiades images, we wanted to explore the capabilities of recently available Pleiades imagery to detect slums through GEOBIA. Images were for the years 2012 to 2015. Lastly, we could obtain the image 'free of charge' for research purpose[19].

The spatial resolution of Pleiades image is 0.5 meters for the Panchromatic, and 2 metres for the red, green, blue and near infrared band. After pan-sharping, the resolution for each band is 0.5 metres. The main problems of acquiring satellite imagery in tropical countries are the high coverage of cloud (Figure 4-2 (b) and (e)). Thus, for each year of the study period, we select the image that has the lowest cloud cover. We managed to choose an image for each year that has cloud cover of less than 10%. However, in some images, we still can find an area that was covered by clouds. Due to this reason, we decide to use two different images for the year of 2013 (Figure 4-2 (b) and (c)).



a. May 2012 b. May 2013 c. October 2013

d. May 2014 e. May 2015

Figure 4-2 Pleiades Imagery that used

4.4.2. Image Pre-processing

Since we work with multi-temporal data, the variation of the atmosphere during this period will affect the outcome. Therefore, image pre-processing needs to be conducted, to ensure a consistent input for the ruleset to be developed. According to the user guide of Pleiades Imagery, this product is offering three processing levels, primary, standard ortho and tailored (ASTRIUM, 2012). We used the Ortho product since it is geometric and radiometric corrected, and it also added additional processing, e.g. colour balancing and pixel sampling (ASTRIUM, 2012).

[19] Obtained from European Space Agency (ESA). The list of available image can be seen in http://www.geo-airbusds.com/en/4871-browse-and-order

According to the parameter that was obtained from the metadata from Pleiades imagery, the images have different in sun angles (Appendix D). Therefore, we need to correct this variation on the image. According to Peg (2013), we need to convert the images into a radiance image, then doing an atmospheric correction. Hence, we can produce a surface reflectance image, which is ready for extracting quantitative information (Peg, 2013).

There are several algorithms that can be used for conducting a radiometric calibration. However, among the algorithms that exist, the Fast Line-of-Sight Atmospheric Analysis of Spectral Hypercubes (FLAASH) has demonstrated their capabilities in this field. For instance, the study by Matthew et al. (2002), Perkins et al. (2005), Manakos, Manevski, Kalaitzidis and Edler (2011) and Guo and Zeng (2012). However, due to a pragmatic consideration, where there is no access to a license for this tool, we plan to convert the image DN value into Image Radiance first, then followed by conducting the atmospheric correction as recommend by Peg (2013). According to the Centre for Earth Observation of the Yale University (n.d.), the radiance value can be obtained from the gain and bias method, and from spectral radiance scaling methods. However, between these two approaches, the gain and bias method is simpler to operate. Therefore, we have selected this method. According to ASTRIUM (2012), converting the DN value to Top of Atmosphere (ToA) radiance is according to Equation 3.

$$L_b(p) = \frac{DC(p)}{Gain(b)} + Bias(b) \qquad \text{Eq. 3}$$

Where $L_b(p)$ is the radiance in the ToA in $W.sr^{-1}.m^{-2}.\mu m^{-1}$, and the DC indicate the DN value for particular pixel. The value of Bias and Gain are different for each band, and this value is provided in the metadata for each year[20] (Appendix D).

After the DN value for each band is converted into the radiance at ToA, we apply a haze correction, and then followed by the correction of the sun angle. The haze correction is following the basic module that is available in ERDAS Imagine, under the haze reduction function. We choose the low point spread type, since according to general visualization (Figure 4-2 (a) to (e)), we found that the haze is not too significant. The next stage is conducting the sun angle correction. According to Faculty of Geo-Information Science and Earth Observation, University of Twente (2013), a simple method to normalize an image is to divide the pixel value of an image by the sine of the sun elevation angle during the image acquisition. In Appendix D, we can see the sun elevation from each image, and its sine value.

Three measurements were taken for measure the f sun elevation (Appendix D), i.e., top centre, centre and bottom centre. We decide to select the sine value in the centre of the image. We expect that it gives a good representation of the image.

Since we work with several dataset, and each of them need similar process, we build a routine rule in ERDAS modeler to reduce the time that needs to conducting every stage that was mentioned before. The process is starting by calculating the image radiance for each band (Figure 4-3). It then followed by stacking each band into a single image. The next step is haze removal, and the last step the sun angle correction.

[20] for Pleiades user: this metadata can be access from file named DIM*.xml in the folder that given by the image provider

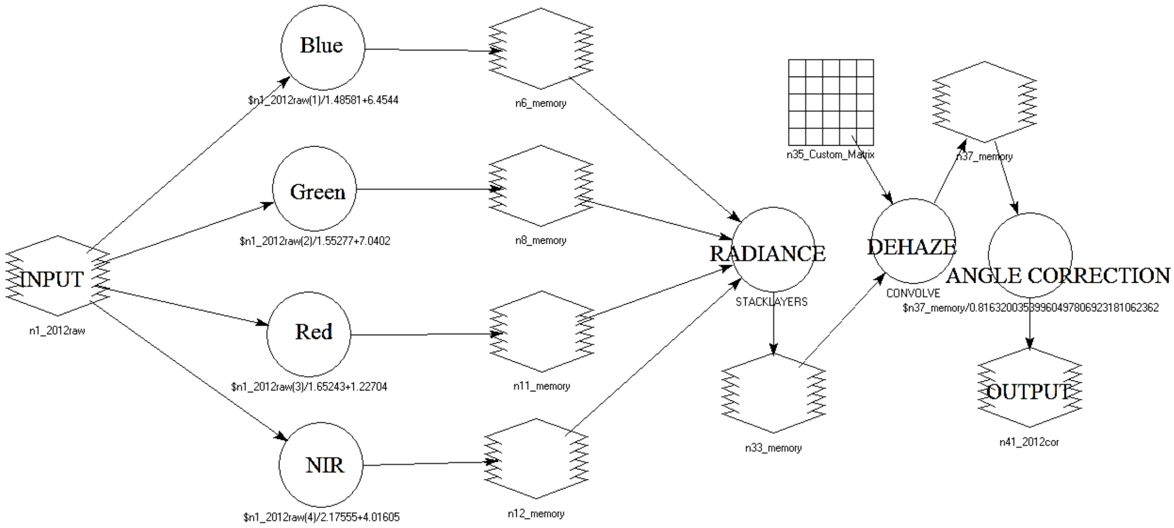
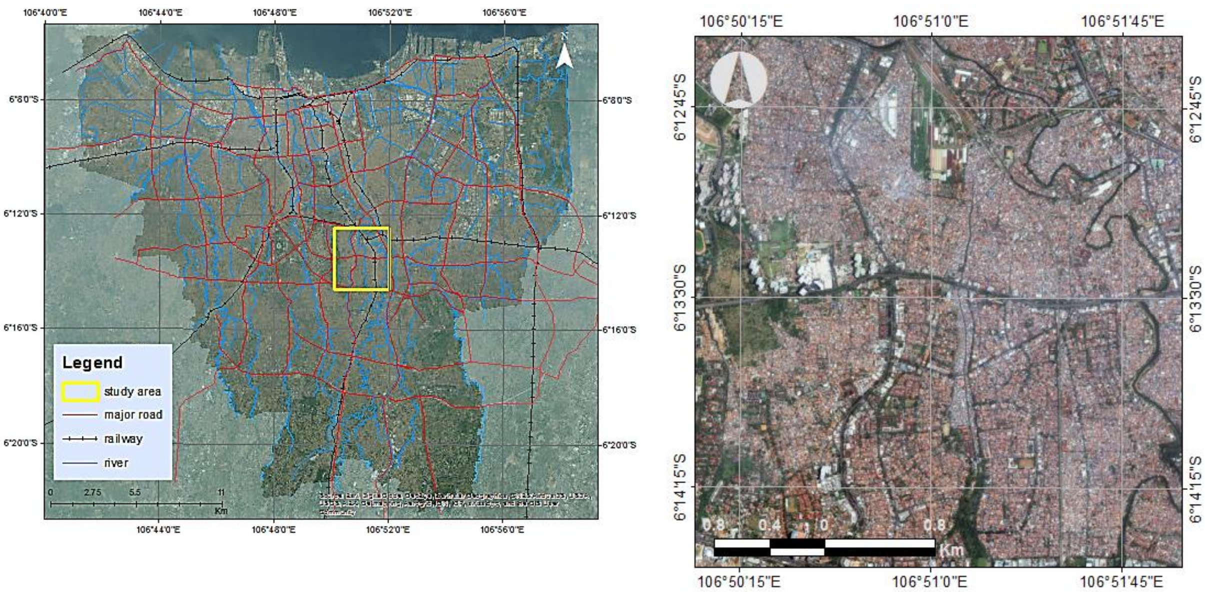


Figure 4-3 Routine Process for Image Pre-processing in ERDAS modeler

4.4.3. Selection of the Subset and Test Area

Since our research aimed to examine the transferability of the ruleset across different spatial conditions, the selected subset should have various characteristics of urban features. During this study, we have selected the area around Tebet district in Jakarta (Figure 4-4 (b)). Firstly, this district consists of various urban features. From high-class residential, central business district (CBD), famous shopping arcade, the central of the transportation hub, and slums. Secondly, Ciliwung River, which often can be associated with slums are passing through. Lastly, in this district several typologies of slums exist, e.g., slums that are located on the riverbank, near the railroad, near the CBD.



a. Map of Jakarta Province (yellow box is the study area) b. Study area

Figure 4-4 Selection of Subset Image

Regarding the selection of the test area, two area were chosen from Figure 4-4 (b). We consider two spatial characteristics while selecting these test areas. First, an area where the slum and non-slums areas are easy to distinct. Secondly, an area where the slum and non-slums areas are difficult to distinct.

4.4.4. The Usage of Ancillary Data

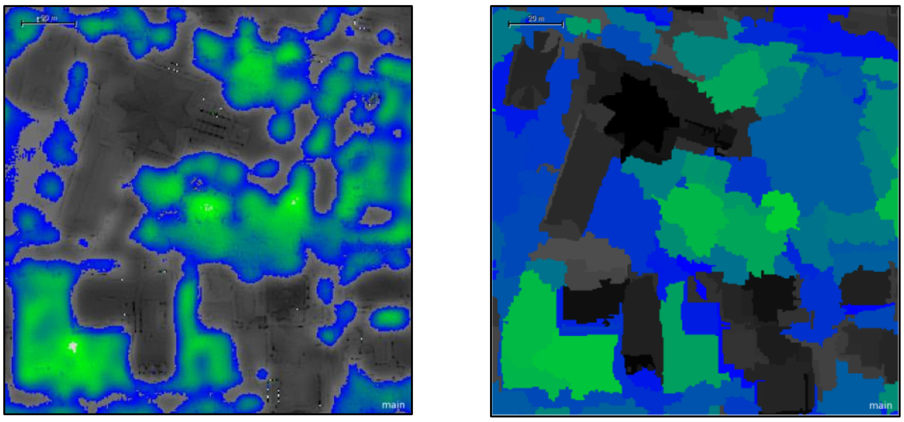
Several studies have demonstrated the usage of ancillary data to assist in the slum detection. For instance, the study from Netzband (2009) combined the VHR and ancillary data to analyse the physical characteristic of deprivation in Delhi, India. The study from Sori (2012) incorporated data related to access to improved water and sanitation, which can be used to distinct slum and non-slum areas, such data area obviously difficult to be obtained from satellite imagery. Another study from Kohli et al. (2013) used water bodies as a thematic layer, to reduce the effort in detecting these features. Therefore, the classification process can focus on determining the slums. Among various ancillary data that are available in Jakarta, we use the data that can assist to characterize slums. For instance, we used land use planning data to determine the slums locations, since the slums are often developed in an area that does not comply with the spatial plan regulations (Table 3-2). The full list of ancillary data that used in this research can be seen in Table 4-2.

Table 4-2 Ancillary Data

No	Data	Year	Note / Source
1	Google Earth Image	2013	Used for local experts interview
2	Google Street Map	2013, 2015	Ground truth data for detected slums
3	Land use planning	2014	Detailed Spatial Plan Jakarta
4	River, water body	2015	Open Street Map Data
5	Road, and transportation network	2014	Open Street Map Data
6	Socio-Economic	2010, 2015	PODES, Jakarta in Figure
7	Administrative Boundary	2014	Detailed Spatial Plan Jakarta
8	Slums neighbourhood map	2007 - 2013	Department of Building and Housing DKI

4.4.5. Segmentation and Classification

The segmentation process is a crucial part in GEOBIA since this process produces the image objects that are used for classification stage. During this research, we used multi-resolution segmentation due to its capabilities in the domain of slum extraction, which are discussed in the subchapter 2.3.1. We applied two strategies to implement the rule-set in e-cognition software. Firstly, we focused on implementing the rule-set in an area where the slums area is easy to distinct. The second strategy is to remove unwanted urban features from the image, followed by identification of slums according to each ontology. We employed two levels of segmentation as recommend by Kohli (2015). In the first level, we select the low value of Scale Parameter (SP), with equal value for smoothness and compactness parameter, which are 0.5. We choose the low value of the SP to ensure that the background class can be detected as precise as possible. Higher SP results in misclassification, where the building are detected as a vegetation (Figure 4-5 (b)). After we extract the background class, we can apply coarse segmentation from the ESP result.



a. SP=1 with NDVI >0 b. SP=40 with NDVI>0

Figure 4-5 Impact of different SP in detecting vegetation

Regarding the classification of the background class, four land cover classes that needs to be detected, which are vegetation, road, railroad and river. To extract the vegetation, we create a threshold from Normalized

Digital Vegetation Index (NDVI). We use the data from Openstreet Map (OSM) to detect the road, railroad and river. After we assign the first four classes, we assign the remaining class as built up. Next, we applied a coarse segmentation for settlements class (level 2 classification).

As mentioned in the previous chapter, the multi-resolution segmentation depends on selecting an appropriate scale parameter. Therefore, we used the Estimation of Scale Parameter (ESP) tool. This tool is loaded with E-cognition software, and it calculates the appropriate scale parameters for each image.

Regarding the classification process, we use the characteristics of each particular land cover class according to its image domain characteristics (subchapter 2.2.4). The classification process is conducted in E-cognition developer. To prepare ancillary data that are used in the classification process, Arc Map 10.3 were used. Related to the different characteristics of slums according to the description from the GSO and LSO, we develop two classification outputs using different rules.

To test the performance of the ruleset, we implemented similar values of the indicator for the different temporal dataset. Hence, we can visually examine the adaptation that needs to be implemented. As discussed in Subchapter 4.4.1, the atmospheric variations have affected the DN value. Hence, it was necessary to apply a correction factor to increasing or decreasing the class threshold values, e.g. increasing or decreasing the NDVI threshold value for vegetations. A trial-and-error process conducted for this process. The stages that taken for segmentation and classification parts can be seen in Figure 4-6.

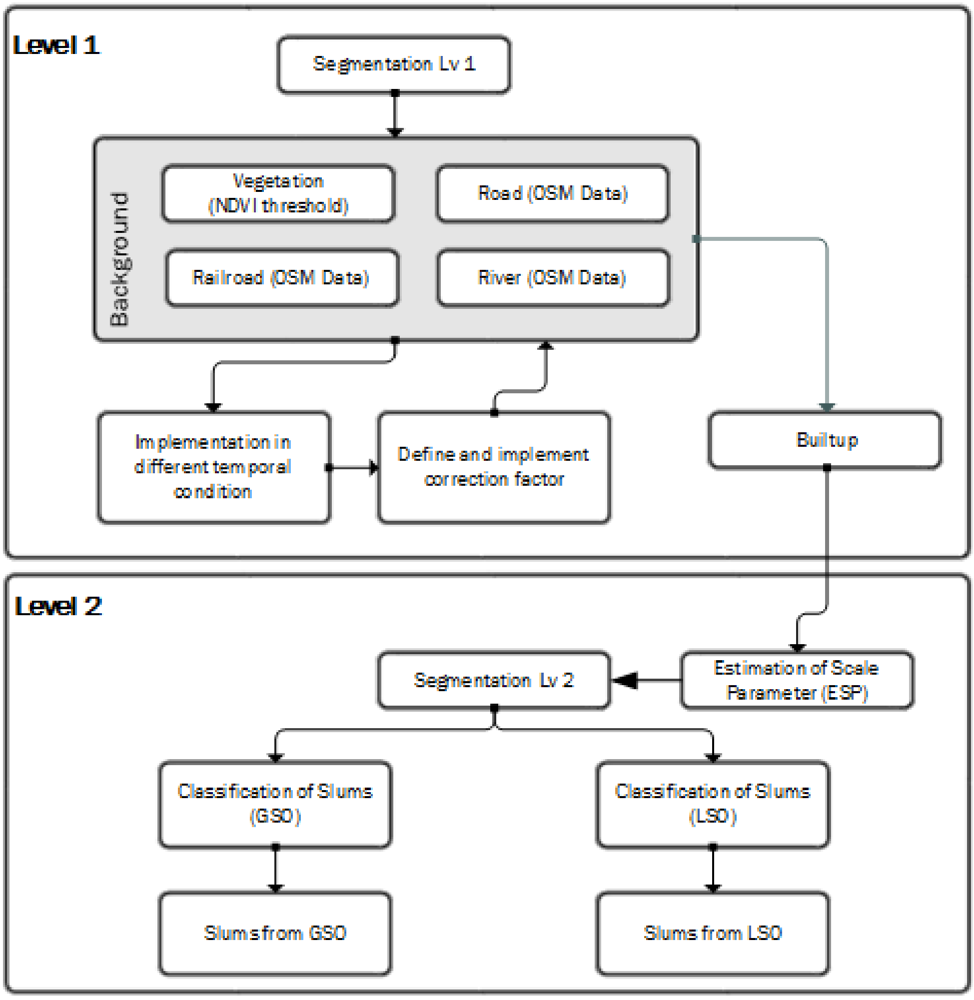
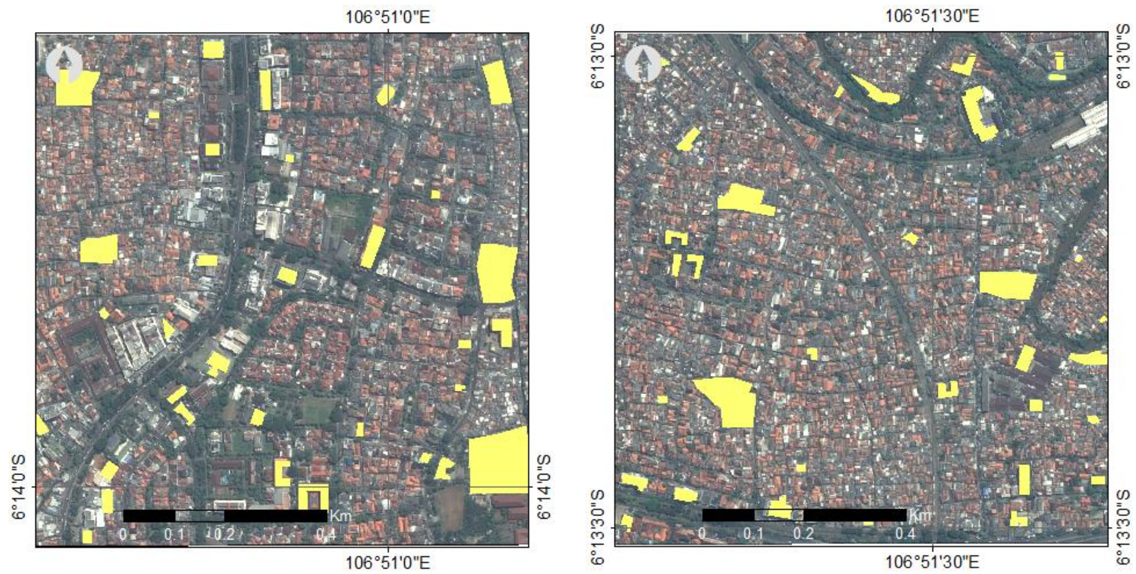


Figure 4-6 Process to detect the slums from the GSO and LSO Ruleset

Among various object accuracy measurement (Subchapter 2.3.1), Montaghi et al. (2013) mentioned that RA_{or}, RA_{os}, AFI and D_{sr} provided the best interpretation to measure the object accuracy. However, we decide to only used location-based measurement, which is the D_{sr}. D_{sr} are measured as the average of Euclidean distance in metre between the centroid of the segmented object and the centroid of the reference object (Montaghi et al., 2013). Since the location of the centroid is also affected by the shape of the object, we can assume that the D_{sr} also describe the goodness of the object shape. The formula that was used to measure the D_{sr} as follow:

$$D_{sr} = \frac{1}{n}\sum_{i=1}^{n}\sqrt{(x_{s(i)} - x_r)^2 + (y_{s(i)} - y_r)^2} \qquad \text{Eq. 4}$$

The value of D_{sr} indicates zero when the distance of segmented object and reference object is in the same location, and the value is increase when there is over or under segmented (Montaghi et al., 2013). As reference data, we create a manual delineation of the various object, i.e., different roof type, size, colour, and slum pocket (Figure 4-7). We then intersect with the object obtained from segmentation result and measure the distance from the centroid.



a. Test Area 1 b. Test Area 2

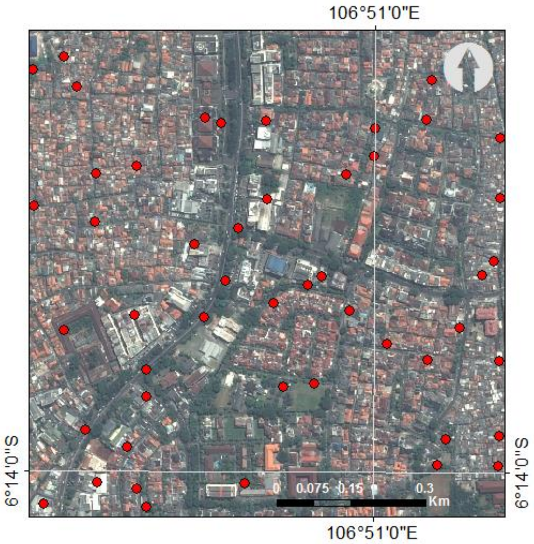
Figure 4-7 Segmentation Accuracy

4.5. Transferability Measurement

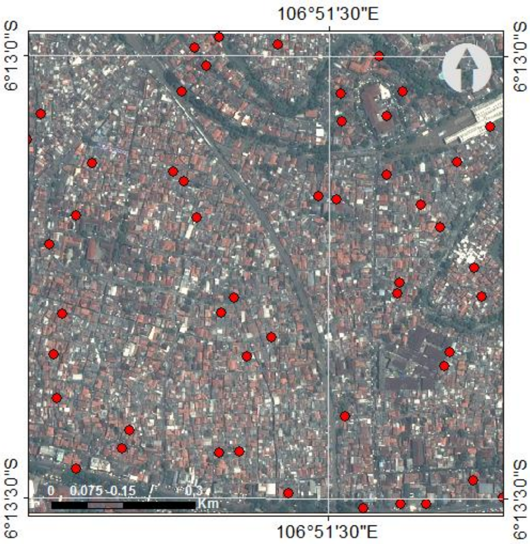
As discussed in the conceptual framework (Figure 1-1), we measure the transferability across different conceptual, spatial and temporal conditions. We employ both quantitative and qualitative measurements.

4.5.1. Quantitative Measurement

We follow the process that was suggested by Tuanmu et al. (2011) (Subchapter 2.3.3). Thus, the accuracy of the result and the consistency of spatial metrics value are used to quantify the degree of transferability. We started by comparing the accuracy across different location to measure the spatial transferability. It is then followed by comparing the accuracy across the different year, to measure the temporal transferability. The reference data for the object quality measurement (Equation 3) is obtained from the local expert. For the confusion matrix based measurement, we employed four indicators, which is overall accuracy Kappa index, producer accuracy and user accuracy. As reference data, we created 50 random points and assigned its land cover class (Figure 4-8).



a. Test Area 1



b. Test Area 2

Figure 4-8 Random Points for Confusion matrix-based Accuracy

To measure the spatial transferability, we compared the difference of accuracy result between the first and the second test area. The lower the difference, the more transferable the ruleset. Meanwhile, for the temporal transferability, we compare the average of accuracy changes. The lower the difference, the more transferable the ruleset. We inverse the value for spatial and temporal measurement to make the graph more easy to be interpreted.

Lastly, we calculated the spatial metrics (Table 2-2) using the classified slum location that is obtained from GEOBIA as an input. Metrics that are used follows the Unplanned Settlements Index (USI). For this study in Jakarta, we selected the spatial metrics that were employed in the case of Delhi. The reasons for this decision are that we believe that the slum characteristics in Delhi are most probable to be more similar with Jakarta, compared to Dar es Salam. During this study, we are not using the USI as a composite index. Regarding the redundancy of DIVISION and MESH (subchapter 2.3.3.2), we select one of them, which is DIVISION. We found that the DIVISION is easier to be interpreted as its range starts from 0 (single patch) to 1 (patch same to the pixel). We compared the value of all metrics from the USI, to compare the spatiotemporal pattern obtained from the GSO and LSO.

Regarding the calculation of spatial metrics, we have conducted this measurement on FRAGSTAT software. FRAGSTAT has been used to analyse the spatial characteristics by employing various metrics, and it has been utilized in different studies that relate to slums. For instance, the study from Baud et al. (2010) demonstrates the usage of FRAGSTAT software to analyse the heterogeneity in Indian metropolitan cities, to give a proper understanding of characteristics of sub-standard residential areas. Another study from Mathenge (2011) used FRAGSTAT to analyse spatial metrics of the classified image of slums obtained from object-oriented image analysis in Kisumu. The study from Sirueri (2015) used FRAGSTAT to analyse spatial metrics to compare the slums characteristics between Nairobi and Dar es Salam.

4.5.2. Qualitative Measurement

We combine the applicability parameter from Sori (2012) and Lantow and Sandkuhl (2015). For the indicator from Sori (2012), we exclude reliability, efficiency and validity. We excluded the reliability since, by definition, reliability refers to the similarity of the output if the given input were repeated. Since the ruleset that was developed is not a stochastic model, where the given input does not consist a random event (Robinson, 1994), we therefore not measure the reliability. We also exclude the efficiency and validity. Both efficiency and validity refer to the accuracy of the ruleset. Therefore, efficiency and validity produce the same measurement with the accuracy measurement (in quantitative measurement). Meanwhile, for the indicator from Lantow and Sandkuhl (2015), we excluded the clarity and understandability indicator. The clarity and understandability are excluded since we do not evaluate the clarity nor understandability of indicator of the slum that mentioned by each ontology. Meanwhile, we excluded the adaptability since this indicator refers to same focus to the generality, which is the adaptation.

Therefore, for the qualitative measurement we employed three indicators, i.e., utility, generality, and reusability. For the utility, we measured how the characteristic of slum from the real-world can be transformed into the image domain definition. The better the real-world definition can be transformed to image domain criteria, the more transferable the ruleset is. For the generality, the less number of indicator that needs adaptation for extracting the slums, the ruleset is more transferable. For the reusability, this indicator was complemented by the measurement that had been done in the quantitative measurement. However, the reusability elaborated and discussed the unexpected results. The summary of qualitative measurement can be seen in Table 4-3.

Table 4-3 Summary of Qualitative Indicator of Transferability

Indicator	Description	How to Measure
Utility	Transferable ruleset can be applied	The higher number of criteria from the real-world definition can be transformed into the image domain definition, the more transferable the ruleset
Generality	Transferable ruleset needs a minimum adaptation to produce similar results	The less number of indicator that requires adaptation for extracting slum, the ruleset is more transferable
Reusability	Transferable ruleset should be able to applied in the different condition	Similar to the quantitative indicator. However, it elaborated and discussed the unexpected result.

5. RESULTS AND DISCUSSION

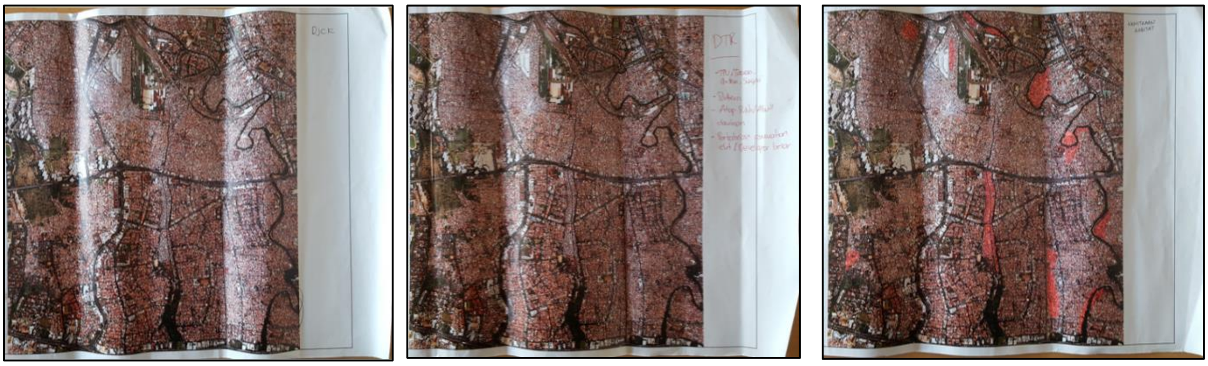
This chapter describes and discusses the results. It starts with the description and discussion of the characterization of slums, which firstly the role of local experts' institutions is discussed. Secondly, the characteristics of the slums according to the local experts are discussed, and variations in conceptualizing slums by local experts are compared. Next, the process in GEOBIA is shown, which starts with selecting the image subset, conducting segmentation by using the scale parameter determined by Estimation of Scale Parameter (ESP). It is then followed by the classification process, which we conducted for the GSO and LSO. We repeated this process for the different years. In the last part, we analyse the transferability of the ruleset.

5.1. Local Characteristics of Slums

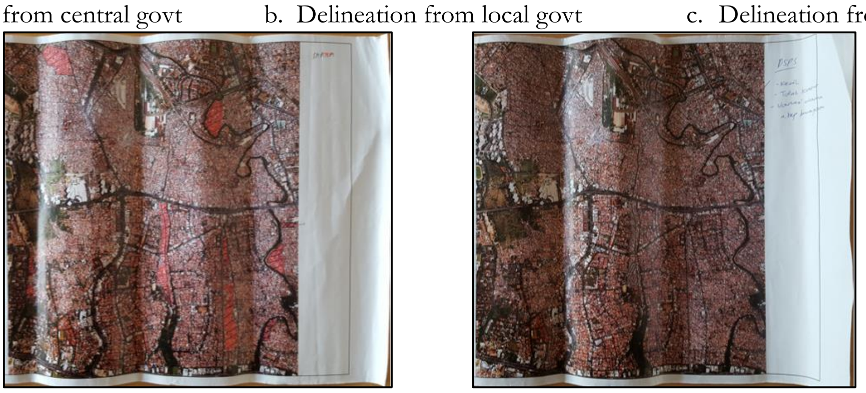
Understanding the local characteristics of slums is crucial for this study. We are adopted the GSO into LSO by understanding the characteristics of slums in the study area. To develop the LSO, we identify the characteristics according to the local experts via interviews, visual interpretation and field observation.

5.1.1. Interview and Visual Interpretation

In this part, we discuss various characteristics of slums in Jakarta, according to the official data, and from the visual interpretation that was conducted by different experts. By the end of this chapter, we can compare how the delineated slum area differs from the various experts. Field observation has been done, to give a better understanding of the different perception of slums. The interview with the local experts resulted in a manual delineation of the slums and the characteristics of the slums (Figure 5-1). These paper maps are then scanned and digitized in ArcGIS (Figure 5-2).



a. Delineation from central govt b. Delineation from local govt c. Delineation from NGO



d. Delineation from SAPOLA Consultant e. Delineation from BSPS consultant

Figure 5-1 Raw Results of Manual Slum Delineations from local experts

According to the interview with an expert from the central government, slums can be characterized due smaller building size compared with non-slum buildings. Their location on the riverbank with irregular building orientation. According to this definition, the respondent has indicated the location of slums in the study area (Figure 5-2 (a)). Meanwhile, an expert on the local government mentioned the slums characteristic by their location on the riverbank and the roof materials is from asbestos. Slums located adjacent to high class residential and CBD. She also argues that slums often occupy a piece of land illegally, i.e., in public parks, river buffer, and railroad buffer. The slum location from the local government expert can be seen in Figure 5-2 (b). Some slums enclaves are located in the western part, where it located nearby CBD. According to the local expert from Kemitraan Habitat NGO, slums in Jakarta can be characterized due to its small sized buildings, compared with non-slums settlements. They also have irregular building orientation, their roofs are made from asbestos, and they are located on the riverbank. This characteristic has similarities with one of the local government, i.e., the roof materials and the location that are on the riverbank. Therefore, the delineated slums from NGO also have similarities with local government. Some areas in the middle of the image (Figure 5-2 (c)) and the north-east have similarities with Figure 5-2 (b). We can notice that, apparently, the roof materials and riverbanks are the common characteristics of slums in the study area. The local expert from the SAPOLA listed slum characteristics similar to the characteristics are given by the local government and NGO experts, which are building size, irregular building orientation, roof materials being dominated by asbestos and their location on riverbanks. Due to the similar characteristics, we can notice that the delineated slums in Figure 5-2 (d) looks similar to Figure 5-2 (a) and (b). Lastly, the local expert from BSPS (having a similar role than the first consultant, see Table 5-1), characterized slums due to two primary factor, which is irregular building orientation and small building size. We summarize the different characteristics listed by local experts (Table 5-1). The first five indicators can be used to characterize slums from visual image interpretations. The last indicator cannot be visually interpreted and need to be extracted from the land use plan.

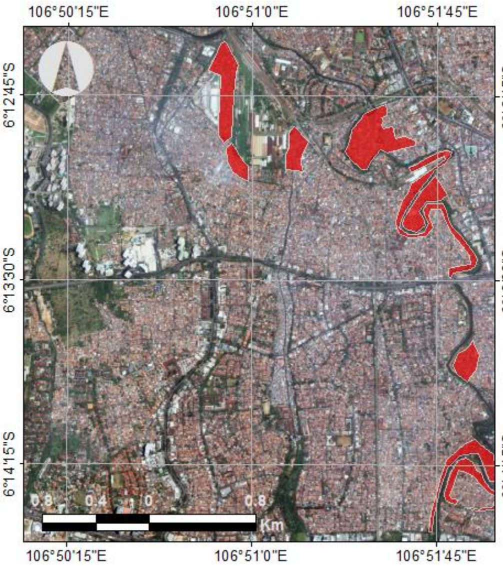
Table 5-1 Different Slum Perception among Expert

Characteristics		Local Expert				
		Central Gov.	Local Gov.	NGO	SAPOLA	BSPS
1	Located on the riverbank/railroad	√	√	√	√	
2	Near to the high-class residential/CBD		√			
3	Small building size	√		√	√	√
4	Irregular building orientation	√		√	√	√
5	Roof material is from asbestos		√	√	√	
6	Built in illegal land		√			

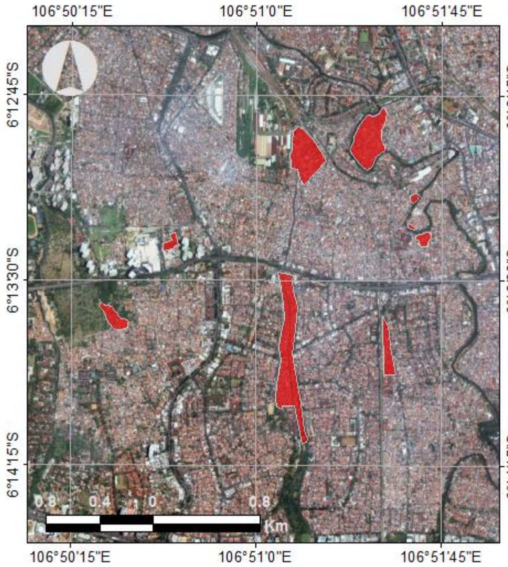
Two official indicators (Table 3-1) were not mentioned by the local experts, which are high area density and poor road materials. Regarding the road materials in the given image (Figure 4-4 (b)), local experts found it difficult to determine the road materials, particularly for the narrow roads. Only the local government selected indicator number 2. Apparently, they explicitly select this characteristic according to the specific context of slums in the image subset (Figure 4-4 (b)). Other experts are selecting the features only according to their visual interpretation of the image. Comparison of the properties of delineated slum area from a different expert can be seen in Table 5-2. Furthermore, in Figure 5-2 we presented the delineated slum from an expert.

Table 5-2 Quantitative comparison of delineated slum

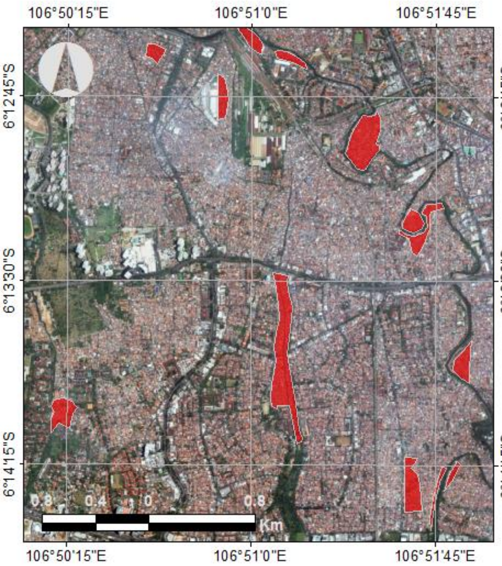
Expert	Patches	Size (Ha)	Max. Size (Ha)	Min. Size (Ha)	Avg. Size (Ha)
Central Govt	11	52.3	11.5	0.6	5.3
Local Govt	9	33.2	12.6	1.6	3.7
NGO	13	43	12.6	0.7	5.3
SAPOLA	11	52.9	12.6	0.9	4.8
BSPS	15	108.6	15.7	1.5	7.2



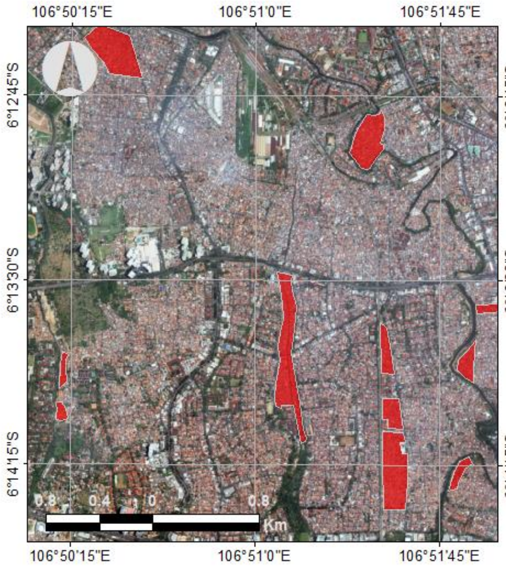
a. Central Government



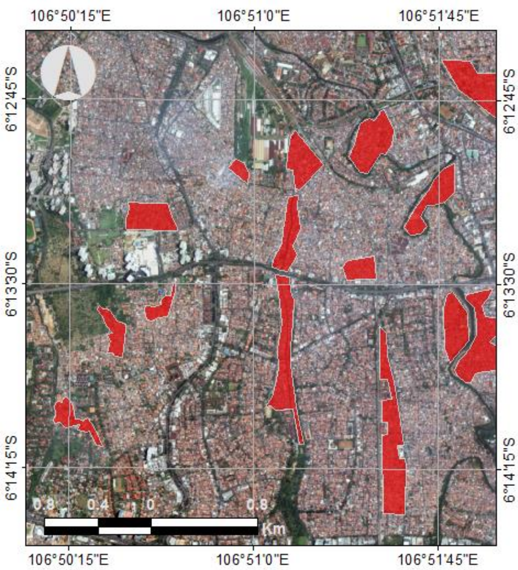
b. Local Government



c. Kemitraan Habitat



d. SAPOLA consultant



e. BSPS consultant

Figure 5-2 Slums Location According to Local Expert

5.1.2. Field Observation

Due to the different characteristics of slums listed by the expert, it was necessary to understand the ground conditions of slums in the study area. The red area indicates a slums location that is selected by five experts. Meanwhile, the orange, yellow, green and blue areas are chosen by four, three, two and one experts respectively (Figure 5-3). In the following subchapter, we discuss the comparison between the visual image interpretation and their condition in the field. However, we did not present these fifteen different areas in this report. We present four example, the first two example for an area that has similar perception, and the last two example for an area with different perceptions.

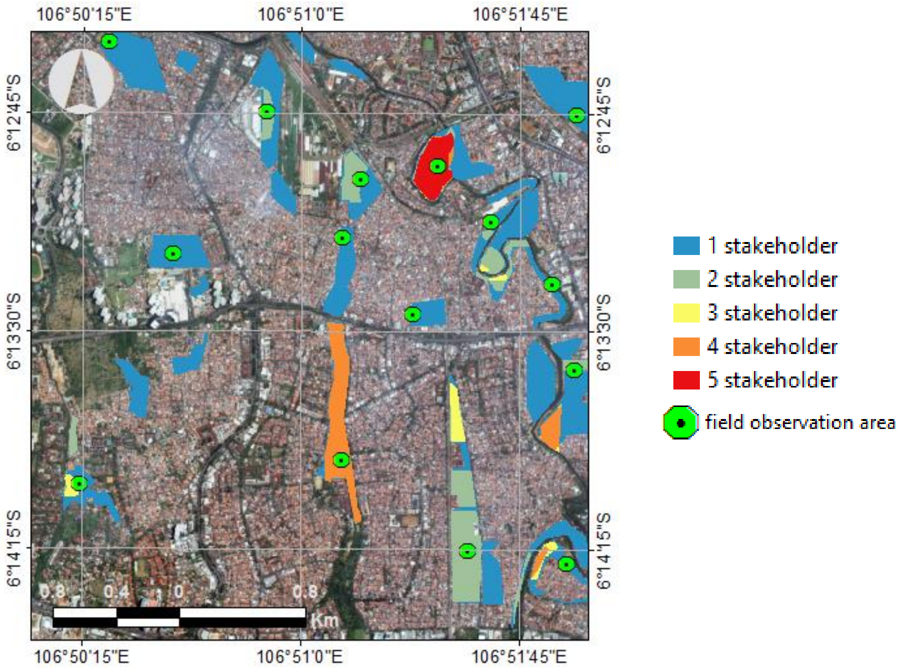


Figure 5-3 Selection of Observation Area

5.1.2.1. Similar Slum Status

For the first area, we choose an area around Manggarai I street. This area has been choose by five experts, and it is indicated as a red coloured area (Figure 5-3). For the second area, we select a location around Tebet Timur Street which was selected by four experts (indicates as an orange coloured area in Figure 5-3).

According to the visual image interpretation, the first area (Figure 5-4) is characterized by its location close to the river. The area has small sized buildings of irregular orientation. After the field observation, some other characteristics are gained, such as the size of the roads that are narrow (which was previously hard to determine from the image). Other features recorded were the existence of infrastructure, such as electricity. This existence is contradicting with the official characteristics of slums (Table 3-1). The existence of permanent buildings in this area proofs that the location is an urban *kampung* (discussed in chapter 3.2.3).

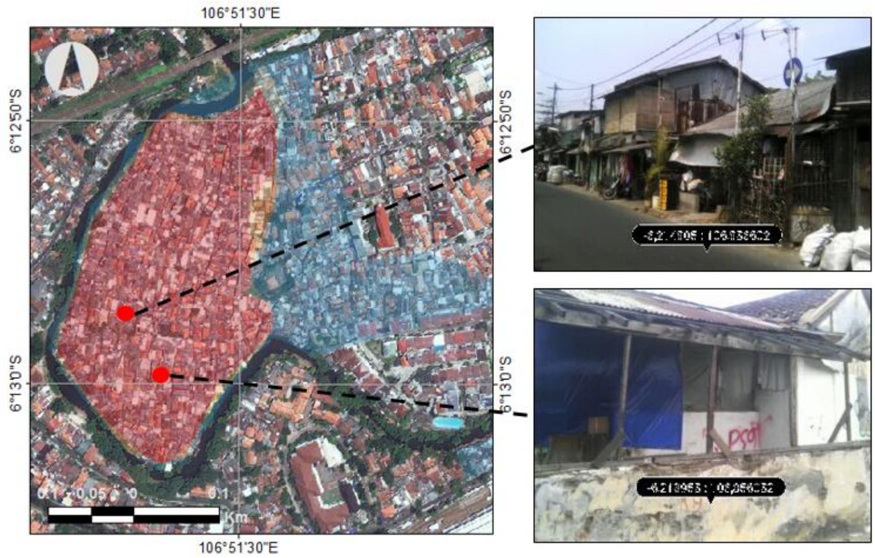


Figure 5-4 Slums condition in Manggarai I Street

The second location (Figure 5-5) shares similar characteristics with the first location, with the addition that the location is close to a high-class residential area. During field observation, this area showed similar characteristics compared with the visual image interpretation. However, the roof material is dominated by corrugated galvanised irons. Regarding sanitation, this area has similar characteristics with the first area.

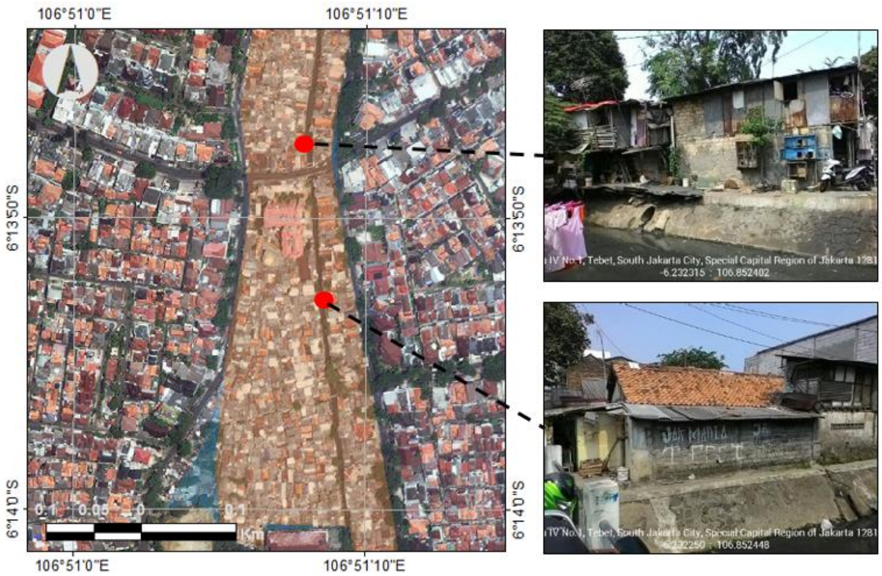


Figure 5-5 Slums condition in Tebet Timur Street

By analysing the field observation from the first to the second location, we can state that field observation confirmed several visual image characteristics. For instance, we found that proximity to the river, roof materials, building orientation and building size, which are identified from the visual image interpretation, could be confirmed the field. During the field observation, the absence of proper sanitation facilities was found in both study areas. We also argue that both areas can be categorized as a slum.

5.1.2.2. Different Slum Status

We have 13 remaining areas that have different agreement among experts (Figure 5-3). However, the information gathered by field observations showed similarities. Hence, in this subchapter, we only presented two of them (the picture of the rest area presented in annex). In the first location, we select an area around Rela IV Street, since this area is located nearby the shopping centre (similar to the slums characteristics in Table 5-1). For the second location, we choose area around Bukit Duri Barat street. According to the image subset in Figure 4-4 (b), this area shares similar locations with the slums in Tebet Timur Street, which are irregular building pattern, and located close to the river. However, only one expert selected this area. Therefore, it also interesting to observe their ground conditions.

The expert from BSPS only selected the slums area in Rela IV Street. He selected this location due to small sized and irregular building pattern. However, according to the image, we can easily recognize a big block building in southern parts of this area (part of the CBD). Apparently, after we observed this area on the ground, this area shows similar characteristics compared to the visual image interpretation. For instance, we found that this area has small sized buildings. Another characteristic that was not mentioned according to visual image interpretation was the absence of proper sanitation facilities. We only can find communal sanitation facilities with pit latrines in this area, and they are located very close to the ground water well.

A small pocket of slums is situated in the southern part (Figure 5-6). This area has similar characteristics compared to the first area. However, this area is surrounded by the high-class apartment building in the eastern and southern parts. Meanwhile, in the western part, we found a commercial block, which proofed that slums might be located adjacent to the CBD and high-class residential areas.

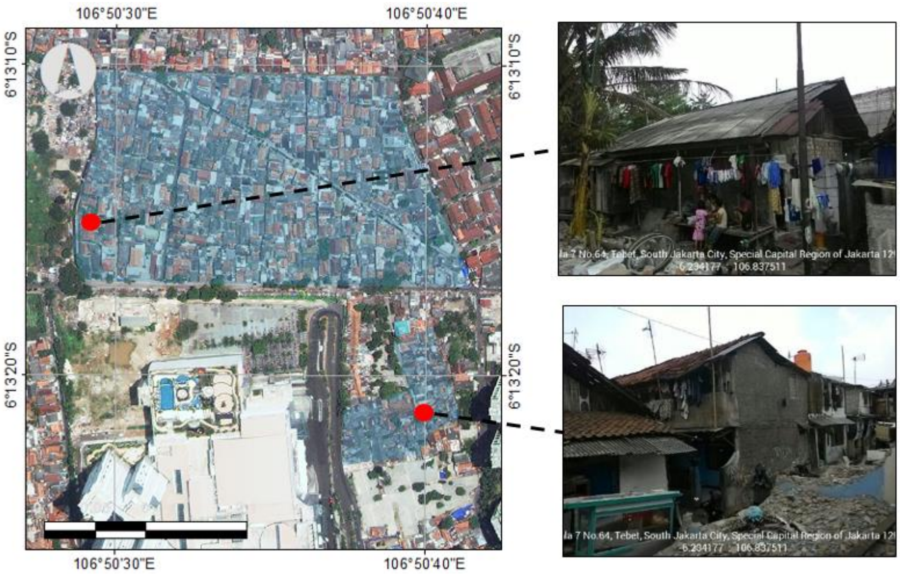


Figure 5-6 Slums condition in Rela IV Street

Bukit Duri Barat Street was selected as the second area. This area (Figure 5-7) has similar characteristics with the area that was shown in Figure 5-5. This area (Figure 5-7) is located in the north. The same river passes through the area. After we had conducted the field observation, we found that the features that can be seen from the image could be found on the field. Additional characteristics are the absence of the proper sanitation facilities, and the narrow street width, which only can be passed by the motorcycle (second photo from Figure 5-7).

Figure 5-7 Slums condition in Bukit Duri Barat Street

5.2. Rule Set Development

To detect the slums from GEOBIA, we need to transform these real-world characteristics into something that is known to the computer. The output of this stage is used in the implementation stage, which is the GEOBIA process. We started this subchapter by comparing the slum characteristics between GSO and LSO. Later on, we discuss the effort to transform the real-world characteristics of slums into image domain.

5.2.1. Comparison between GSO and LSO

According to the GSO, common location characteristics (environs level) of slums are their location in hazardous sites, e.g. flood zones, marshy areas, along railways and on the steep slope (Kohli, Sliuzas, et al., 2012). Also in Jakarta, slums are often found in the riverbank area. Regarding the second features, Kohli, Sliuzas et al. (2012), mentioned that the location of slums is related to the socio-economic factors, where they are often located close to opportunities for unskilled or low skilled jobs (e.g. industries and CBD). Apparently, this is also found in the case of Jakarta, where slums appear nearby the CBD (Figure 5-6). However, we need to be aware that *kampungs* (which constitute most of this area) exist even before the existence of the CBD. In Jakarta, slums also might be located adjacent to a high-class gated community (Figure 5-6). The characteristics of slums in the environs level (Table 5-3) are similar for the GSO and LSO, with small distinction on the associated urban features (CBD or industrial; CBD or high-class residential).

According to the GSO, at the settlement level, slums can be characterized due to their shape and density (Kohli, Sliuzas et al., 2012). Moreover, slums can also be characterized due to its irregular pattern (Kohli, Sliuzas et al., 2012). Among several characteristics regarding shape that are mentioned in the GSO, only the irregular pattern of the settlement was referred to by the local experts. Regarding the density characteristics, Kohli, Sliuzas et al. (2012) mentioned that slums have high roof coverage with less open space or vegetation. However, density differs locally, and cannot be used exclusively without considering different indicator (Kohli, Sliuzas et al., 2012). For instance, it related to the age of settlements, and the association with planned settlements (Kohli, Sliuzas et al., 2012). Similar with Jakarta, local experts do not choose the density since it is not different from slums and non-slums. The comparison between slums characteristics from GSO and LSO in the settlement level can be seen in Table 5-3.

At the object level (in GSO), slums can be characterized due to their access network and building characteristics (Kohli, Sliuzas et al., 2012). Apparently the local experts in Jakarta did not consider access networks as one of the slums characteristics. Experts mentioned that the road in Jakarta have a good materials quality, where most of the streets are paved with an asphalt or concrete (Subchapter 5.1.3). Slums can have a paved road, even though the wide is narrow (Figure 5-4). Regarding the building characteristics, as mentioned by Kohli, Sliuzas, et al. (2012), slums building can be characterized by a combination of its roof materials, footprint, shape and orientations. They also mentioned that some of the indicators could not be observed from the image, such as the height of the building and the number of floors. Regarding the local characteristics of the building, we found that among six local characteristics of slums that were mentioned by the local experts, half of these characteristics are at the object level. The first indicator considers the size of the object. The second indicator is related to the roof materials. For the GSO, Kohli, Sliuzas et al. (2012) mentioned the examples of the roof materials, e.g. tin or iron sheets. In Jakarta, we found similar materials, with the addition the asbestos. Furthermore, all local experts indicated that the slums have no proper sanitation facilities. This characteristic is unobservable from the satellite imagery. Therefore, ancillary data is needed. The comparison between slums characteristics from the Generic Slum Ontology (GSO) and LSO at the object level can be seen in Table 5-3.

Table 5-3 Comparison of Slums Characteristics from GSO and LSO

Characteristics		GSO	LSO
Environs	Location	1. Near with hazardous area, e.g. riverbank/railroad	1. Located on the riverbank/railroad
	Neighbour-hood	2. Near with CBD or industrial area	2. Near with CBD/high-class residential 3. Build in illegal land
Settlement	Shape	3. Elongated urban features (river, road, railway), irregular pattern	4. Irregular pattern
	Density	4. High density 5. Absence of vegetation/open space	Not applicable
Objects	Access Network	6. Irregular pattern, small, unpaved	5. Narrow road
	Building Characteristics	7. Small building size 8. Roof materials from corrugated galvanised iron	6. Small building size 7. Roof from corrugated iron or asbestos 8. poor sanitation

According to the comparison between characteristics of slums based on GSO and LSO, the next stages has transformed this conceptualization into image domain. This description is discussed in the next subchapter.

5.2.2. Transformation Into the Image Domain

As discussed in sub-chapter 2.2.3 then followed by a detailed description in sub-chapter 2.2.4, to transform the real world into image characteristic of slums, e.g., association, shape, texture and the size. We also consider the usage of ancillary data, since some of the characteristics are difficult to observe in an image. This issue has been discussed in chapter 4.4.4, particularly in Table 4-2. In Table 5-4, we can see how the conceptualization of slums in the real world domain are transformed into image characteristics.

Table 5-4 Real World to Image Domain Characteristics

Real World Characteristics	Image Domain Characteristics	Application GSO	Application LSO
Located on Riverbank/railroad	Association: Distance to River/Railroad	√	√
Near with Economic Hotspot	Association: Distance to CBD/Industrial/High-Class Residential	√	√
Built in illegal land	Ancillary data: Land Use Plan	-	√
Irregular pattern of building	Shape: Irregular	√	√
High density	Texture: GLCM	√	-
Absence of green opens space/ vegetation	Association: Distance to vegetation/green open space	√	-
Irregular, small and unpaved road	Shape: Irregular	√	√
Small building size	Size: small	√	√
Poor roof materials	Tone: Asbestos, iron	√	√
Poor sanitation	Ancillary data: Sanitation	-	√

We can notice that the conceptualization of slums from GSO and the LSO differs. Hence, we can argue that this two concept produce different slums location.

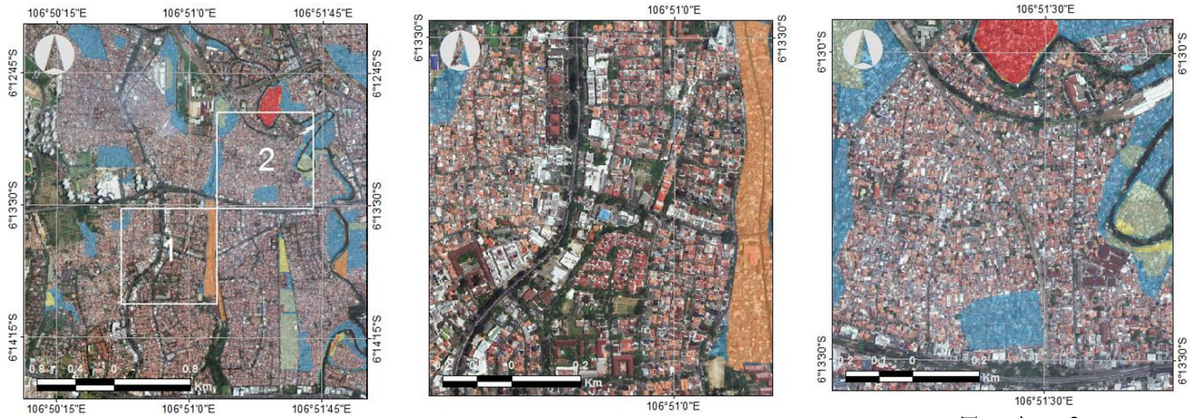
5.3. GEOBIA Process

During this part, we operationalized the rule-set that is developed from the early parts. The discussion of this subchapter starts with discussion related to the issues of multi-temporal data. The segmentation and classification process then follows it.

5.3.1. Selection of the Test Area

During the GEOBIA process, we use a Portable Personal Computer under Windows 10 64-bit environment, with 4 GB of RAM and 1.4 GHz Processor. We are aware that this specification is not designed for high computation operations. Therefore, to give an opportunity to produce results (within an acceptable time constraint) from a different combination of the parameter, we select smaller parts of the image subset. We decide to make a subset size of one square kilometre. By considering that the rule-set that is developed should work in any image conditions, we tested this for two different locations and the different temporal data (2012 to 2015).

For the first location (Figure 5-8 (b)), we have selected an area that has similar slum characteristics. Slums in this test area are located in the eastern parts near to the river. Four local experts have selected this area. Meanwhile, in the western parts we can notice a formal residential area with a regular pattern. For the second location (Figure 5-9 (c)), we select an area that has various characteristics of slums. In this area various urban features exist that can indicate slums, such as a railroad and river. For the first test area, we were tested on every different temporal image. However, for the second test area, we excluded the image taken from March 2013, due to the high cloud cover.



a. Study Area b. Test Area 1 c. Test Area 2

Figure 5-8 Selection of Test Area

5.3.2. Segmentation and Classification

As discussed in Subchapter 4.4.2, we employ two levels of classification. The aims of the first level are to remove the background objects, where the second level aimed to detect the slums. Results for both classification level are discussed below.

5.3.2.1. Level 1 Classification (Background Removal)

For the Level 1 classification, we were extracted four land cover classes, namely river, road, railroad, and vegetation according to the strategy that was discussed in Subchapter 4.4.2. Next, we were assigned the Unclassified class as a built up. We started the level 1 classification from the first test area. The result can be seen in Figure 5-9 (a) and (c)). In the 2013_1 image (Figure 5-9 (a)) we can notice that few of vegetation areas are detected, which means we need to decrease the minimum threshold for the NDVI. Meanwhile, in the 2013_2 (Figure 5-9 (c)) image, too much vegetation was detected. Hence, we need to increase the minimum threshold for the NDVI (Appendix D). The value is obtained from the trial-and-error approach, and each image has a different threshold. The results from the adaptation changed from Figure 5-9 (a) into (b) (for 2013_1 image) while the 2013_2 image is changed from Figure 5-9 (c) into (d).

a. 2013_1 image before adaptation b. 2013_1 image after adaptation

c. 2013_2 image before adaptation d. 2013_2 image after adaptation

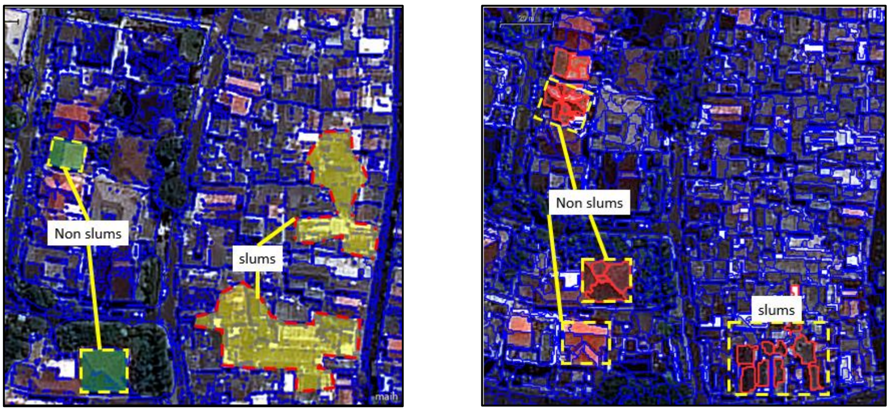
Figure 5-9 Level I Classification Before and After Adaptation

Besides adapting the NDVI for each temporal scene (Appendix D), we also adopted roof tone indicators, which relate to the colour (Appendix D) for the classification level 2. After implementing the adaptation, we assume that the result is comparable, regarding transferability for detecting slums.

5.3.2.2. Level 2 Classification (Slums Detections)

We use the data from the first test area in the year of 2012. We argue that a transferable ruleset should result in similar performance when it applied in the different period. Therefore, the ruleset should able to extract the slum in any period. We use the ESP tools to determine the SP for a particular image (Appendix D). We use the same value for smoothness and compactness parameter, which are 0.5. According to the estimation from the ESP, the SP value for first test area in 2012 data is 102 (Appendix D).

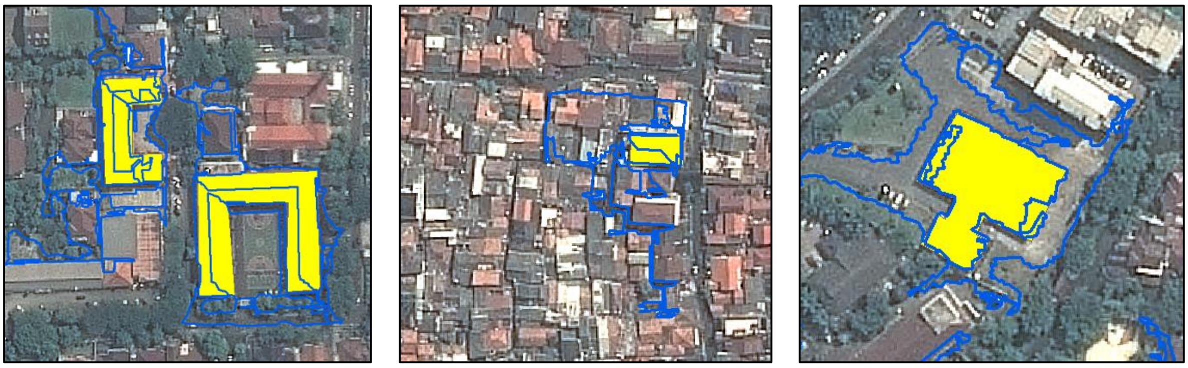
As we can see in Figure 5-10 (a), by applying the scale parameter that was recommended by the ESP, we extract formal buildings (green polygon) as a single solid object. However, slum buildings are detected as a clumps object (yellow polygon). We reduce the SP to 10 to extract smaller objects (Figure 5-10 (b)), but this affected the formal building, which is divided into some object. Furthermore, the outline of the slum buildings also not outlined well.



a. Building with SP=102 b. Building with SP=10

Figure 5-10 Impact of Scale Parameters to Building Object

The segmentation results in a various pattern according to the object characteristics (Figure 5-11). For instance, a large object with a non-flat surface, having different roof colour was segmented into different objects. Meanwhile, a small object, it segmented as a clumps object. This result is similar to the previous discussion, particularly related to Figure 5-10. Meanwhile, an object with a flat surface and being relatively large can be segmented as a single object (Figure 5-11 (c)).



a. Large object, non-flat surface b. Small objects c. Large object, flat surface

Figure 5-11 Performance of Object Segmentation

We conducted the segmentation for different temporal and test area using the value from the ESP. The difference segmentation results on object level can be seen in Figure 5-12.

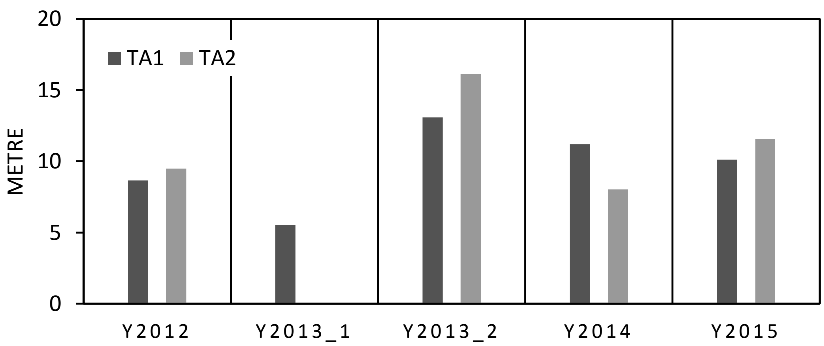


Figure 5-12 Segmentation Accuracy (D_{sr}) value

In the case of the first test area, the D_{sr} value is 8.67 metre. It means that, in average, the distance between the centroid of the segmented object and its reference object is 8.67 metre. The accuracy of segmentation varies between the test areas, as well among different years (Figure 5-12). Indeed, we expected that the segmentation accuracy would be as close as possible to zero. However, many factors have affected the outcome of the segmentation accuracy. For instance, a small building is detected as clumps object (Figure 5-10).

After the level 2, segmentation had been done, we applied the characteristic of the slum (Table 5-4). Both ontologies have used the distance to river or railroad as the characteristics of slums. Therefore, we tested whether this feature can be used to distinct the slums from non-slums. We choose four random points from the detected slums and observe its situation by using google street view (Figure 5-13).

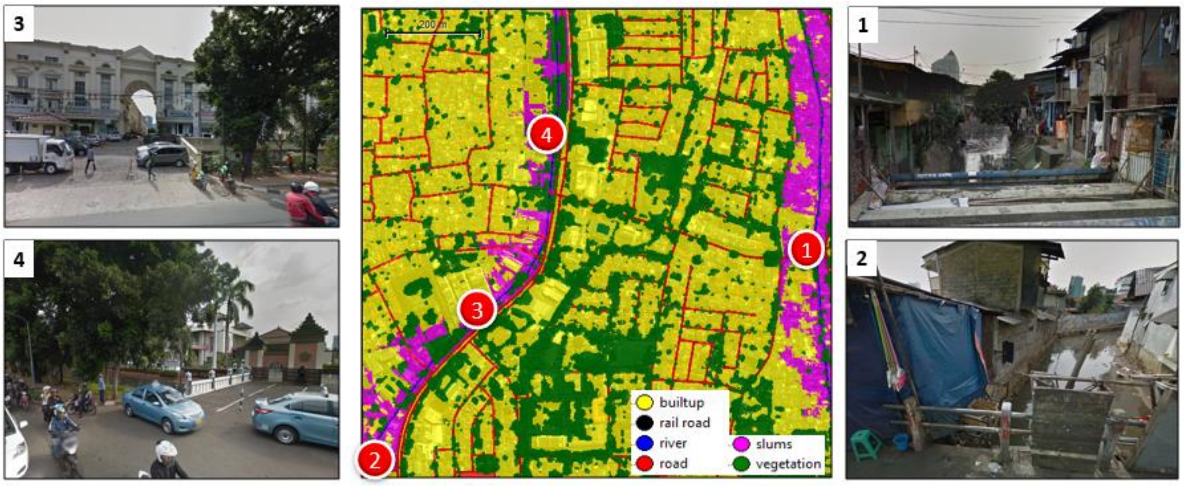


Image sources: Google Street View

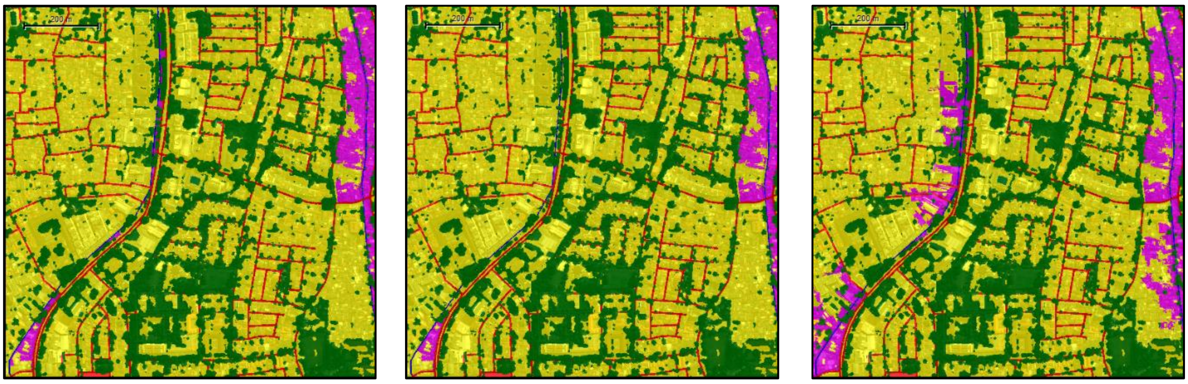
Figure 5-13 Object Association with River

We can notice that proximity to the river might indicate the location of slums. However, we should also be aware that not every building that is located near the river is part of a slum. The location 3 and 4 (Figure 5-13) are not slums.

Regarding the second characteristic, slums are often located close to economic hotspots, we found that this characteristic could not be used to distinct slums in our subset. Since we work with 1 square kilometre, the CBD is not present in this test area. Hence, we do not use this characteristic.

The third characteristics are related to the land tenure of the settlements. Regarding the source of tenure data, we develop a raster image and define the value one as a conservation area and 0 as non-conservation area. This indicator is only used for the LSO. We assume that the settlement object can be categorized as a slum if more than a quarter of the area is located in the conservation zone. By combining the proximity to the river with the tenure status, the number of slums is reducing (Figure 5-13 into Figure 5-14 (a)). As we can see in Figure 5-14 (a), slums patches can be found in the eastern parts of the subset, and some slum pockets in the south-west part.

In the next stage, we include the building patterns, slums have less compact pattern compared with non-slums. The compactness is a colour-related indicator. Since slums are segmented as clumps object, the variation of roof colour is higher. Therefore, within e-cognition, it was defined that slums have a lower value of compactness parameter. In Figure 5-14 (b) we can notice only small changes of the mapped slums compared with Figure 5-14 (a). Meanwhile, without considering the tenure status, the distribution of slums in Figure 5-14 (c) looks similar to Figure 5-13. If we compare Figure 5-14 (a) and (b), also 5-13 and 5-14 (c), apparently, the objects located close to the river also have low compactness value. Similar objects located near to the river are not necessarily illegal, which is indicated by the reduced number of slums comparing Figure 5-13 and 5-14 (a) and (b).



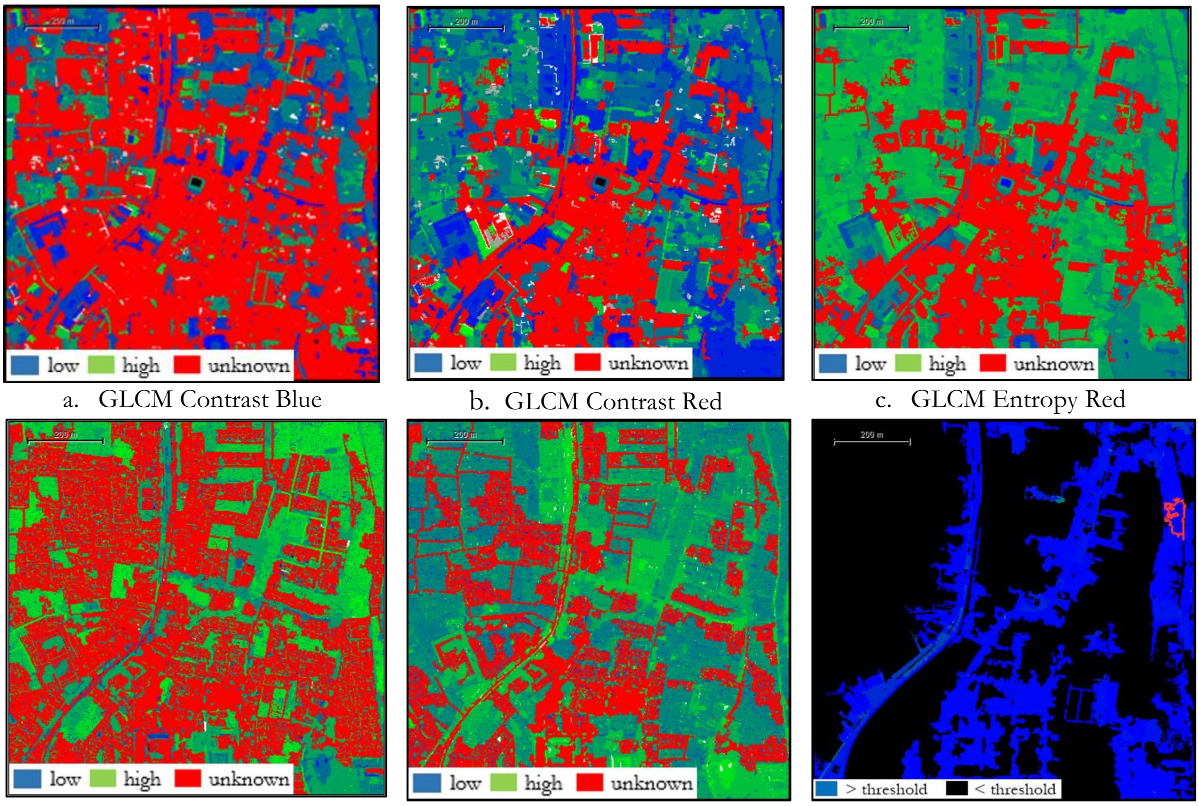
a. Proximity to river combined with the tenure status

b. Proximity to river, tenures status and compactness

c. Proximity to river combined with compactness

Figure 5-14 Land Tenure and Settlements Pattern Characteristics

As discussed in Subchapter 2.2.4, there are various types of GLCM metrics and the selection of the most appropriate metrics relies on purpose for a particular topic. However, we start with following the study from Kohli et al. (2013) that used the GLCM contrast in the blue and red band. They also used the GLCM entropy of the red band to distinct built-up areas. The result from this metrics can be seen in Figure 5-15 (a) to (c).



a. GLCM Contrast Blue

b. GLCM Contrast Red

c. GLCM Entropy Red

d. GLCM Entropy Blue

e. GLCM Homogeneity Red

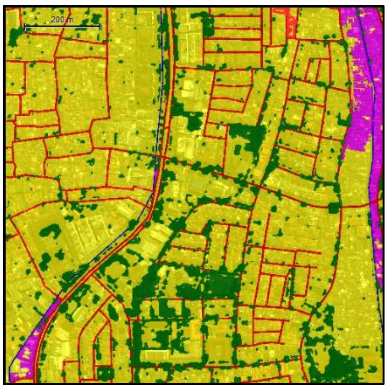
f. GLCM Dissimilarity All band

Figure 5-15 Various GLCM result

Apparently, the result of Figure 5-15 (a) to (c) is not performing well. The large red area indicates unknown value. We are not further examined the source of this unknown value. E-cognition measured the average of GLCM value in an image object, and we were applied two level of segmentation. We argue that sometimes it is difficult to measure the difference of the average grey level value of an adjacent object with different SP. Apparently, GLCM contrast of the blue and red band failed to capture the difference between slums and non-slums, where both areas have similar value (western and eastern parts of Figure 5-15 (a) and (b) result in similar greenish colour). However, GLCM entropy of the red band performed better than the GLCM contrast. It shows that built-up area gives higher value (green), where the non-built up have a blue colour. Since we found that these three metrics are not performing well, we expanded our experiment with others metrics (Figure 5-15 (d) to (e)). Apparently, GLCM dissimilarity produced better results in detecting slums. As we can see, the western part of the image, which is dominated by slums, has a higher value (blue colour), where the backgrounds objects are black. Further experiments could explore the impact of the direction, band and windows size. However, since producing GLCM results is resources consuming, we decide to use the GLCM Dissimilarity. These results can be seen in Figure 5-16 (a).

Regarding the existence of the vegetation, we put an assumption that the vegetation covers should be low. This indicator is only applicable for the GSO ruleset (Table 5-4). We set a threshold of the number of adjacent pixels labelled vegetation and settlement to be less than 750 pixels. We obtained this value through trial-and-error approach. The following features of slums are their irregular shape or narrow road. However, we cannot get the data of informal roads. Therefore, we did not consider this characteristic. Similar to the small sized buildings since we found a dilemma when applying a size-related threshold. The slums and non-slums might be detected as a similar object. Hence, we are not using the building size as a characteristic of distinct slums. The following characteristics are the tone of the roof materials. As can be seen in Table 5-4, both ontologies mentioned that asbestos and corrugated galvanised iron roofs are the dominant roof materials of the slums. Since the tone of the roof is affected by the variation of the atmospheric condition, we applied a correction factor (Appendix D). The detected slums can be seen in Figure 5-16.

a. Proximity to river, compactness, GLCM dissimilarity, vegetation and roof colour (Final result of GSO)



b. Proximity to river combined with tenure status, compactness and roof colour (Final result of LSO)

builtup river road slums vegetation

Figure 5-16 Slums with addition of roof materials

Both ontologies resulted in the similar location of slums (Figure 5-16). Some difference can be noticed in the eastern parts. According to the image interpretation and the ground truth observation (Figure 5-5), this area can be categorized as slums. However, when we include tenure in the rule set, we found only northern part classified as slums. While we compare this two results with the delineated slums area that can be seen in Figure 5-2 (b), the extracted slum showed in Figure 5-16 (a) are more similar compared to Figure 5-16 (b). The last characteristic is only applicable for the LSO, which is a lack of access to proper sanitation facilities. However, we found problems to operationalize this indicator since data available have the lowest aggregation at the sub-district level. This level is a way to high, which would cause that the entire test area 1 have similar value. Hence, we decide not to use this characteristic.

Following the similar stages that conducted in the first test area, we were applied to the second test area in the same year. The extracted slum from the second test area can be seen in Figure 5-17.

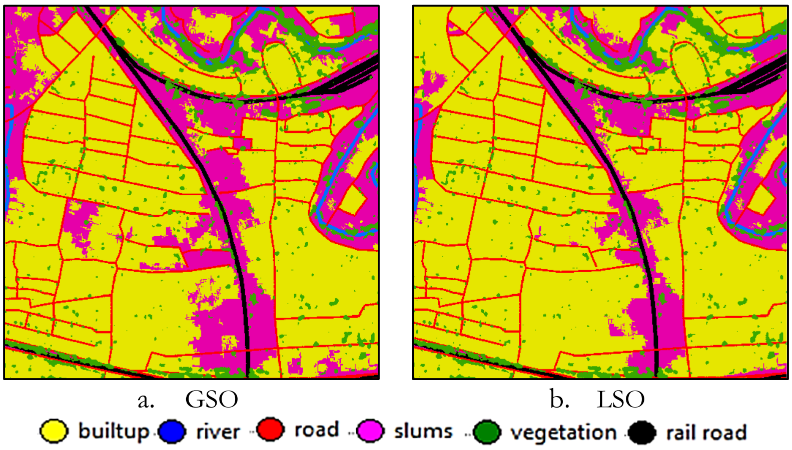


Figure 5-17 Slums in the second test area

Both rulesets extracted different slum extent. For instance, a slum patches located in the western and north-western part was not detected by the LSO. Both rulesets resulted in similar slum location in the eastern part and the slum located close to the railroad directed east-west. Some difference of slum extent can be found in the area close to the railroad directed south-north.

5.4. Transferability Measurement

As discussed in the conceptual framework, our focus is to measure the transferability of the GSO in different conceptualization, spatial and temporal characteristics. We employ two transferability measurement, which is quantitative and qualitative measurement.

5.4.1. Quantitative Measurement

For the quantitative measurement, we employed three measurements, i.e., spatial transferability, temporal transferability and spatiotemporal comparison. Discussion for each measurement as follow.

5.4.1.1. Spatial Transferability

The main characteristic of the first test area is the clear difference between slum and non-slum. Meanwhile, the second area is difficult to distinct. Firstly, we discussed the spatial transferability from both ontology in the first test area. As we can see in Figure 5-18, the slum was detected in the western and eastern part of the image. The areas labelled 1 and 3 were indicated as a slum by both ontologies. According to the ground observation from Google Street View (Figure 5-18, picture 1 and 3), this area was confirmed as a slum. This area is characterized by overcrowded building with semi-permanent building materials.

The pictures labelled 2 and 4 were labelled as a slum only by the GSO. In picture 2, we can notice an area with the semi-permanent building. However, we also can notice the presence of public facilities (for sports activities). Although this area also located close to the river, the building density in this settlement is not high. Meanwhile, in the area labelled 4, cannot be confirmed as slum according to the ground observation. This area is also located close to the river. Apparently, the colour of the carpark resulted in similar reflectance with the roof of the slum building. Therefore, it was detected as slums.

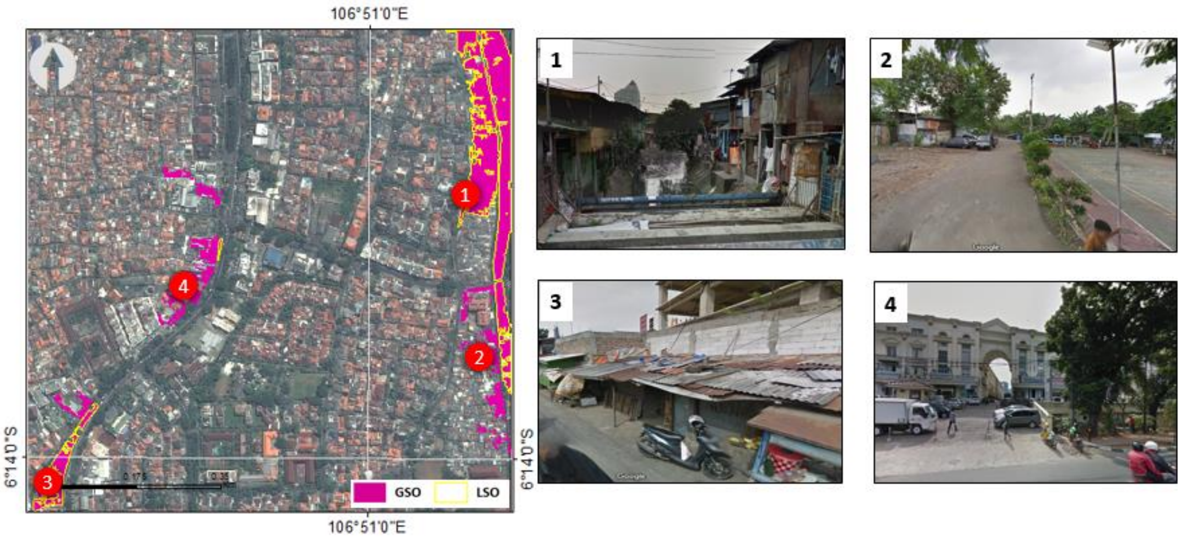


Image sources: Google Street Map

Figure 5-18 Comparison of Extracted Slum (GSO and LSO) in test area 1

After we had discussed the comparison of a slum in the first test area, we presented the comparison of the second test area in Figure 5-19.

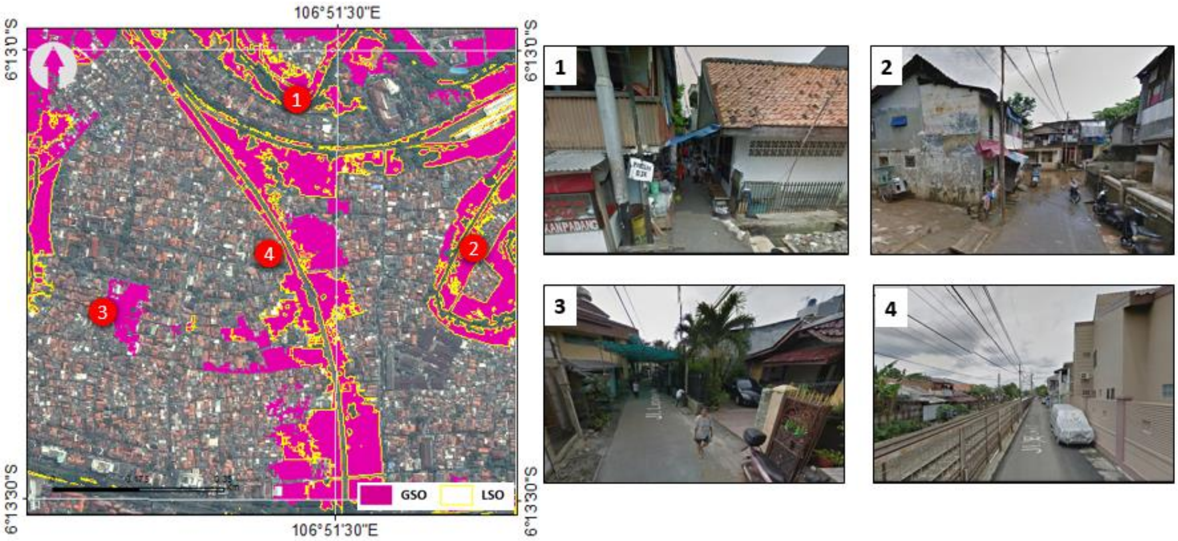


Image sources: Google Street Map

Figure 5-19 Comparison of Extracted Slum (GSO and LSO) in test area 2

The extracted slum from the GSO (pink colour) was higher than the LSO (yellow box) (Figure 5-19). Some slum area from the GSO was overlapped with the LSO, i.e., point 1, 2 and 4. From the ground observation[21], the area labelled 1 and 2 were indicated as a slum, and it was indicated as a slum by both ontologies. In area labelled 1, we can see an overcrowded settlement with a narrow road in front of it. Meanwhile, in the area labelled 2, we found slums with the poor building materials. At the end of the street, we found an area that is often flooded. In the area labelled 4, we found a slum that was detected as slum from both ontologies. This area is located adjacent to the railroad. In the left side of this picture (number 4), we found small buildings with poor materials. Meanwhile, on the right side, we found bigger buildings in a good condition. Therefore, we argue that this area shared similar characteristic between slum and non-slum settlements. Meanwhile, in the area labelled 3 was detected as slums by the GSO. Although we found an overcrowded

[21] Obtained from Google Street View

settlement, this area cannot be confirmed as slums. We can notice a house with a good building material, with a car parked in front of it. This area also has electricity, and the road is paved with asphalt.

Regarding the accuracy of confusion-based measurement, the result from GSO and LSO in the first and second test area can be seen in Figure 5-20.

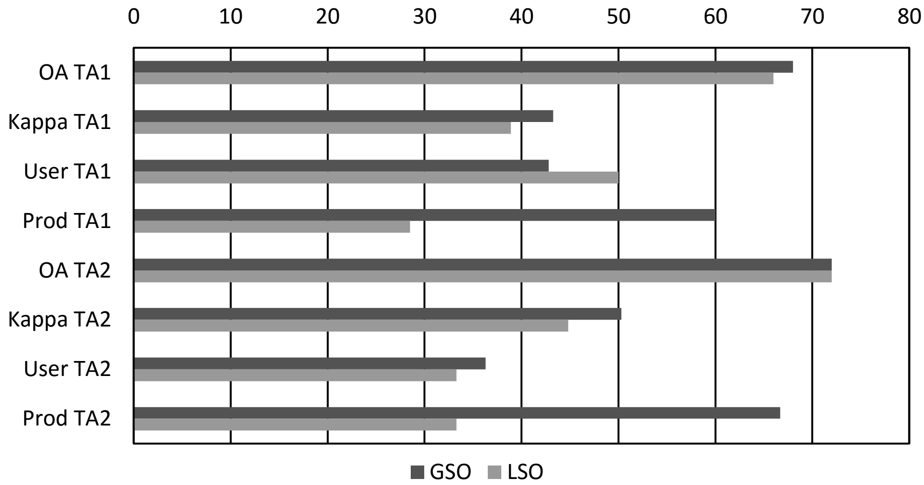
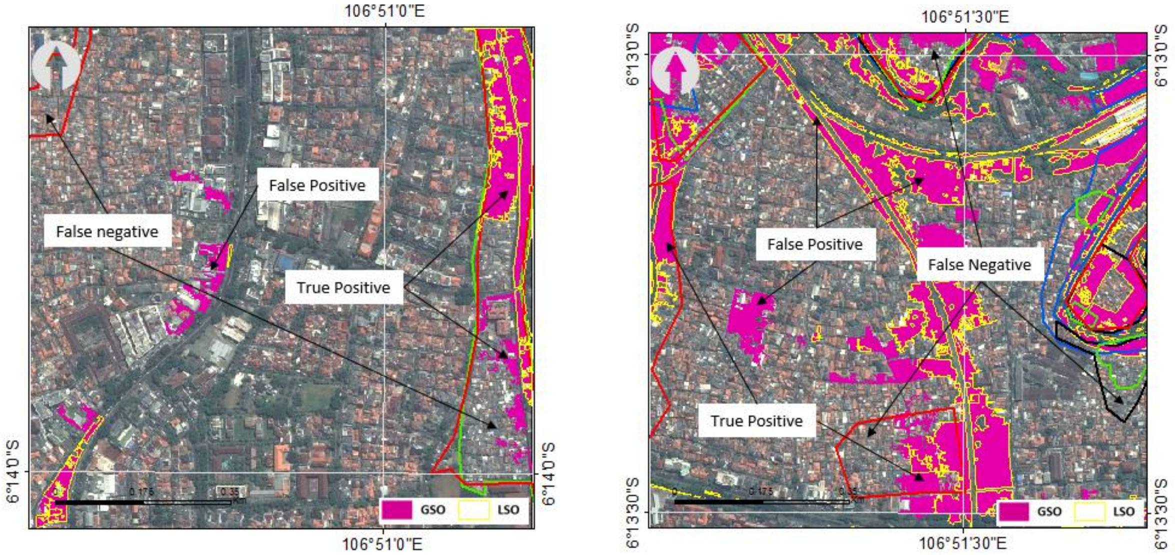


Figure 5-20 Comparison of Classification Accuracy between GSO and LSO

According to the OA measurement in the 2012 data, we can notice that the GSO resulted in higher overall accuracy compared with the LSO in test area 1 (Figure 5-20). Meanwhile, for the test area 2, both rulesets led to the same accuracy. However, the user and producer accuracy of the slum for both ruleset are relatively low. For the GSO in the first test area, the user accuracy of slums is lower than producer accuracy. The user accuracy of slums is 42.8%, which indicated we could expect that roughly 42.8% of the extracted slum are the slum on the field. For the producer accuracy, which is 60%, indicated that we only extracted 60% of the slum pixels in the image. The LSO result higher user accuracy (50%), which means that we can expect the slums extracted from the LSO is more accurate than GSO on the ground. This result as expected by us. The GSO extracted non-slum as a slum in the western part of the image (Figure 5-18), which justify the higher user accuracy obtained by the LSO. However, the lower value of producer accuracy indicated that the LSO extracted less number of a slum on the image compared by the GSO. It can be seen in Figure 5-18 where the extent of slum extracted by the GSO is greater than the LSO. We argue this result be due to the usage of tenure status in the LSO ruleset. In Figure 5-18, we noticed that the slum patch located in the south-eastern part are not detected as a slum by the LSO since the tenure status indicate the object is not an illegal settlement. Since the GSO does not consider the tenure status, this area was detected as slums.

Regarding the second test area, we found that the GSO resulted slightly higher on user accuracy compared with the LSO, which is 36.3% and 33.3% respectively. However, for the producer accuracy, we found that the GSO resulted in twice-higher value compared with the LSO. It indicated that the GSO extracted higher slum compared by the LSO. These results are not as we expected, where we assume that the result for the LSO should be better compared with the GSO. We also can notice that the overall accuracy and kappa index for this area are higher, compared with the first area, which also not as we expected.

The different concept and delineation of slums have made difficulties in deciding the actual slum boundary. This difference has caused difficulties to measure the accuracy of the automatic slum extraction (from the ruleset). We argue that the phenomenon of the *kampungs* has caused these difficulties. For instance, we can notice the uncertainties caused by different conceptualization in the first and second test area (Figure 5-21).



a. test area 1 b. test area 2

Figure 5-21 Manual and Automated Comparison for slum extraction

Due to the difficulties to determine the exact slum boundary for accuracy assessment, we decide to merge the slum boundary from the local expert and put them as a reference data. We conducted accuracy assessment as suggested by McKeown and Cochran (1999), and we found that the quality result from GSO and LSO in very low (Table5-5).

Table 5-5 Quality of Classification Results

Dataset	True Positive (m^2)	False Positive (m^2)	False Negative (m^2)	Quality (%)
2012TA1GSO	40776.49	14508.09	74634.2	31.39
2012TA1LSO	34809.77	4696.34	80600.93	28.98
2012TA2GSO	85331.67	145663.58	106208.86	25.31
2012TA2LSO	52969.27	99405.95	138571.26	18.21

The highest quality of classification result is obtained by the GSO ruleset in the first test area, whereas the lowest is from LSO in the second test area. The GSO is resulted in higher TP in both test area compared by the LSO. It indicated the GSO resulted in the higher overlap area between automated and manual method. However, the GSO also resulted in higher FP, which shows the number of slum from automated extraction that not detected by manual delineation is higher than LSO. For the FN value, the GSO resulted in lower FN compared with the LSO. It indicated that the manual slum detection that not extracted by automated detection was lower than LSO.

Although the quality of classification is low, we noticed that the first area resulted in higher accuracy compared to the second area. This result is as we expected since the difference between slum and non-slum in the first area is clearer than the second area. However, the low accuracy value resulted by the LSO is not as we expected. We expect the LSO should be higher since the LSO was built by adapting the GSO into the local characteristic. We argue the low accuracy value of the LSO is due to the lower slum area that extracted from automated detection. As shown in Table 5-4, the tenure status was added as characteristics of a slum in the LSO. However, the tenure status is not possible to be observed from the visual image interpretation. Therefore, the quality of classification result from the LSO is lower since the difference between extracted slum and the reference data is higher than GSO.

According to the indicator mentioned in Table 2-3, a transferable ruleset resulted in similar accuracy when it applied to the different area. Therefore, we calculate the difference of accuracy result between the GSO and LSO between the first and second test area (Appendix D).

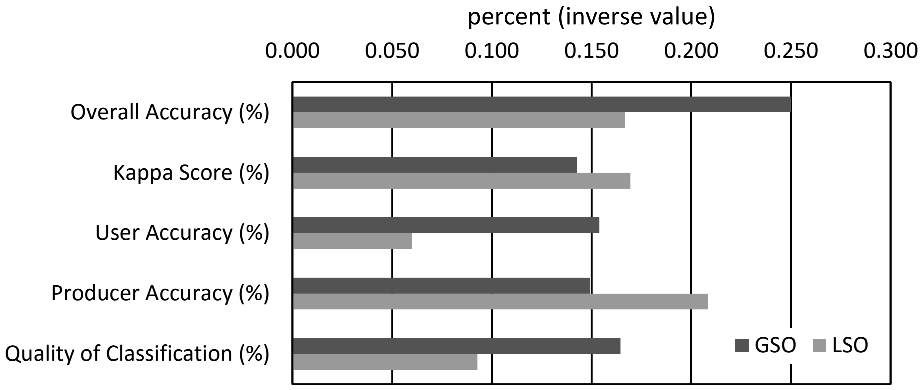


Figure 5-22 Summary of Spatial Transferability

The difference between accuracy score in the first and second test area should be as low as possible. We measure the accuracy difference between the first and second area for both ruleset (Figure 5-22). We inverse the value. Therefore, the graph is easier to be interpreted. As we can see, the GSO resulted in higher transferability (lower value) in the three measurements, whereas the LSO only better in Kappa and Producer accuracy. Therefore, for the spatial transferability, we can conclude that the GSO is more transferable than LSO. The result is unexpected since we assume the local adaptation (LSO) will increase the accuracy of extracted slums.

5.4.1.2. Temporal Transferability

In this part, we tested the ruleset for different temporal conditions. For the first and second test area using the GSO and LSO. Figure 5-23 shows the detected of slums in the first test area between 2012 to 2015 according to the GSO, the result for the LSO are presented in figure 5-24.

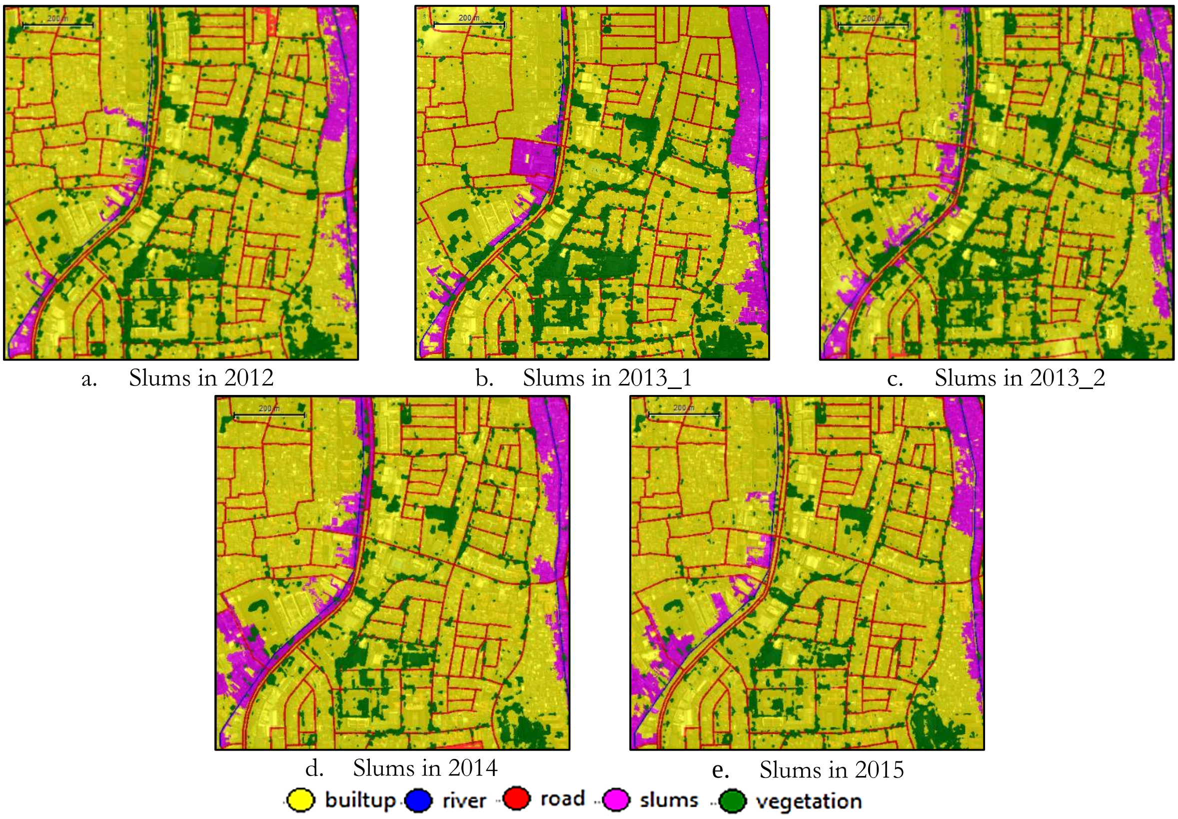
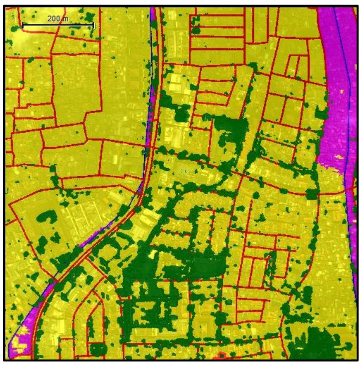


Figure 5-23 Spatiotemporal pattern of slums (First area, GSO)

According to the GSO, the slums are reducing between 2012 and 2015 (Figure 5-23). The slums can be divided into two patches, eastern and western part. Both patches show the different extent of extracted slums. However, some areas in the western part cannot be categorized as slums (Figure 5-23). Some of them had similar characteristics with the eastern parts. For instance, location nearby the river and with a similar colour. However, the area in the western part not a slum, but a car park with similar colour with asbestos (Figure 5-18, object number 4).

a. Slums in 2012



b. Slums in 2013_1

c. Slums in 2013_2

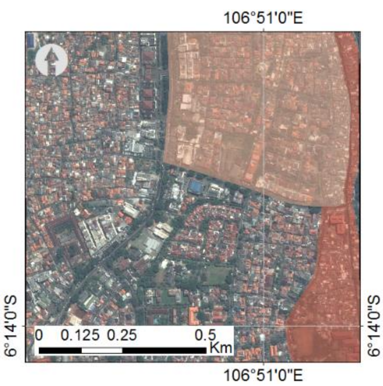
d. Slums in 2014

e. Slums in 2015

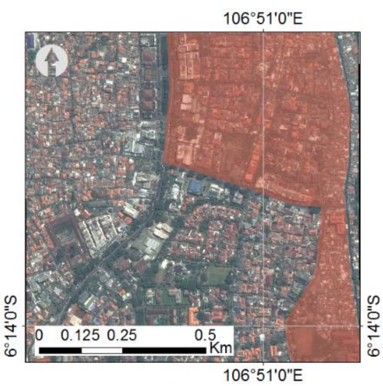
builtup river road slums vegetation

Figure 5-24 Spatiotemporal pattern of slums (First area, LSO)

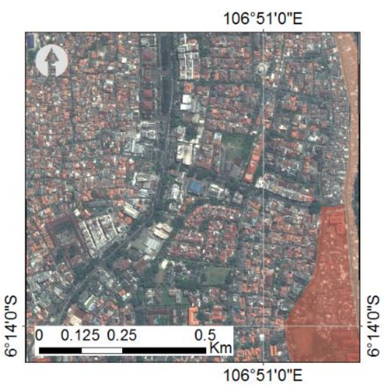
The slums that are detected by LSO (Figure 5-24) resulted in a smaller area. In the western part, only small areas of slums were detected. It is also similar in the eastern part. Although we can notice similar irregular patterns in the eastern parts that indicate slums, this area is not detected as slums. The area is not detected because of using the tenure of the land as one of the indicators. We compared the resulted slums from GSO and LSO (Figure 5-23 and 5-24), with the slum neighbourhood map in the first test area (Figure 5-25). Although the indicators that were used to detect slums differs between GSO, LSO and the official data (Table 3-1), comparing their results gave a better understanding regarding the quality of the result.



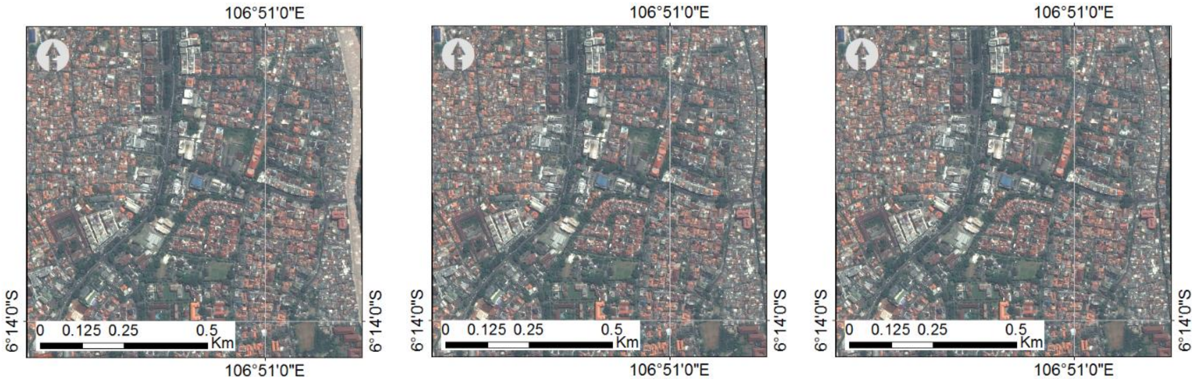
a. 1997



b. 2001



c. 2004

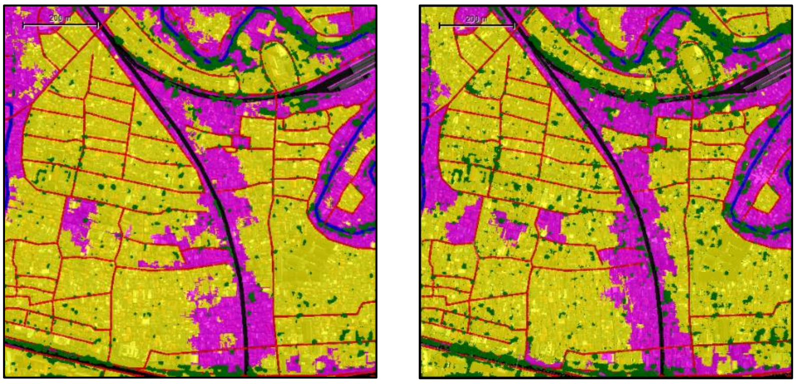


d. 2008 e. 2012 f. 2013

heavy slum medium slum light slum very light slum

Figure 5-25 Spatiotemporal pattern of slums in the first area (Department of Building and Settlements DKI, 2014)

According to the official data, slums are decreased between 1997 to 2013 in the first test area (Figure 5-25). In 2008, we only found a very light slum in the eastern parts of the image (Figure 5-21 (d)). In 2012 and 2013, slums do not exist in this test area. Relatively stable slums can be found in the southeast part of the image, which exists as a heavy slum between 1997 to 2004 (7 years). In 2008, the status was changed from a heavy slum into non-slum. This status does not change to 2013. Apparently, for the eastern part, both rulesets resulted in small changes in the slums boundary between 2012 and 2015. However, in the western part, the GSO indicates a dynamic change of slum boundaries (Figure 5-23), which are different with the LSO. We repeat a similar procedure to detect slums in the second study area (Figure 5-26 and 5-27). Detecting slums in this study area are more challenging since the slums and non-slums are more difficult to distinct. For the second test area, the data obtained from May 2013 have a high cloud cover. Hence, we exclude this image.



a. Slums in 2012 b. Slums in 2013_2

c. Slums in 2014 d. Slums in 2015

builtup river road slums vegetation rail road

Figure 5-26 Spatiotemporal pattern of slums (Second area, GSO)

According to Figure 5-26, we can notice differences in slums locations between 2012 and 2015. For slums that are located near the railroad with the direction from south north were changed. A similar result is obtained for the slums that are located on the riverbank in the eastern parts. Meanwhile, for slum areas along the railroad directed to east west are relatively stable.

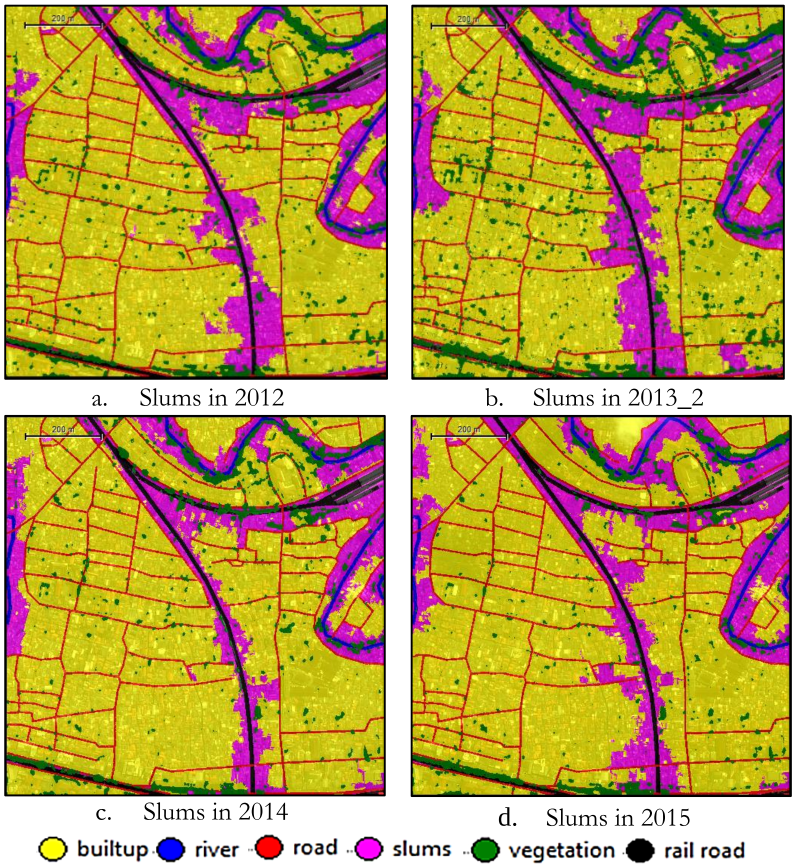
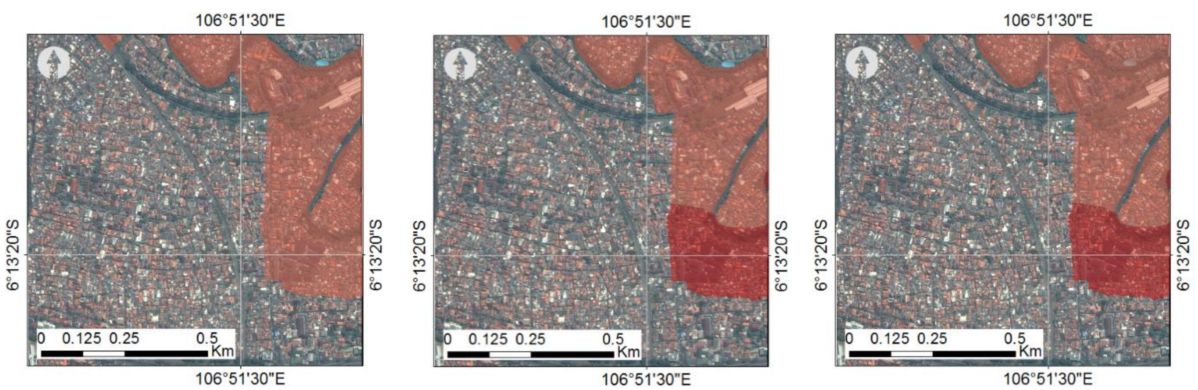


Figure 5-27 Spatiotemporal pattern of slums (Second area, LSO)

Figure 5-27 shows the result of the LSO (also excluding the image from May 2013 due to the high cloud cover). Firstly, we can notice relatively stable slum locations in the western part. Only small changes occurred in this location during 2012 and 2015. A similar location which is more stable is located nearby the railroad in an east-west direction. This pattern apparently seems to be analogous to the results from GSO. Outside this place, we also found slum areas that are relatively stable on the riverbank on the north side of the test area. We compared the resulted slums from GSO (Figure 5-26) and LSO (Figure 5-27), with the slum neighbourhood map (subchapter 3.1), in the second test area (Figure 5-28).



a. 1997 b. 2001 c. 2004

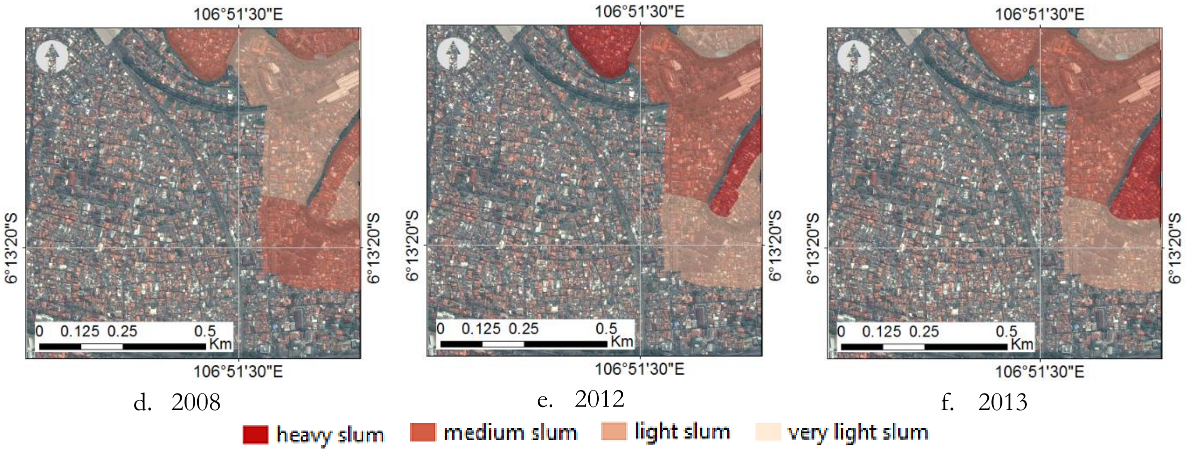


Figure 5-28 Spatiotemporal pattern of slums in the second area (Department of Building and Settlements DKI, 2014)

The official data indicated slums in the second test area are changing between 1997 and 2013, showing both increase and decrease. However, no slum area turns into non-slum (Figure 5-28). A slum in the eastern part is relatively stable compared to slums extracted by the GSO (Figure 5-26) and the LSO (Figure 5-27). Apparently, the eastern part is also categorized as a slum in the official data, and it remains a slum between 1997 and 2013 (Figure 5-28). From official data (Figure 5-28) no slum appears in the western part, nor in an area close to the railroad directed south north. Therefore, we can conclude that the spatiotemporal pattern of slum from the GSO (Figure 5-26) and LSO (Figure 5-27), have similarities with the official data only for the eastern part.

We compared the accuracy result from the GSO and LSO in the first and second test area, from 2012 to 2015 (Appendix D). For the first test area, the difference of the average of OA value between GSO and LSO is small. The GSO resulted in a slightly higher average of accuracy than LSO, which is 70.8% and 70.4% respectively. Meanwhile for the second test area, the LSO resulted in a higher average of OA, which is 67.5%. The average of user accuracy obtained from LSO in the first test area is much higher compared with the GSO. In the discussion on spatial transferability (Subchapter 5.4.1.1), we employed the 2012 data to measure the transferability. The result indicated that the GSO performs better. However, after we used a different temporal image, we found changes in every measurement. For instance, we found the increased value of user accuracy from the LSO in the first test area. Where it caused the increased average value of the user accuracy. As discussed in Subchapter 4.5.1, the transferable ruleset resulted in similar performance when applied to the different temporal image. Hence, we calculated the average of the accuracy changes (Figure 5-29). To make the comparison easier, we inverse the value.

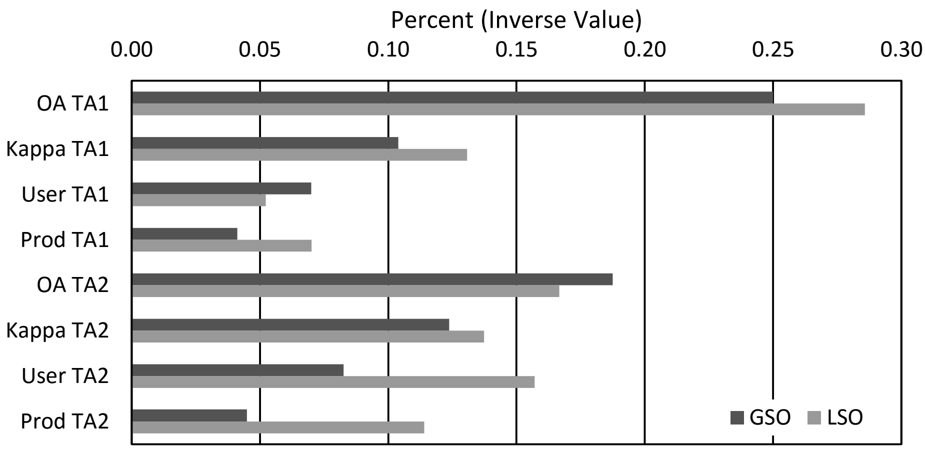


Figure 5-29 Summary of Temporal Transferability

The difference between accuracy score in the across different period should be as low as possible. We measure the accuracy difference in the multitemporal image, for the first and second area for both rulesets. We calculate the average of accuracy changes to make the result comparable. We inverse the value. Therefore, the graph is easier to be interpreted.

For the first test area, we can notice the LSO produce a higher score (lower difference of accuracy across years) in three of four indicators. Meanwhile, in the second area, the GSO resulted in a higher score. Therefore, in term of temporal transferability, the LSO is more transferable to be applied in the first area, while the GSO is more transferable in the second area.

5.4.1.3. Spatiotemporal Pattern Comparison

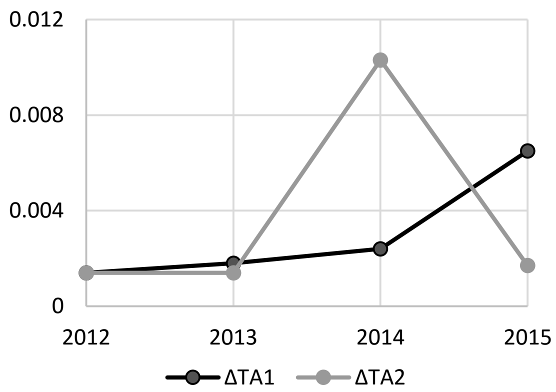
After we compare the accuracy of segmentation and classification process, the next discussion is related to its spatial metrics pattern. The third indicator of the transferable ruleset is they should result in the similar spatiotemporal pattern. Hence, we calculate the difference between each spatial metrics value between the GSO and LSO in the first and second test area (Figure 5-30). Since the 2013_1 is only applicable to the first test area, and we compare the first and second area, we exclude 2013_1 result.

Regarding the interpretation of the graph, the Landscape Division (LD) (Figure 5-30 (a)) indicated that both ontologies resulted in similar patch size in the first and second area in 2012 and 2013. For 2012, the LD value for GSO and LSO in the first area is 0.9821 and 0.9807 respectively. Meanwhile, for the second area, the LD value for GSO is 0.9804, and for LSO is 0.9790. The value approaching one indicates that the size of the patches is small. For 2014, we can notice a difference in pattern of the first and second area. For the first area, the difference of LD value between GSO and LSO is relatively small. However, for the second area, the difference is larger. The LD value for the GSO was 0.9769, and for the LSO was 0.9666, which are lower. Therefore, the patch size of LSO is relatively higher than the GSO.

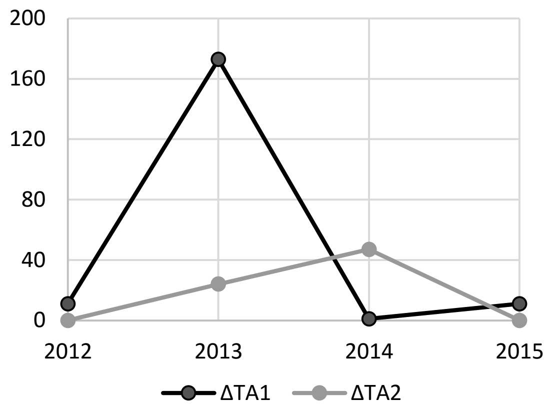
For the Patch Density (PD) value indicated the number of patches in 100 hectares. The result from GSO and LSO is relatively similar in both areas in 2012 (Figure 5-30 (b)). However, for 2013, we noticed a large difference of PD in the first test area (Appendix D). In 2012, the PD value for the GSO was 16.983, and it was highly increased to 217.782 (thirteen times higher). Although we also noticed a increased number of PD for the LSO, which is 5.994 to 44.955, the increased value is lower (eight times higher) compared to the GSO. The possible sources of this difference are due to the different time of image acquisition. For 2012 data, the image was taken on May, where 2013 data the image was taken on October.

Regarding Aggregation Index (AI) (Figure 5-30 (c)), the graph indicated the aggregation of patches. The difference between GSO and LSO is relatively higher in the first test area compared to the second test area. The LSO resulted in higher AI (Appendix D) from 2012 to 2015 compared with the GSO. It indicated that the extracted slum patches from the LSO were more aggregated.

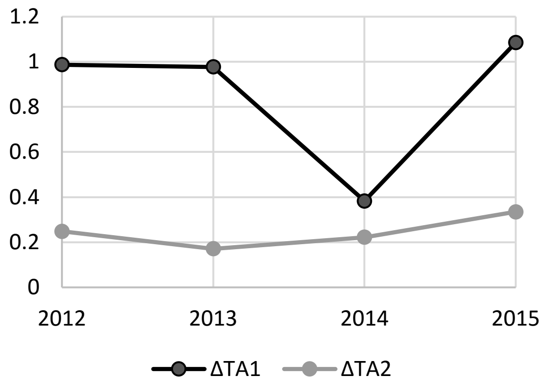
For the Shannon's Evenness (SHEI) and Contagion Index (CONTAG) (Figure 5-30 (d) and (e)) shows a similar pattern between first and second test area. In General, SHEI and CONTAG measure the distribution of the patch in the landscape. A high value of SHEI indicates an equal distribution of patches across the landscape. Meanwhile, a high CONTAG value indicates that the patches are clumped. In general, the SHEI and CONTAG values for the GSO (Appendix D) are relatively higher than LSO in each different time and test area. The graph (Figure 5-30 (d) and (e)) indicates that both rulesets show increased difference between GSO and LSO result, which means the spatial pattern are more difference across years.



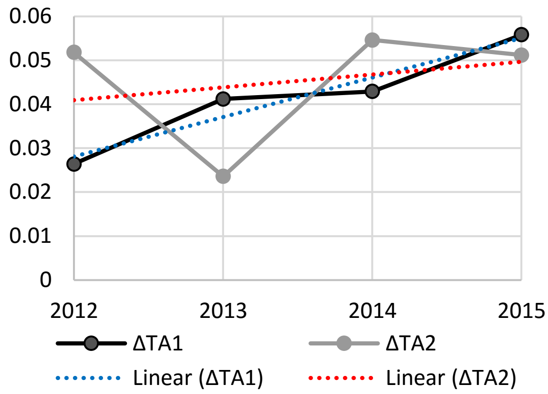
a. Landscape Division



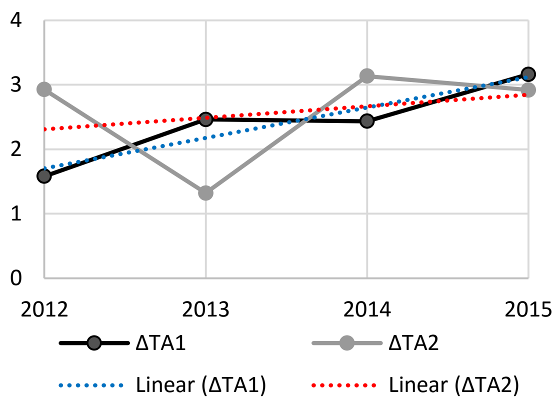
b. Patch Density



c. Aggregation Index



d. Shannon's Evenness Index



e. Contagion Index

Figure 5-30 Comparison of Spatial Metrics Value

Regarding Landscape Division (Figure 5-30 (a)), we can conclude that between 2012 and 2013 both rulesets are transferable. Meanwhile for 2014, both rulesets are more transferable to the first area, wherein 2015 they are more transferable to the second area. For the Patch Density (Figure 5-30 (b)), we can conclude both rulesets are transferable in both areas in 2012 and 2015. Also, both ruleset are transferable in 2014 only for the first area. Regarding the Aggregation Index (Figure 5-30 (c)), we can conclude that the GSO and LSO are only applicable to the second area. The Shannon's Evenness (Figure 5-30 (d)) and Contagion Index (Figure 5-30 (e)) resulted similar pattern. Both of them indicated that both rulesets are not transferable. Firstly, the difference between ruleset is large in both test area. The slightly smaller difference appeared in 2013 for the second test area. Secondly, the difference between GSO and LSO in both area indicated increasing trend, where we can expect the difference become higher in the future.

5.4.2. Qualitative Measurement

According to the discussion of each characteristic of slums in subchapter 5.3.2.2, we can evaluate whether a particular characteristic can be used to detect the slums. Three qualitative measurements were used, which are utility, generality and reusability (Subchapter 4.4.3).

5.4.2.1. Utility

Regarding the utility, eight indicators of slums are described by the GSO (Table 5-4). Meanwhile, the LSO also described eight indicators (Table 5-4). After we implemented the indicators of slums from the real-world to image domain characteristics, some indicators cannot be implemented (Table 5-6).

Table 5-6 Utility of GSO

Domain		Utility	
Real World	Image	Yes	No
Located on Riverbank/railroad	Association: Distance to River/Railroad	√	
Near with Economic Hotspot	Association: Distance to CBD/Industrial/High-Class Residential		√
Irregular pattern of building	Shape: Irregular	√	
High density	Texture: GLCM	√	
Absence of green opens space/ vegetation	Association: Distance to vegetation/green open space	√	
Irregular, small and unpaved road	Shape: Irregular		√
Small building size	Size: small		√
Poor roof materials	Tone: Asbestos, iron	√	

Among eight real-world domain indicators from the GSO (Table 5-6), five of them can be used to detect slums in the study area. Meanwhile, three of them cannot be used due to some reasons. For instance, the different level of aggregations, (e.g. distance to the economic hotspot), or unavailability of data (e.g. irregular road and small building size). Therefore, 62.5% of the GSO indicators can be used to detect slums. Meanwhile, for the LSO, the evaluation of the utility is presented in Table 5-7.

Table 5-7 Utility of LSO

Domain		Utility	
Real World	Image	Yes	No
Located on Riverbank/railroad	Association: Distance to River/Railroad	√	
Near with Economic Hotspot	Association: Distance to CBD/Industrial/High-Class Residential		√
Tenure Status	Ancillary data: Land Use Plan	√	
Irregular pattern of building	Shape: Irregular	√	
Irregular, small and unpaved road	Shape: Irregular		√
Small building size	Size: small		√
Poor roof materials	Tone: Asbestos, iron	√	
Lack of Sanitation	Ancillary data: Sanitation		√

From eight real-world domain indicators from the LSO (Table 5-7), only four of them (50%) can be used to detect the slums. The reasons were the different level of aggregation or unavailability of the data, which are similar with the GSO.

Therefore, according to the comparison in Table 5-6 and Table 5-7, we conclude that the GSO is more transferable than LSO, in term of utility.

5.4.2.2. Generality

The next indicator for measuring the applicability is the generality. We measure the generality according to the adaptation needed to result in similar result. For the generality, the less adaptation required for extracting the slums, the more transferable the ruleset. Comparison of generality between GSO and LSO can be seen in Table 5-8.

Table 5-8 Generality of the GSO and LSO

Indicator	Adaptation	Application GSO	LSO
Distance to vegetation/green open space	Threshold for NDVI (Annex D)	√	
Roof Materials	Threshold for Mean red and green ratio (Annex D)	√	√

For the GSO, two adaptations are needed to detect the slums (Table 5-8), which are the adaptation of NDVI value (for detecting vegetation), and the mean red/green ratio (for detecting the roof materials of slums). Meanwhile, since the LSO is not used association to vegetation (Table 5-7), the adaptation needed is only for roof materials (Table 5-8). Therefore, in term of generality, the LSO is more transferable compared to the GSO.

5.4.2.3. Reusability

The last indicator for measuring the applicability is the reusability. This measurement aims to complement the result obtained from the quantitative measurements. As we can notice from the previous discussion (Subchapter 5.4.1.1, 5.4.1.2 and 5.4.1.3), the detection of slums is a subject of uncertainties. For instance, in measuring the spatial transferability, we conclude the GSO resulted in higher transferability compared to the LSO. This result is unexpected since we assumed the local adaptation would increase the accuracy. We argue that the different perception of slum boundaries that were used as reference caused this unexpected result (Figure 5-21). Furthermore, the usage of tenure status as indicator, which is not observable by visual image interpretation, has affected the accuracy of the LSO since the reference data for the accuracy assessment are developed from visual image interpretation (Figure 4-8). Therefore, the LSO resulted in a lower accuracy. Similar to the research of Kohli (2015), the reference from manual image interpretation have some form of uncertainties since slums often have fuzzy boundaries, different way to conceptualize, and lack of local knowledge.

Similar with the temporal transferability, we expected the LSO would show a higher transferability than GSO in every area. However, the result shows the GSO have a higher temporal transferability in the first area. This result is unexpected. Three sources of uncertainties might explain this unexpected result. Firstly, the static concept and dynamic changes. As mentioned by Arvor et al. (2013), a real-world object changes over time, but the description of an object remains static in the ontology. For instance, we assume the tenure status of a particular area was not change between 2012 and 2015, but in the real world, they might change. Secondly, the real world and image domain issue. Our knowledge of particular features is often qualitative and subjective, but the information contained in an image is quantitative (Arvor et al., 2013). For instance, we argue that the lack of open green space is one characteristic of slums. This real world definition needs to be translated into the image domain. Hence, we applied a specific NDVI threshold to detect the green area. Although we applied different NDVI threshold for the different images, it also possible that the thresholds are not precisely correct. For instance, during the dry season, the leafs of a trees are brown coloured. Lastly, similar to the uncertainties in spatial transferability, the usage of tenure status also resulted in a low accuracy of LSO.

6. CONCLUSIONS AND RECOMMENDATIONS

This chapter provides the conclusions of this study. We also describe the limitations and the recommendations for further research. This chapter is structured as follows: it started with the conclusions, divided into sub-chapter according to the sub-objectives. This also includes the findings and answers to the individual research questions. In the last subchapter, we provide recommendations for further studies.

6.1. Conclusions

The overall aim of this study was to analyse the transferability of the Generic Slum Ontology (GSO) to multi-temporal imagery applied in Jakarta. To achieve this objective, we had four sub-objective and seven research question. Findings and conclusions for each sub-objective are described below.

6.1.1. Local Characteristics of Slums

Four questions need to be answered in this sub-objective. Firstly, the difference of slum characterization among experts. Secondly, the difference of slum boundaries among experts. Thirdly, the difference of slum characteristics between visual interpretation and field observation. Lastly, the local characteristics of slums in the study area.

Related to the first question, local experts indicated different characteristics of slums (Table 5-1). For instance, only the expert from the local government (Table 5-1) indicated the proximity to the CBD as characteristic of slums. Apparently, this expert has local knowledge regarding the field condition of the specific area given in the image (Figure 4-4 (b)). Therefore, as discussed in Subchapter 5.5.1, the different of abilities, experiences and background of the expert resulted in a different interpretations of slums.

Related to the second question, apparently the slum boundaries among experts differ (Figure 5-2 and Figure 5-3). This result is similar to the results of Kohli (2015), showing that slums often have fuzzy boundaries, the different ways to conceptualize, lack of local knowledge, and this caused uncertainties in the delineation process. Due to the different agreements of slum boundaries (Figure 5-4), it is necessary to understand the ground situation, to be able to decide on the local characteristics of slums.

According to the field observations (Figure 5-4 to Figure 5-8), we found some differences in slum characteristics, between the visual image interpretation and field observation. For instance, we found three characteristics observed in the field, which are narrow roads, built on illegal land, and lack of access to sanitation, which cannot be observed from the image (Table 5-3). We also noticed that the human eye might result in misinterpretation in visual image interpretation. For instance, although only selected by one expert (Figure 5-7 and Figure 5-8), these areas can be categorized as slums from the field observations. This demonstrates the uncertainties of the slums detection, as discussed in Subchapter 5.5.

By extrapolating the results from the local experts in relation with the ground observation, we conclude the local characteristics of slums (question 4). Firstly, slums are located on the riverbanks or close to the railroad. Secondly, slums are located near to the high-class residential/CBD area. Small building sizes with irregular building orientations are the third and fourth characteristics respectively. Fifth, the roof material is dominated by asbestos and galvanized iron. The small size of roads is the sixth characteristic of slums. Lastly, the lack of tenure and poor sanitation are the seventh and eight characteristics of slums.

6.1.2. Development of the Rule-set

The question that needs to be answered to fulfil this sub-objective is to define the criteria that allow extracting the slums in the study area. Two sets of criteria can be used to extract slums in the study area, the criteria are developed for the GSO and LSO.

According to the GSO, slums can be detected by five characteristics, namely distance to hazardous areas, irregular patterns, high density, lack of vegetation and the unique roof materials. We used the close proximity to river or railroad as a hazardous area. Regarding the irregular patterns, we used compactness threshold less than five as an indicator. For the high density, we employed a GLCM dissimilarity (all band), with a threshold of greater than 0.0005. Meanwhile, for the vegetation, we used the distance to vegetation as an indicator. We obtained the threshold from a trial-and-error process, which is less than 750 pixels. Lastly, for the roof material, we used a colour threshold indicator, where we used the ratio between the average of the red and the green band. We applied different values for the different image subsets (Appendix D).

For the LSO four indicators were used, three of them were similar with the GSO (distance to hazardous area, irregular shape and the unique roof materials). Meanwhile, for the fourth indicator, the LSO employed tenure status. The complete ruleset used to extract slums in the study area can be seen in Appendix A and B.

6.1.3. Detection of slums

The questions need to be answered to fulfil the third objective are the comparison of extracted slums among different locations and temporal conditions. We apply two classification stages as suggested by Kohli (2015), first background removal with low Scale Parameter (SP=1) and second conducting a coarser segmentation with higher SP to detect the slums. In the second level classification, we focused on detecting slums from the built up class. This part was done by conducting a new segmentation process with coarse SP obtained from the ESP.

On the landscape level, both rulesets resulted in the similar location of extracted slums in both areas. For instance, in the first area slums located in the eastern and western part of the image. The extracted slum extent varied between 2012 and 2015 for both rulesets. On the settlement level, we can clearly notice differences between extracted slum boundaries from the GSO and LSO.

6.1.4. Transferability Measurement

Two question need to be answered to fulfil the last objective, which is the development of the transferability indicators, and the transferability result. We employ two transferability measurements, which are quantitative and qualitative measurements. For the quantitative measurements, we follow the transferability measurement framework by Tuanmu et al. (2011) with an addition of criteria and some adaptations. Hence, the measurements used included the performance across different spatiotemporal conditions, and similarities of spatial patterns that were measured by spatial metrics. For the qualitative measurements, we developed a framework by combining the indicators from Sori (2012) and Lantow and Sandkuhl (2015). As a result from this combination, we use three indicators for measuring the applicability, which are utility, generality and reusability.

Regarding the spatial transferability (quantitative measurements), we found the GSO is more transferable compared to the LSO. Three measurements (OA, User Accuracy and Quality of Classification) indicated lower variations of accuracy performance of the GSO when applied to the different areas (first and second test area). We expect the LSO would result in higher spatial transferability. However, as indicated by the accuracy measurements, the GSO showed a better performance.

For the temporal transferability, we found the LSO resulted in higher transferability in the first test area, where the GSO is higher in the second test area. This result is unexpected since we assume that the LSO would also result in higher transferability in the second test area. Lastly, for the similarities of spatial patterns, both ontology were transferable for a particular year. For instance, according to the LD, both ruleset were only transferable between 2012 and 2013. Another example is PD, both ruleset were only transferable in 2012 and 2015.

For the qualitative measurement, we conclude the GSO is more transferable than LSO in terms of utility. The usage of local characteristic, i.e., access to sanitations, cannot be implemented due to the different level of measurement. Although the GSO resulted in higher transferability, some indicator could not be utilized to extract slums. Physical characteristics of roads in slums are hardly observed from the satellite imagery. For instance, narrow road are often covered by the roof of slums building (Figure 5-7). Furthermore, locally available data of informal roads are scarce. Regarding the small building sizes, our research has shown it is hard to extract slum buildings (Figure 5-10). Regarding the generality measurement, we found the LSO is more transferable compared with the GSO. The number of adaptation needed (by changing the threshold) for the LSO is less than for the GSO.

For the reusability, we can notice some uncertainties, which caused some unexpected results for the quantitative measurements. Firstly, for the spatial transferability, the disagreement in slum boundaries by local experts has contributed to problems in generating reference data. The differences of slum boundaries cause uncertainties, e.g. fuzzy boundaries of slums and the different way to conceptualize (Kohli, 2015). The usage of the non-observable indicator (tenure status) in the LSO has affected the low performance of LSO since the reference data was created from visual image interpretation by local experts. Secondly, for the temporal transferability, two sources of uncertainties have resulted in an unexpected result. The first uncertainty is the difference between the static concept of the ontology and the dynamic changes of a slum in the real-world. The second uncertainty is due to the difference between the qualitative and subjective definition of slums on the ground, and the quantitative information contained in the image. The usage of the non-observable indicator (tenure status) also contributed the low temporal transferability of LSO.

6.2. Limitations and Recommendations

This research has contributed to the transferability assessment of the Generic Slum Ontology (GSO) to be applied in different spatiotemporal conditions. This research also made some suggestions regarding the advantage and the drawback of using the GSO to detect slums. However, we argue that this research has some limitations, and further research needs to be done. The limitations and recommendations as follows:

1. **Selecting the most appropriate segmentation parameter**
   Although the ESP is very useful, we found limitations of our study while applying this tool. Firstly, lack of elaboration regarding the impact of smoothness and compactness parameter. Since the ESP tool required a pre-defined value for smoothness and compactness parameter, and the resulted SP may vary according to the value that we entered (Drăguț et al., 2010). However, we decided to choose a similar value for smoothness and compactness from the trial-and-error process, which is 0.5. Indeed, it will be hard to identify the most appropriate value of SP, without doing a trial and error process (Drăguț et al., 2010). A study from Kavzoglu and Yildiz (2014) discussed the impact of SP, smoothness and compactness parameter on the quality of image objects. However, the process is more a manual step-by-step approach. Hence, we argue that it will be important for further research to focus on developing automated parameter estimation tool that could be used to define the most appropriate smoothness and compactness parameter.

2. **Coping with the uncertainties of slum**
   We discussed sources of uncertainties in our research (Subchapter 5.5). Firstly, during our research, we applied the assign class algorithm, by put the threshold in the ruleset (e.g., roof colour, distance to the river). Indeed, this method is capable of extracting slums when they are easy to distinguish (for instance, first area). Furthermore, this method is easier to operate compared to other classification algorithms. However, we argue this algorithm is not the best way to deal with the fuzziness of the slum object. This method does not allow a ‘transition zone’, where an object might have more than one class probability. This is shown by the slum extraction for the second area,

where there is no exact boundary between slum and non-slum areas. Therefore, we recommend using fuzzy classification methods for further research.

Secondly, the disagreement of slum extent caused difficulties to measure the accuracy of the automatic slum extraction. In our research, we obtained the slum extent from the local expert interviews. This method did not allow the discussion among experts to arrive at an agreement regarding slum extent. Therefore, for the further research, we argue that a focus group discussion will give a better opportunity to define the location of slums with a higher agreement.

3. **Incorporation of different data**

   Although the images used in this research have a high spatial resolution (0.5 metre after pansharping), we are not able to extract the slum buildings as an individual objects. Therefore, an indicator related to the property of slum buildings (size, shape, and pattern) is not applicable to our case. However, different data can be used to extract buildings, for instance, by combining with the Light Detection and Ranging (LIDAR) data. Combining optical and LIDAR data demonstrated high utility in some studies. For example, the study from Ebert et al. (2009), which combined LIDAR, optical satellite and GIS data to assess the urban social vulnerability. Another research from McKeown and Cochran (1999) showed the potential of combining (fusion) several data sources for building extraction. Therefore, we recommend for further research to utilize different type of data to enhance the quality of slum detection in GEOBIA.

   We also argue that the study related to transferability of the GSO can be further developed. Although the uncertainties are the nature of slum itself, development of the more robust ruleset will give a better opportunity to monitor the dynamic of the slum. In our research, we tested the transferability in the different spatiotemporal condition. We recommend for further research to test the transferability of the ruleset in multi-temporal data obtained from the different image sensor.

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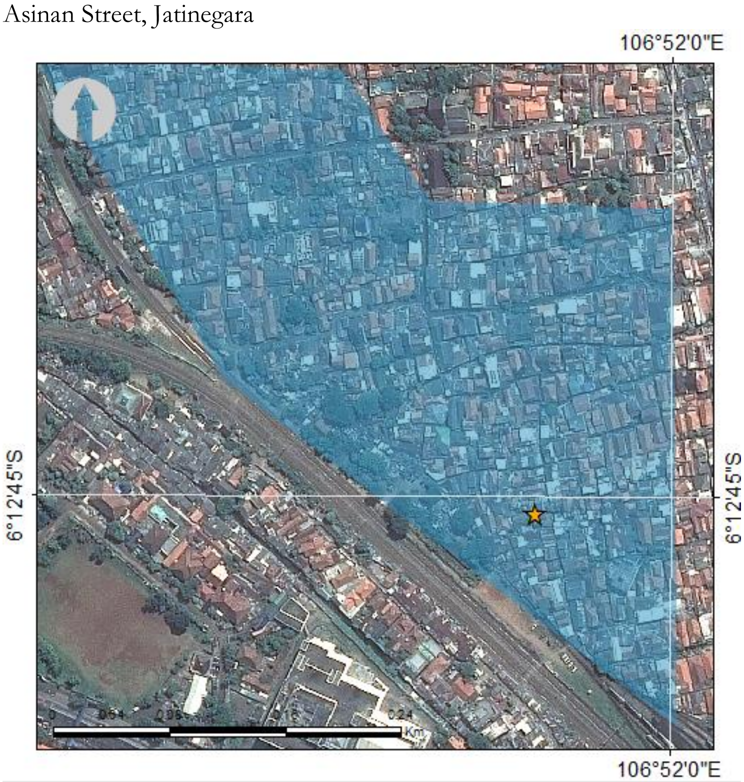
APPENDICES

APPENDIX A: Ground Conditions from the Survey Area

<table>
<tr><th>Location and Map</th><th>Ground Conditions</th></tr>
<tr><td>Asinan Street, Jatinegara


</td><td>

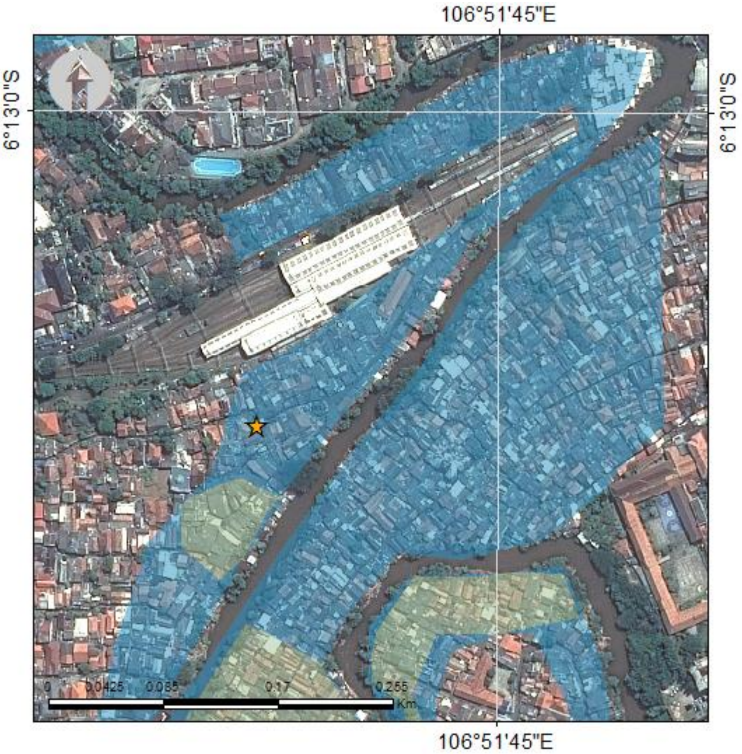

</td></tr>
<tr><td>Kampung Melayu Kacil Street


</td><td>


</td></tr>
</table>

<table>
<tr><th>Location and Map</th><th>Ground Conditions</th></tr>
<tr><td>Setia Street

</td>
<td>


</td></tr>
<tr><td>Bukit Duri Street

</td>
<td>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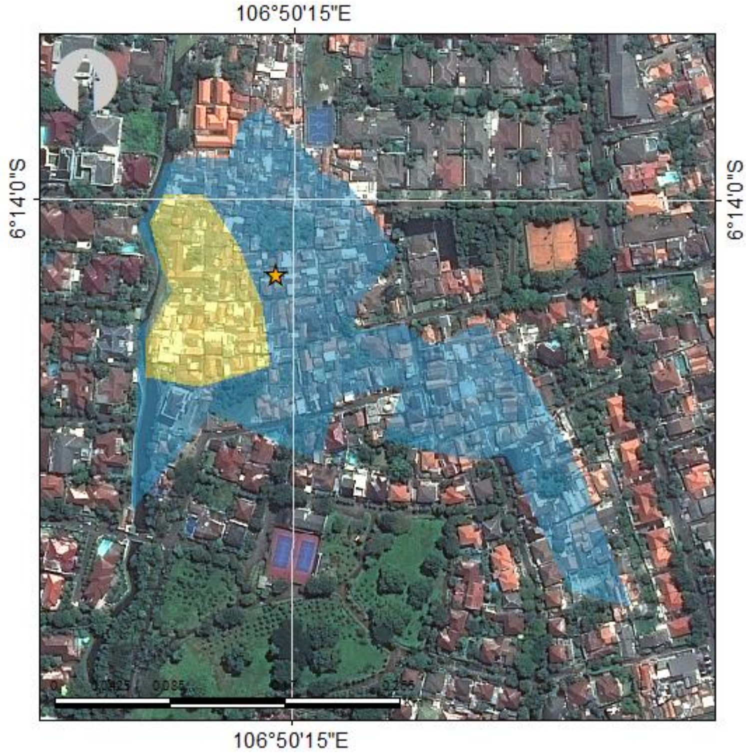
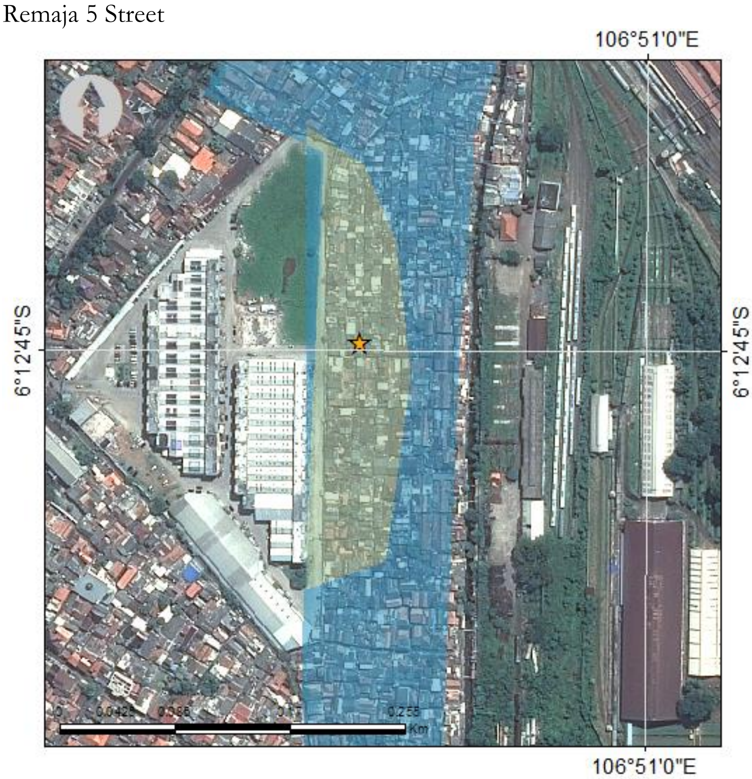
</table>

<table>
<tr><th>Location and Map</th><th>Ground Conditions</th></tr>
<tr><td>Rasamala 3 Street



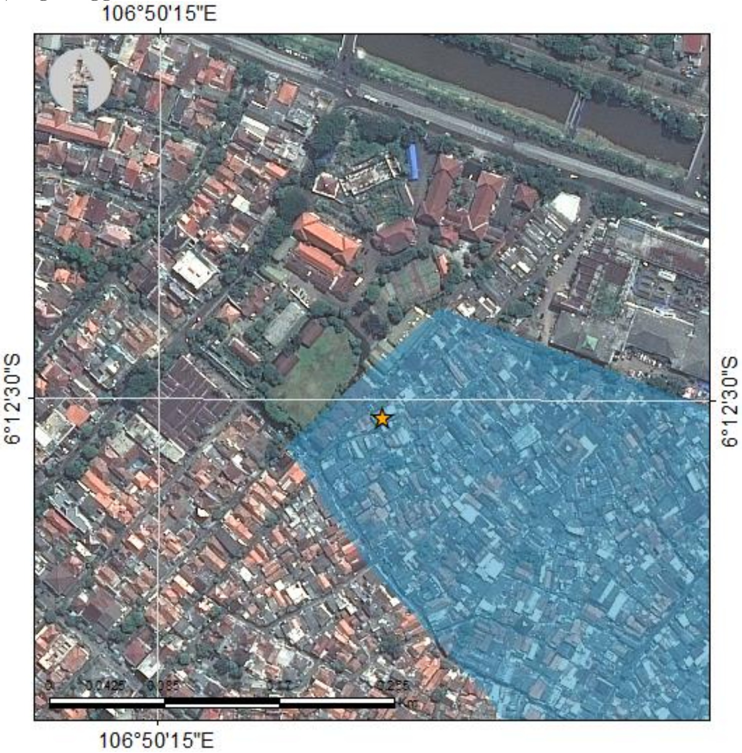
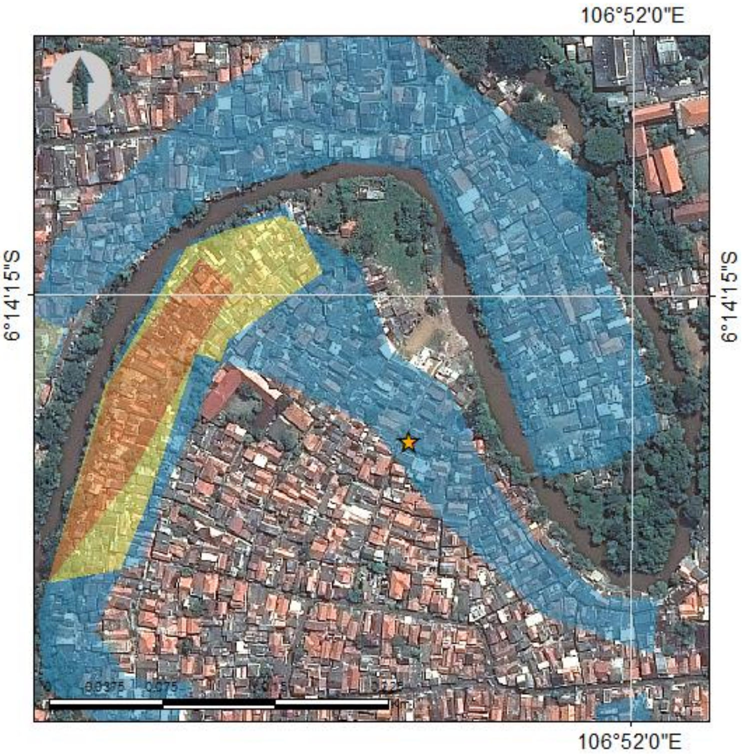
</td><td>

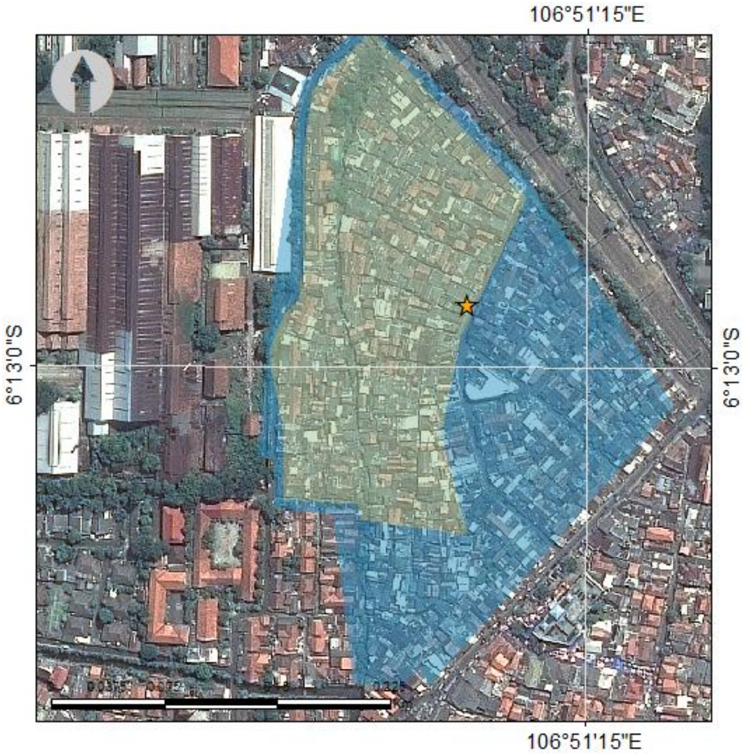
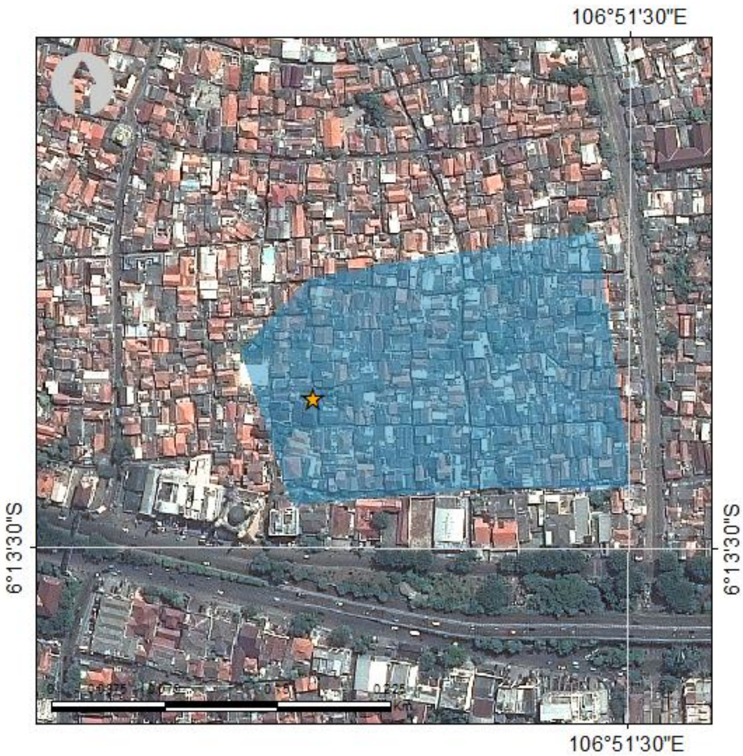

</td></tr>
<tr><td>Remaja 5 Street



</td><td>


</td></tr>
</table>

Location and Map	Ground Conditions
Ujung Unggaran Street 	 
Kebon Baru 5 Street 	 

Location and Map	Ground Conditions
Gelatik Street 	 
Sawo Kecil 4 Street 	 

APPENDIX B: E-cognition Ruleset for Slums Identification in Study Area

- jakarta
  - reset
    - delete 'New Level'
    - at New Level: remove classification
  - Level 1 Background Removal
    - segmentation
      - 1 [shape:0.5 compct.:0.5] creating 'New Level'
    - classification
      - background
        - vegetation
          - unclassified with NDVI >= -0.06 at New Level: vegetation
          - vegetation at New Level: merge region
        - road
          - unclassified with Min overlap [%]: Thematic Layer 1 = 100 at New Level: road
          - road at New Level: merge region
        - rail road
          - unclassified with Min overlap [%]: Thematic Layer 3 = 100 at New Level: rail road
          - rail road at New Level: merge region
        - river
          - unclassified with Min overlap [%]: Thematic Layer 2 = 100 at New Level: river
          - river at New Level: merge region
        - builtup
          - unclassified at New Level: builtup
  - Level 2 Slums
    - segmenting slums settlement
      - builtup at New Level: 88 [shape:0.1 compct.:0.5]
    - slums settlement
      - reset
        - slums at New Level: builtup
      - GSO
        - builtup with Border to river > 0 Pxl or Border to rail road > 0 Pxl or (Border to vegetatic
      - local ontology
        - builtup with Border to river > 0 Pxl or Border to rail road > 0 Pxl or (Compactness <= 5

APPENDIX C: Slums Indicator According to the GSO and LSO

a. GSO Indicator

Type	Value 1	Operator	Value 2	Unit
◢ OR				
Condition	Border to river	>	0	Pixels
Condition	Border to rail road	>	0	Pixels
◢ AND				
Condition	Border to vegetati...	<=	750	Pixels
Condition	Compactness	<=	5	No Unit
Condition	red/green	>=	1	No Unit
Condition	red/green	<=	1.075	No Unit
Condition	GLCM Dissimilarit...	>=	0.0005	No Unit

b. LSO Indicator

Type	Value 1	Operator	Value 2	Unit
◢ OR				
Condition	Border to river	>	0	Pixels
Condition	Border to rail road	>	0	Pixels
◢ AND				
Condition	Compactness	<=	5	No Unit
Condition	red/green	>=	1	No Unit
Condition	red/green	<=	1.075	No Unit
Condition	Mean Layer 5	>	0.25	No Unit

APPENDIX D: Value and Parameters

a. Image Metadata

Gain and Bias from the Pleiades Image (value not rounded)

	2012	2013_1	2013_2	2014	2015
Gain Blue	1.48581	0.797643	1.62489	0.921986	0.759993
Bias Blue	6.45440	5.362360	21.60680	11.38800	5.174850
Gain Green	1.55277	0.830470	1.43820	0.961949	0.795310
Bias Green	7.04020	5.817140	6.49353	10.908800	9.889810
Gain Red	1.65243	0.903344	1.72727	1.052050	0.874927
Bias Red	1.22704	0.437403	35.07320	2.050450	-0.270860
Gain NIR	2.17555	1.327770	1.99498	1.571520	1.281510
Bias NIR	4.01605	3.469500	23.04320	6.794810	2.875860

Source: Metadata from Pleiades Dataset

Sun Elevation and Sine Value (value not rounded)

Dataset	Top Centre		Centre		Bottom Centre	
	sun elevation	sine	sun elevation	sine	sun elevation	sine
2012	54.71809387	0.816320035	54.70001532	0.816137745	54.68193797	0.815955385
2013_1	57.42212686	0.842660400	57.40626892	0.842511341	57.39042445	0.842362343
2013_2	70.96275147	0.945306721	70.96345673	0.945310736	70.96414107	0.945314632
2014	53.06364269	0.799303498	53.04937368	0.799153817	53.02799051	0.798929417
2015	57.16226962	0.840209696	57.14487736	0.840045053	57.12746626	0.839880153

Source: Metadata from Pleiades Dataset

b. Threshold Modifications

Adaptation Value for Classification Level 1 and 2

Years	Test Area	NDVI	SP Lv2	Roof Tone (Mean R/Mean G)
2012	**1 (base data)**	**≥0**	102	1 ≤ tone ≤ 1.1
	2	≥0	109	1 ≤ tone ≤ 1.1
2013_1[22]	1	≥-0.14	86	0.92 ≤ tone ≤ 1.008
	2	Not used		
2013_2	1	≥0.13	55	0.6 ≤ tone ≤ 0.85
	2	≥0.13	153	0.6 ≤ tone ≤ 0.85
2014	1	≥-0.06	99	0.9 ≤ tone ≤ 1.1
	2	≥-0.06	88	0.9 ≤ tone ≤ 1.1
2015	1	≥0	95	1≤ tone ≤ 1.075
	2	≥0	95	1 ≤ tone ≤ 1.075

[22] Image in second test area has high cloud cover. Therefore, we only used the first test area.

c. Accuracy Results

Multitemporal Comparison of Accuracy Result

Test Area 1								
Year	Generic Slum Ontology (GSO) (%)				Local Slum Ontology (LSO) (%)			
	OA	Kappa	User (slum)	Prod (slum)	OA	Kappa	User (slum)	Prod (slum)
2012	68.0	43.3	42.8	60.0	66.0	38.9	50.0	28.5
2013_1	72.0	53.7	62.5	71.4	70.0	48.5	60.0	42.9
2013_2	74.0	58.7	60.0	85.7	74.0	56.1	80.0	57.1
2014	68.0	43.3	50.0	28.5	70.0	46.1	66.7	28.6
2015	72.0	50.9	75.0	42.8	72.0	49.6	100.0	28.6
Avg	**70.8**	**50.0**	**58.1**	**57.7**	**70.4**	**47.7**	**71.3**	**37.1**
Test Area 2								
Year	Generic Slum Ontology (GSO) (%)				Local Slum Ontology (LSO) (%)			
	OA	Kappa	User (slum)	Prod (slum)	OA	Kappa	User (slum)	Prod (slum)
2012	72.0	50.3	36.3	66.7	72.0	44.8	33.3	33.3
2013_2	64.0	40.6	25.0	33.3	66.0	41.5	33.3	28.5
2014	64.0	36.3	22.2	33.3	70.0	43.5	33.3	33.3
2015	56.0	26.1	0.0	0.0	62.0	27.0	14.2	16.6
Avg	**64.0**	**38.3**	**20.9**	**33.3**	**67.5**	**39.2**	**28.5**	**27.9**

d. Spatial Metrics Value

Dataset	Test Area	Ruleset	Landscape Division	Patch Density	Aggregation Index	Shannon's Evenness	Contagion Index
2012	1	GSO	0.9821	16.983	96.9093	0.5681	67.3685
		Local	0.9807	5.994	97.8961	0.5417	68.9508
	2	GSO	0.9804	141.929	97.3116	0.6645	62.8331
		Local	0.979	141.929	97.063	0.6127	65.7601
2013_1	1	GSO	0.9795	20.979	98.0815	0.6282	64.1766
		Local	0.9778	27.972	98.4472	0.5795	66.8511
2013_2	1	GSO	0.9842	217.7822	95.5388	0.6142	62.0362
		Local	0.9824	44.955	96.5159	0.573	64.4974
	2	GSO	0.9848	174.9125	96.7159	0.6998	58.8611
		Local	0.9834	198.9005	96.5448	0.6762	60.1827
2014	1	GSO	0.9823	13.986	97.3958	0.5573	68.1475
		Local	0.9799	12.987	97.779	0.5144	70.5824
	2	GSO	0.9769	169.915	96.9492	0.6413	64.0078
		Local	0.9666	216.8916	96.7265	0.5867	67.1427
2015	1	GSO	0.9818	14.985	97.4544	0.549	68.4719
		Local	0.9753	3.996	98.5391	0.4932	71.6339
	2	GSO	0.9794	115.942	97.2174	0.6448	63.8988
		Local	0.9777	115.942	96.8827	0.5936	66.8176