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Impervious Surface Mapping Using Robust Depth Minimum Vector Variance Regression

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Abstract

This paper proposes a reliable minimum vector variance regression algorithm for robust supervised impervious mapping.The mapping is done with a conventional two phase process; training and mapping process. The outcome of training process is the robust regression models useful for the knowledge base of mapping land cover. The robust regression model is built from the existing robust depth minimum vector variance subsample. The case of research is a metropolitan area consisting of megacities surrounding Jakarta, Jabodetabek. The urban population in the Jabodetabek area is very high. The urbanization is closely related to the percentage of impervious area and indicates the quality of the environment. The evaluation mapping provides that the robust depth minimum vector variance regression is an effective method for the impervious land cover mapping of Jabodetabek.

Keywords: depth function, impervious, minimum vector variance, robust

1. Introduction

An impervious surface is defined as a surface which cannot be infiltrated by water, primarily associated with buildings, rooftops, paved roads, and parking lots (Yuan & Bauer, 2007).One of the key indicators in assessing urban environments is the impervious surface area in the region (Lu & Weng, 2006). According to Stankowski (1972) and Arnold & Gibbons (1996), the population growth and urbanization is closely related to the percentage of impervious area and indicates the quality of the environment. Furthermore, the increase of impervious surface area can also indicate the transition from agricultural land (Tsutsumida, Comber, Barrett, Saizen, & Rustiadi, 2016).

This paper proposes a reliable robust minimum vector variance regression algorithm for supervised impervious land cover mapping. The land cover mapping is conducted in two processes: the training and mapping process. The objective of the training process is to build the robust regression model for the knowledge base of land cover mapping. To conduct the training process, the robust depth minimum vector variance algorithm is applied to define a subsample of robust regression. The advantage of a depth function is does not require any matrix inversion. The function only needs a computation of a symmetric matrix determinant, consequently its computational time is highly reduced (Djauhari& Umbara, 2007; Herwindiati et al., 2013).

The main purpose of the robust regression is to provide resistant (stable) results in the presence of outliers (Rousseeuw & Leroy, 1987). In this paper, we discuss an effective and efficient robust regression algorithm based on the existing robust subsample providing the minimum vector variance dispersion using the depth function. The responses of the model are the limited multi-dependent variables associated with the

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category of land covers. A limited dependent variable is defined as a dependent variable whose range is substantively restricted (Baum, 2013). The outcome of the training process is the three regression models associated with the three land cover categories which are impervious, water, and green land.

The mapping process is organized by the outcome of the training process. The good performance of the regression model will produce good land cover mapping. The mapping result of the Jabodetabek megacities illustrates the real condition. The evaluation of the mapping results is done at the end of the discussion. Regarding the evaluation, the robust depth minimum vector variance regression is found to be reliable and can be considered for classifying and mapping the impervious surface from a satellite imagery.

2. The Case Study of the Research

The case study of this research is the multispectral imaging from Landsat 8 satellite of the Jabodetabek area. The Jabodetabek is a metropolitan area consisting of megacities surrounding Jakarta, the capital city of Indonesia (Fig. 1). The surrounding cities are Bogor, Depok, Tangerang, and Bekasi. The area is the political and economic center of the country which has a total area of 6,659 square kilometers with 27.2 million of people (Tsutsumida et al., 2016; Hudalah & Firman, 2012). Moreover, approximately 20% of Indonesia's urban population is in the Jabodetabek area (Guilmoto & Jones, 2015), and in the Jakarta alone, the population density in 2010 was around 14,469 people per square kilometers (Central Bureau of Statistics, n.d).

The dramatical rise of the urban population in the region since the 1980s (Hudalah & Firman, 2012) lacks sufficient urban planning which leads to uncontrolled land use conversion. One of the devastating effects of such conversion is the routine flooding of Jakarta. Study of Jones & Douglass (2008) reports that 80-90% of wetland areas in the North Jakarta have been converted into the impervious land which causes the flood even in the dry season when the sea tide is high. Furthermore, the area of Jabodetabek has a bowl-like landscape such that the water from the surrounding areas flows to the sea in the north area of Jakarta. In the rainy season, the water from thesurrounding area flows to Jakarta causing massive floods in the city.The severe floods in Jakarta lately can also be attributed to the deforestation and rapid development of housing, shopping malls, and business districts in the Bodetabek area which, in the past, acted as the absorption area.Therefore, a mapping of the impervious surface area is needed in the future urban and suburban development planning in the region.

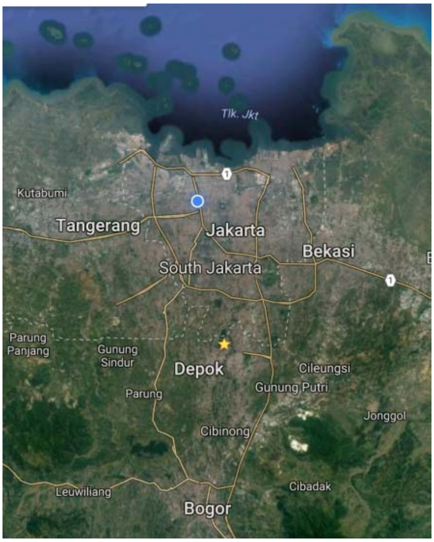


Figure 1. The Jabodetabek Area (source: Google Maps)

Surfaces are anthropogenic features which can be hard to detect because of the complexity of urban landscapes (Lu & Weng, 2006). Some methods can be employed to map the surface, such as ground surveys, aerial photos, and satellite remote sensing (Stocker, 1998). Particularly, the studies of Ji & Jensen (1999) demonstrated the advantages of remote sensing technology to classify the impervious surface area. The remote sensing method utilizes satellite imagery which can cover a large area in a single spectral image, albeit at lower spatial resolution.

The Landsat 8 is the latest satellite from the Landsat program which launched on February 11, 2013, and the imagery can be obtained freely from the GloVis or the EarthExplorer website. The satellite is equipped with two sensors: the Operational Land Imager (OLI) with nine spectral bands of visual, near-infrared, and shortwave infrared; and the Thermal InfraRed Sensor (TIRS) (Rozenstein, Qin, Derimian, & Karnieli, 2014; Roy et al., 2014). Table 1 shows the detail of the OLI sensors. The second to the seventh spectral band are consistent with the previous Landsat satellites sensors, while the new coastal / aerosol and cirrus bands provide new data for detecting water and high thin clouds.

3. Robust Minimum Vector Variance (MVV) and Minimum Covariance Determinant (MCD)

Minimum covariance determinant (MCD) is a famous robust measure proposed by Rousseeuw (1985). The measure uses the minimizing of multivariate dispersion, which is called covariance determinant, to compute the robust estimator. The application of the MCD was limited to a few hundred objects in a few dimensions.The Fast Minimum Covariance Determinant (FMCD) was proposed by Rousseeuw & van Driessen (1999) to improve the MCD performance.

The FMCD estimator is a highly robust estimator of multivariate location and scatter.

The FMCD is an impressive robust algorithm, but it has several problems caused by the characteristics of covariance determinant. The first problem is that the covariance determinant becomes zero if at least one variable has zero variance or if at least one variable is a linear combination of the other variables. The second problem is that the covariance determinant requires the covariance matrix to be nonsingular.

Herwindiati et.al (2007) proposed the Minimum Vector Variance (MVV) to solve the FMCD problem. MVV is generated from the vector variance multivariate dispersion. The MVV does not require the covariance matrix to be nonsingular. In addition to that, compared to the FMCD algorithm, the MVV algorithm has a lower computational complexity.

Geometrically, vector variance is the square of the length of the diagonal of a parallelotope generated by all principal components of X. Suppose X is a random vector and Σ is the covariance matrix. If $\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_p \geq 0$ are the eigenvalues of Σ of size $p \times p$, then:

Covariance determinant = $|\Sigma| = \lambda_1 \times \lambda_2 \times \ldots \times \lambda_p$ (1)

Vector variance = $Tr(\Sigma^2) = \lambda_1^2 + \lambda_2^2 + \cdots + \lambda_p^2$ (2)

The computational complexity of vector variance is of order $O(p^2)$. On the other hand, based on Cholesky decomposition for a large value of p, the number of operations in the computation of covariance determinant is $p + p(p-1) + (p-1)\sum_{i=1}^{p}(p-i-1)(p-i)$ which is of order $O(p^3)$.

Suppose T_{MVV} and S_{MVV} are the MVV estimators for location parameters and covariance matrix. Let random samples $X_1, X_2, \ldots, X_n$ from p-variate distribution of location parameter μ and a positive definite covariance matrix Σ. The MVV estimators for location parameters and covariance matrix are defined as the pair (T_{MVV}, S_{MVV}) minimizing $Tr(S_{MVV}^2)$ among all possible $h = \frac{n+p+1}{2}$ sets H, where $T_{MVV} = \frac{1}{h}\sum_{i \in H} X_i$, $S_{MVV} = \frac{1}{h}\sum_{i \in H}(X_i - T_{MVV})(X_i - T_{MVV})^t$, and $Tr(S_{MVV}^2) = s_{11}^2 + s_{22}^2 + \cdots + s_{pp}^2 + 2\sum_{i=1}^{p}\sum_{j \neq i}^{p} s_{ij}^2$ (see Herwindiati et al. (2007)).

4. The Algorithm of Robust Depth Minimum Vector Variance for Determining the Regression Subsample

The supervised impervious mapping is done with a conventional two-phase processes: the training process and the image cell classification. The objective of the training process is to build the robust regression model for the knowledge base of land cover mapping. To conduct the training process, the algorithm of robust depth minimum vector is applied to define a subsample of regression.

Robust regression is an important tool for analyzing data that are contaminated by outliers. The main purpose of robust regression is to provide resistant (stable) results in the presence of outliers (Rousseeuw & Leroy, 1987). In this paper, we discuss the algorithm of robust regression subsample based on the existing subsample of robust depth minimum vector variance.

Herwindiati et al. (2013) proposed the robust depth minimum vector variance to estimate multivariate location-scale parameters using minimum vector variance dispersion and the depth function. The method is valuable for the computation of a large dataset.

The depth function $|M_i|$ is proposed by Djauhari & Umbara (2007). The function is equivalent to the Mahalanobis depth for reducing the level of complexity of the FMCD and MVV. An advantage of $|M_i|$ as a measure of depth is that the measure does not need any matrix inversion in its computation.

Let $X_1, X_2, \ldots, X_n$ be a random sample from p-variate distribution where the second moment exists. The sample mean vector and sample covariance matrix are, respectively,

$$\bar{X} = \frac{1}{n}\sum_{i=1}^{n} X_i \tag{3}$$

$$S = \frac{1}{n-1}\sum_{i=1}^{n}(X_i - \bar{X})(X_i - \bar{X})^t \tag{4}$$

The sample version of the Mahalanobis depth of X_i is defined as:

$$MD_i = \frac{1}{1+(X_i-\bar{X})^t S^{-1}(X_i-\bar{X})} = \frac{1}{1+d_i^2} \tag{5}$$

where d_i^2 is the Mahalanobis distance.

We see that the denominator of MD_i is the Mahalanobis distance, so we need the inversion of the sample covariance matrix S. The computational complexity of the inversion is high. To address the problem, Djauhari & Umbara (2007) introduced a new depth function M_i which is less complicated than the Mahalanobis depth.

$$M_i = \begin{bmatrix} 1 & (X_i - \bar{X})^t \\ (X_i - \bar{X}) & S \end{bmatrix} \tag{6}$$

A matrix of size $(p+1) \times (p+1)$ is associated with $X_1, X_2, \ldots, X_n$. If $|S|$ and $|M_i|$ are the determinant of S and M_i respectively, then

$$MD_i = \frac{|S|}{2\,|S| - |M_i|} \tag{7}$$

We see that $MD_i \le MD_j$ if and only if $\left(2\,|S| - M_j\right) \le (2\,|S| - M_i)|M_i|$ and MD_i define the same multivariate ordering. The advantage of this depth function is that it does not require any matrix inversion. Its only calculation is the computation of the determinant of a symmetric matrix which consequently reduced the computational time.

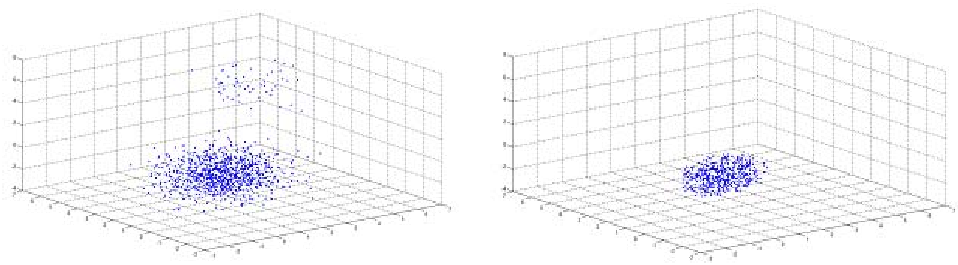
The basic idea of the procedure to determine the robust subsample is to identify the subsample containing $h = \frac{n+p+1}{2}$ of the observations that are associated with the smallest vector variance. This is equivalent to finding the robust subsample with the minimum vector variance dispersion using the depth function.

The algorithm of the robust depth minimum vector variance is described as follows:

1. Assume a dataset of p-variate observations $\{X_1, X_2, \ldots, X_n\}$.
2. Let $H_0 \subset \{1, 2, \ldots, n\}$ with $|H_0| = h$ and $h = \left[\frac{n+p+1}{2}\right]$.
3. Compute the mean vector $\bar{X}_{H_0}$ and covariance matrix S_{H_0} of H_0.
4. Compute $M_i = \begin{bmatrix} 1 & (X_i - \bar{X}_0)^t \\ (X_i - \bar{X}_0) & S \end{bmatrix}$ for $i = 1, 2, \ldots, n$.
5. Sort M_i in decreasing order, $M_{\pi(1)} \ge M_{\pi(2)} \ge \cdots \ge M_{\pi(n)}$.

6. Define $H_W = \{X_{\pi(1)}, X_{\pi(2)}, \dots, X_{\pi(h)}\}$.
7. Calculate the new mean vector $\bar{X}_{H_W}$ and covariance matrix S_{H_W} of H_W.
8. If $Tr\left(S^2_{H_W}\right) = 0$, the process is stopped. If $Tr\left(S^2_{H_W}\right) \neq Tr(S^2_{H_0})$, repeat steps 2 – 8. The process is continued until the k-th iteration or if $Tr\left(S^2_k\right) - Tr\left(S^2_{k+1}\right) \leq \epsilon$ where ϵ is a small constant.
9. Let T_{VV} and M_{VV} be the location and covariance matrix given by that process. The subsample of robust depth minimum vector variance is defined as subset $H_W = \{X_{\pi(1)}, X_{\pi(2)}, \dots, X_{\pi(h)}\}$ of T_{VV} and S_{VV}.

An illustration of robust subsample is described in Fig. 2 and Fig. 3. Consider a dataset $\{X_1, X_2, \dots, X_n\}$ of p-variate observations. Let $H_1 \subset \{1, 2, \dots, n\}$ with $|H_1| = h$, $T_1 = \frac{1}{h}\sum_{i \in H_1} x_i$ and $S_1 = \frac{1}{h}\sum_{i \in H_1}(x_i - T_1)(x_i - T_1)'$. The subsample of robust depth minimum vector variance is defined as subset $H_W = \{X_{\pi(1)}, X_{\pi(2)}, \dots, X_{\pi(h)}\}$ minimizing vector variance.



(a) (b)

Figure 2. The scatter of: (a) original dataset $\{X_1, X_2, \dots, X_n\}$*; (b) the subset data* $H_W = \{X_{\pi(1)}, X_{\pi(2)}, \dots, X_{\pi(h)}\}$

5. Robust Depth Minimum Vector Variance Regression Using Limited Multi-Dependent Variable

In this section, we discuss an effective and efficient robust regression algorithm using a limited multi-dependent variable for classification and mapping of three types of land cover: impervious, water, and green land.

Basically, a limited dependent variable is a dummy variable for dependent variable or response. A dummy variable is an artificial variable created to represent an attribute with two or more categorical representation. A limited dependent variable, Y, is defined as a dependent variable whose range is substantively restricted (Baum, 2013). In the common case, a limited dependent variable is defined as a binary response model, coded as a dummy variable, $Y_i \in \{0, 1\}$.

The three categorical land covers will be represented by limited multi-dependent variable Y_1, Y_2, and Y_3. They are taken from the value of either 0 or 1. The value of 0 means that the response is zero. Conversely, the value of 1 means that the response has a significant value. Assume Y_1 is impervious defined as $(1, 0, 0)$, Y_2 is water defined as $(0, 1, 0)$, and

Y_3 is the green land defined as $(0, 0, 1)$. Overall, the limited multi-dependent variable for the three land covers can be seen in Table 2.

Table 2. The Limited Multi Dependent for Three Types of Land Covers

Category of Land Cover	Y_1	Y_2	Y_3
Impervious	1	0	0
⋮	⋮	⋮	⋮
Impervious	1	0	0
Water	0	1	0
⋮	⋮	⋮	⋮
Water	0	1	0
Green Land	0	0	1
⋮	⋮	⋮	⋮
Green Land	0	0	1

The estimation of robust regression model is started from the simple description as follows: assume the general model for the i-th observation $(i = 1, 2, \ldots, n_R)$, p-variates, and the k-th categorical $(k = 1, 2, 3)$, which can be formulated as:

$$y_{ki} = b_1 x_{1i} + b_2 x_{2i} + \cdots + b_p x_{pi} + e_i \quad (8)$$

where

$$X = \begin{bmatrix} x_{11} & x_{21} & \cdots & x_{p1} \\ x_{12} & x_{22} & \cdots & x_{p2} \\ \vdots & \vdots & \vdots & \vdots \\ x_{1n_R} & x_{2n_R} & \cdots & x_{pn_R} \end{bmatrix}; \quad \vec{e} = \begin{bmatrix} e_1 \\ e_2 \\ \vdots \\ e_{n_R} \end{bmatrix}; \text{ and } \quad \vec{b} = \begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_p \end{bmatrix}$$

with n_R is the subsample of robust.

The limited multi-dependent variable is $\vec{y}_k = [y_1, y_2, \ldots, y_{n_R}]^T$ for $k = 1, 2, 3$. The estimator of regression coefficient for each of the k-th land cover categorical $(k = 1, 2, 3)$ is: $\vec{b} = (X'X)^{-1}X'\vec{y}$ (9)

6. The Training and Mapping Process

6.1 The Training Process

The case study is the megacities surrounding Jakarta,i.e. Jakarta, Bogor, Depok, Tangerang, and Bekasi (Jabodetabek). The training data are acquired from the Landsat 8 satellite imagery and consist of pixels of the impervious, water and green areas. We determine the locations of those areas from visual inspection, and the coordinates can be obtained from the Google Maps. The pixels of the locations are located in the Landsat 8 images by cropping the longitude and latitude coordinates of the corresponding area.

The procedures of training process are as follows:

a. Crop the images of impervious, water, and green area in size $(a \times a)$ pixels based on the longitude and latitude coordinates of the corresponding area.

b. Assume that the dataset of p-variate pixels as training data (input).

c. Define the robust subsample for building the regression model.

d. Estimate the robust depth minimum vector variance regression.

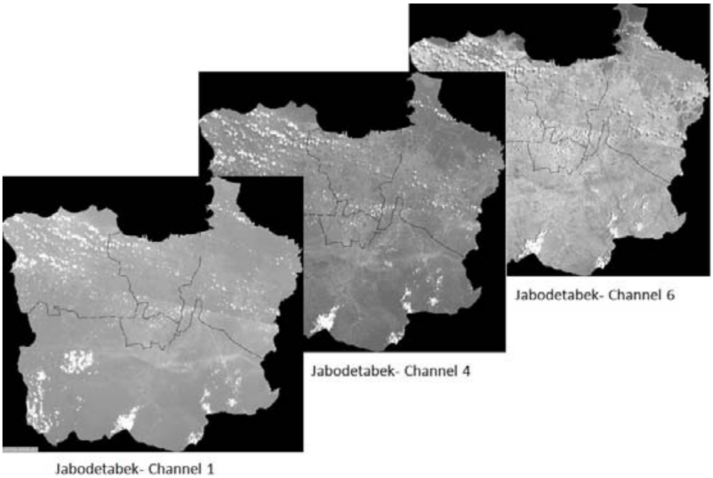


Figure 4. The multispectral Landsat 8 satellite image of Jabodetabek (2016) for channel 1, 4, and 6.

The robust regression using the limited dependent variable will be estimated based on the robust subsample n_R. The model estimation cannot be interpreted as the change in response y given one unit increased of x_p because of $y \in \{0,1\}$. The output of the training process is three robust regression models of three land cover; i.e. y_{imp} for impervious, y_{wtr} for water, and y_{grn} for green area.

$$y_{imp} = -10.9178x_1 + 11.1564x_2 - 8.6365x_3 + 11.0898x_4 + 0.9105x_5 + 0.6169x_6 - 2.7454x_7 \quad (10)$$

$$\boldsymbol{y_{wtr} = 2.4132x_1 - 1.6886x_2 + 3.4382x_3 - 3.0289x_4 - 0.9241x_5 + 0.3416x_6 - 0.5231x_7} \quad (11)$$

$$\boldsymbol{y_{grn} = 10.3608x_1 - 10.5875x_2 + 5.5361x_3 - 8.8908x_4 + 0.0457x_5 - 1.0394x_6 + 3.5139x_7} \quad (12)$$

6.2 The Mapping Process

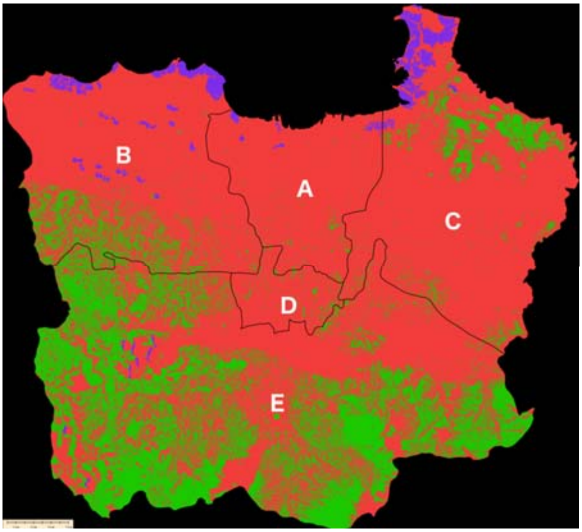
The robust regression models are the potential measure for classification or mapping of land covers. Assuming $T_1, T_2, \dots, T_n$ are the pixels of Jabodetabek area having p-variates, the mapping of the land covers are conducted by three regression models on each pixel T_j, $j = 1, 2, \dots, n$. Each pixel is classified into one of the three classes based on the value of the regression models $(y_{imp}; y_{wtr}; y_{grn})$. The pixel of T_j is classified as the impervious land if $y_{(j)imp}$ is the greatest value among the others. Fig. 5 displays the result of the land cover mapping. The impervious area is labeled with red color, purple for the water area, and green area is represented by green color. Table 3 shows the percentages of impervious and non-impervious area in Jabodetabek (2016).

Table 3. Percentages of impervious and non-impervious area in Jakarta, Bogor, Depok, Tangerang, and Bekasi (Jabodetabek) in 2016.

City	% Impervious	% Non-Impervious
Jakarta	93.94156959	6.05843041
Bogor	56.18744292	43.8125571
Depok	94.08056075	5.91943925
Tangerang	85.37760712	14.6223929
Bekasi	86.84936621	13.1506338

7. Evaluation

An evaluation process is needed to evaluate whether the mapping provides a reliable result. The evaluation will be conducted on the impervious surface in Jakarta and green land in Bogor. To perform this process, we use the Google Earth and our ground truth data. The results of the evaluation is shown in Fig. 6 and Fig. 7. The percentage of impervious area in Jakarta city is very high, mainly due to the construction of mass rail transport (MRT) in the area. The figures provide good evidence that the robust depth minimum vector variance regression is a reliable method that can be considered for classifying and mapping the impervious surface from a satellite imagery.



(A = Jakarta; B = Tangerang; C = Bekasi; D = Depok; E = Bogor)

Figure 5. The mapping of impervious and non-impervious area in Jabodetabek (2016). The impervious area is labeled with red color, water area is purple, and green for the green area.

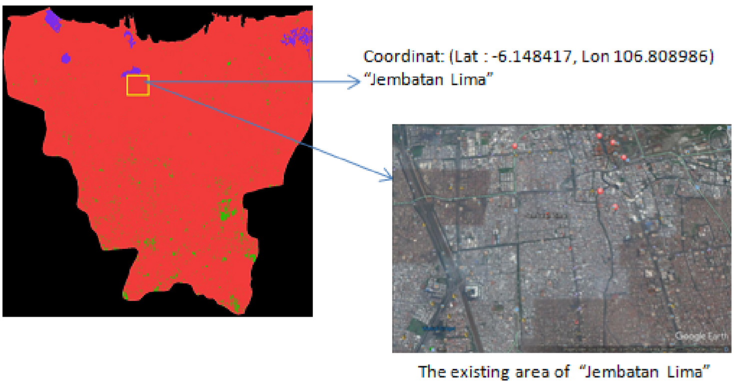


Figure 6. The evaluation of impervious surface, Jakarta-Jembatan Lima (2016).

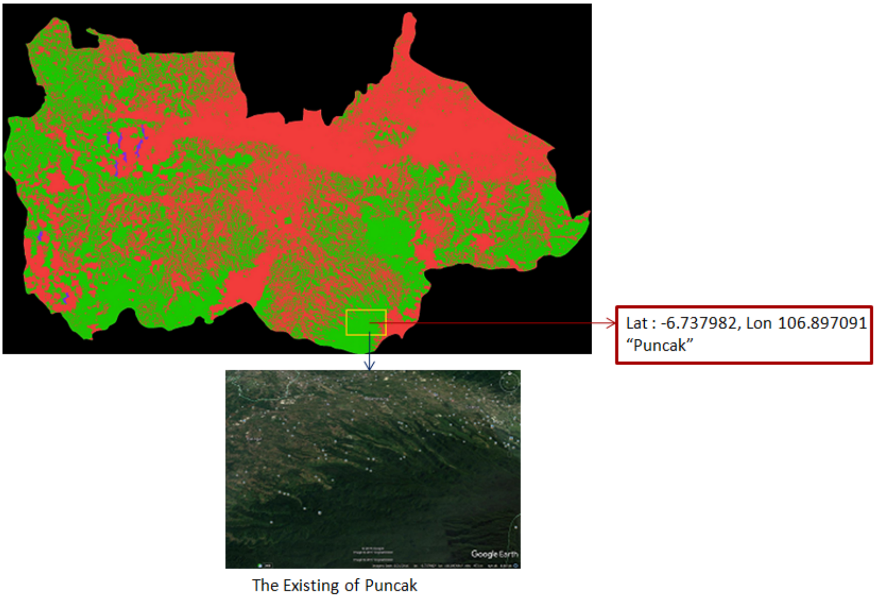


Figure 7. The evaluation of green land, Bogor-Puncak (2016).

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