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Herwig Unger · Sunantha Sodsee
Phayung Meesad *Editors*

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Proceedings of the 14th International Conference on Computing and Information Technology (IC2IT 2018)

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e-mail: kacprzyk@ibspan.waw.pl

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Editors

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Editors
Herwig Unger
LG Kommunikationsnetze
Fern Universität in Hagen
Hagen, Germany

Sunantha Sodsee
Faculty of Information Technology
King Mongkut's University of Technology
North Bangkok
Bangkok, Thailand

Phayung Meesad
Faculty of Information Technology
King Mongkut's University of Technology
North Bangkok
Bangkok, Thailand

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Preface

This proceedings volume contains the papers of the 14th International Conference on Computing and Information Technology (IC2IT 2018) held on July 5–6, 2018, in Chiang Mai, Thailand. IC2IT is a platform for researchers to meet and exchange knowledge in the field of computer and information technology. The participants in IC2IT present their current research new findings and discuss with partners to seek new research directions and solutions as well as cooperation.

Springer has published the proceedings of IC2IT in its well-established and worldwide-distributed series on Advances in Intelligent and Soft Computing, Janusz Kacprzyk (Series Editor). This year there were total 88 submissions from 16 countries. Each submission was assigned to at least three program committee members, and at least two members must accept a paper in order to include in the proceedings. The committee accepted 33 papers for presenting at the conference and publishing the papers in the proceedings. The contents of the proceedings are divided into subfields: Data Mining, Machine Learning, Natural Language Processing, Image Processing, Network and Security, Software Engineering, and Information Technology.

We would like to thank all authors for their submissions. We would also like to thank all the program committee members for their support in reviewing assigned papers and in giving good comments back to the authors to revise their papers. In addition, we would like to thank all university partners in both Thailand and overseas for academic cooperation. Special thanks also go to the staff members of the Faculty of Information Technology at King Mongkut's University of Technology North Bangkok who have done many technical and organizational works. Without the painstaking work of Dr. Watchareewan Jitsakul, the proceedings could not have been completed in the needed form at the right time.

Finally yet importantly, we would like to thank all the speakers and audiences for their contributions and discussions at the conference that made the conference a success. We hope that the proceedings IC2IT will be a good source of research papers for future references with the state of the art.

April 2018

Herwig Unger
Sunantha Sodsee
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Contents

Software Engineering

Robust Kurtosis Projection Approach for Mangrove Classification

Dyah E. Herwindiati[1(✉)], Janson Hendryli[1], and Sidik Mulyono[2]

[1] Faculty of Information Technology, Tarumanagara University, Jakarta, Indonesia
{dyahh, jansonh}@fti.untar.ac.id
[2] The Indonesian Agency for the Assessment and Application of Technology (BPPT), Central Jakarta, Indonesia
sidik.mulyono@bppt.go.id

Abstract. Mangroves are coastal vegetations that grow at the interface between land and sea. It can be found in tropical and subtropical tidal areas. Mangrove ecosystems have many ecological roles spans from forestry, fisheries, environmental conservation. The Indonesian archipelago is home to a large mangrove population which has enormous ecological value. This paper discusses mangrove land detection in the North Jakarta from Landsat 8 satellite imagery. One of the special characteristics of mangroves that are distinguishing them from another vegetation is their growing location. This characteristic makes mangrove classification using satellite imagery non trivial task. We need an advanced method that can confidently detect the mangrove ecosystem from the satellite images. The objective of this paper is to propose the robust algorithm using projection kurtosis and minimizing vector variance for mangrove land classification. The evaluation classification provides that the proposed algorithm has a good performance.

Keywords: Kurtosis · Mangrove · Multivariate · Projection pursuit
Robust · Satellite imagery · Vector variance

1 Introduction

In this paper, we discuss a robust kurtosis projection minimizing vector variance for mangrove detection. Robust kurtosis projection minimizing vector variance is a procedure which combines two advantages of both kurtosis projection pursuit and robust estimation minimizing vector variance. Projection pursuit is a technique that explores a higher to lower dimensional space by examining the marginal distributions of low dimensional linear projections.

Robust statistics has been developed since almost sixty years ago. Huber [16] introduced the robust estimator because the assumptions of normality, linearity, and independence stucked on the classic estimation are frequently not satisfied. The major goal of robust statistics is to develop the statistics measures that are robust against one or more outliers hidden in the dataset [9]. There are several outlier definitions; the word "outlier" is closed to the word "inconsistent". Hawkins [6] defined an outlier as an

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observation that deviates so much from other observations as to arouse suspicion that it was generated by a different mechanism. Since the 20th century, the robust method has been used by scientists to eliminate the influence of anomalous observations in numerous applications.

The robust kurtosis projection minimizing vector variance method was proposed by Herwindiati et al. [4]. The algorithm works in two stages. In the first stage, it has been proposed the projection approach finding the orthonormal set of all vectors that maximize the kurtosis of the projected standardized data. This approach improves on the slow convergence rate proposed by Friedman [11]. In the second stage, we estimate robust covariance matrix minimizing vector variance to identify the data contamination which is the labeled outlier.

Robust minimum vector variance (MVV) is a measure minimizing vector variance to obtain the robust estimator. Robust MVV was proposed by [3]. The multivariate dispersion vector variance (VV) is a measure of dispersion. Geometrically, VV is a square of the length of the diagonal of a parallelotope generated by all principal components [13]. Robust kurtosis projection has a good performance and robust to detect data contamination in a low, moderate, high, even very high percentage.

Mangroves are coastal vegetations that grow at the interface between land and sea [12] and can be found in tropical and subtropical tidal areas. Mangrove ecosystems have many ecological roles; spans from forestry, fisheries, and environmental conservation [1]. The Indonesian archipelago is home to a large mangrove population which has enormous ecological values.

The input data of this research is derived from Landsat 8 satellite imagery. One of the special characteristics of mangroves that are distinguishing them from another vegetation is their growing location. Detecting mangrove might not be enough by focusing only on NIR, red, and green spectral band from satellite imagery, but also the existence of the water, particularly the sea, around the ecosystem. Because of that fact, existing approaches for detection using vegetation indices cannot effectively detect the mangrove ecosystem. We need an advanced method that is able to confidently detect the mangrove ecosystem from satellite images.

The objective of this paper is to propose a robust algorithm using kurtosis projection and minimizing vector variance for mangrove detection. The case study is the area of coastal and waters of North Jakarta, Indonesia.

2 Case Study - Mangrove

Mangroves are coastal vegetations that grow at the interface between land and sea [12] and can be found in tropical and subtropical tidal areas. Mangrove ecosystems have many ecological roles, spans from forestry, fisheries, and environmental conservation [1]. Nutrient cycling and fish spawning grounds are other services provided by the mangrove ecosystem [5]. The erosion of coastal areas can also be prevented by mangrove forests. Lately, mangrove ecosystems have also been studied as the object of conservation for reducing the effects of the tsunami in Asia [8].

The Indonesian archipelago is home to a large mangrove population which has enormous ecological value. The total area of mangrove forests in Indonesia accounts for 49% of mangroves in Asia, followed by Malaysia (10%) and Myanmar (9%) [2]. In spite of that, it is estimated that the area of mangrove forests in Indonesia has been reduced by about 120,000 hectares from 1980 to 2005, mainly due to the changes in land use for agriculture. In 2007, the ministry of forestry released a report stated that 70% of the total area of the mangrove ecosystem in Indonesia, which is 7,758,410.595 hectares, are damaged. Conservation of mangroves in Indonesia should be prioritized for the benefits of the environment and ecosystems [5].

Some of the mangrove conservation areas in Indonesia are in the northwest of Java, particularly in the North Jakarta, Tangerang, and Bekasi region. Figure 1 shows Google Earth image at North Jakarta, Indonesia. According to the Department of Forestry West Java province, 1,000 hectars of the mangrove forest at Jakarta bay in 1977 have been reduced to only 200 hectares. The mangrove forest at the area faces serious threats from urban development and waste, in addition to the lack of conservation plans from the government.

Fig. 1. The area of mangrove forest at North Jakarta, Indonesia

The near-infrared (NIR), red, and green spectral bands are often used for vegetation detection from satellite images. The normalized difference vegetation index (NDVI), which is the ratio of the difference of the red and NIR spectral band divided by their sum, is widely used in remote sensing studies of vegetation [14]. However, the characteristics of mangrove vegetation might be different, so that some vegetation indices may not be able to detect it well. One of the special characteristics of mangroves is their growing location, that is the coastal areas. Detecting mangrove might not be enough by focusing on NIR, red, and green spectral band, but also the existence of the sea around the ecosystem. Furthermore, the location of mangrove can coincide with another green vegetation, as in Fig. 2, and make it harder for remote sensing methods to correctly detect it.

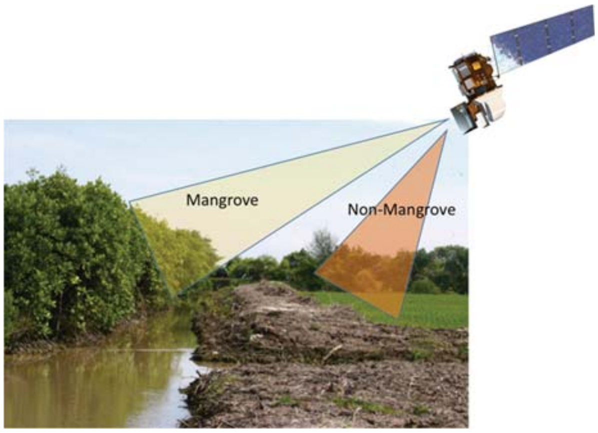


Fig. 2. The challenge of mangrove detection from satellite imagery

3 The Kurtosis Projection Approach Using Minimum Vector Variance

The kurtosis coefficient is a measure of how peaked or flat the distribution is. The dataset with high kurtosis tends to have heavy tails and sharp density peak near the center point. Kurtosis can be formally defined as the standardized fourth population moment about the mean.

$$K = \frac{E(X-\mu)^4}{\left(E(X-\mu)^2\right)^2} = \frac{\mu_4}{\sigma^4} \tag{1}$$

Projection pursuit [11] is a technique aiming at identifying low dimensional projections of data that reveal interesting structures. The framework of projection pursuit is formulated as an optimization problem with the goal of finding projection axes that minimize or maximize a measure of interest called projection index. Projection pursuit is a technique that explores a high dimensional data by examining the marginal distributions of low dimensional linear projections. The two basic components of projection pursuit are its index and its algorithm [15].

The algorithm of robust kurtosis projection minimizing vector variance (MVV) works in two stages. In the first stage, the projection approach finds the orthonormal set of all vectors that maximize the kurtosis of the projected standardized data. The algorithm of projection is inspired by Pena and Prieto [7]. In the second stage, we estimate robust covariance matrix MVV to estimate spectral characteristic of mangrove

Let $X = (x_1, x_2, \ldots, x_n)'$ be a data matrix of size $n \times p$ as the observation result of p variables to n individual objects. The orthogonal projection of each observation results on to one dimensional space spanned by d is $y_i = d'x_i$ where d is a unit vector in $\mathbb{R}^p$.

As the projected data is written as $Y = (y_1, y_2, \ldots, y_n)$, the kurtosis of the projected data is formulated as in Eq. 2.

$$K = \frac{\frac{1}{n}\sum_{i \in \mathbb{N}_n} (y_i - t)^4}{s^4} \tag{2}$$

where $t = \frac{1}{n}\sum_{i \in \mathbb{N}_n} y_i$ and $s^2 = \frac{1}{n}\sum_{i \in \mathbb{N}_n} (y_i - t)^2$ are the sample mean and the sample of the data Y respectively. It should be noted that s^4 is the square of s^2 and $\mathbb{N}_n$ is the set of all natural numbers less than or equal to n.

Centering and scaling transformation of Y gives a new data $Z = (z_1, z_2, \ldots, z_n)$ where for all $i \in \mathbb{N}_n$, $z_i = \frac{y_i - t}{s}$. Since the sample mean of Z is 0 and the sample varaiance of Z is 1, the kurtosis of Z can be formulated as in Eq. 3.

$$K = \frac{1}{n}\sum_{i \in \mathbb{N}_n} z_i^4 \tag{3}$$

The sample mean t and the covariance matrix S of the data matrix X can be defined as in Eqs. 4 and 5. Then, the kurtosis K can also be written as in Eq. 6.

$$t = \frac{1}{n}\sum_{i \in \mathbb{N}_n} x_i \tag{4}$$

$$S = \frac{1}{n}\sum_{i \in \mathbb{N}_n} (x_i - t)(x_i - t)' \tag{5}$$

$$K = \frac{1}{n}\sum_{i \in \mathbb{N}_n} \left(\frac{d'(x_i - t)}{\sqrt{d'Sd}} \right)^4 \tag{6}$$

Consider the objection function f defined as in Eq. 7. We assume that κ_1 is the eigen value of $\frac{1}{n}\sum_{i \in \mathbb{N}_n} (d'y_i)^2 y_i y_i'$ and d is the corresponding eigenvector. Multiplying Eq. 7 by d' from the left gives us the following result in Eq. 8.

$$f(d) = \frac{1}{n}\sum_{i \in \mathbb{N}_n} (d'y_i)^4 - \lambda(d'd - 1) \tag{7}$$

$$\kappa_1 = d' \left(\frac{1}{n}\sum_{i \in \mathbb{N}_n} (d'y_i)^2 y_i y_i' \right) d = \frac{1}{n}\sum_{i \in \mathbb{N}_n} (d'y_i)^4 = K \tag{8}$$

So the unit vector d that maximizes K is the eigenvector of $\frac{1}{n}\sum_{i \in \mathbb{N}_n} (d'y_i)^2 y_i y_i'$ corresponding to the maximum eigenvalue of that matrix. We will call such eigen vector by d_1. The Fig. 3 illustrates the good performance of kurtosis projection from $X = (x_1, x_2, \ldots, x_n) \in \mathbb{R}^3$ to d_1.

The measures of kurtosis relate to the fourth moment of the data and emphasize the tails of the distribution. This paper use the algorithm of robust projection of maximizing kurtosis which was discussed by [4] for classification of mangrove. The good

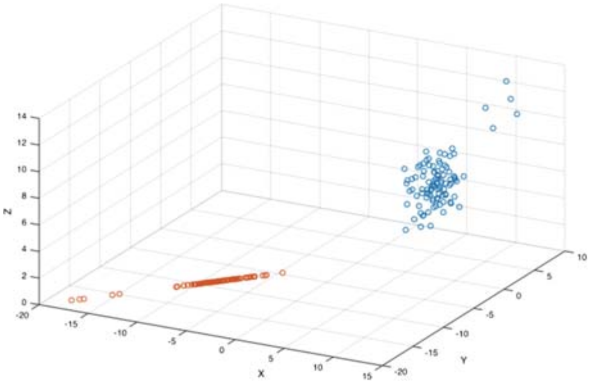


Fig. 3. Illustration of kurtosis projection based on simulation

performance of robust approach will be applied for detection and mapping of mangrove land in Jakarta.

The kurtosis projection approach is used in the initial step of robust kurtosis projection minimizing vector variance. Suppose a matrix data $X = (x_1, x_2, \ldots, x_n)'$ of size $n \times p$, t is the sample mean, and S is the sample covariance matrix of X, the kurtosis projection algorithm can be derived as follows:

1. Standardize the matrix X such that the projected data has mean 0 and variance 1.

$$y_i = S^{-\frac{1}{2}}(x_i - t) \tag{9}$$

2. Find the first unit vector d_1 as the eigenvector of $\frac{1}{n}\sum_{i \in \mathbb{N}_n}(d'y_i)^2 y_i y_i'$ corresponding to the maximum eigenvalue of that matrix.
3. For $k = 2, 3, \ldots, p$, find the k-th unit vector d_k as the eigenvector of $\left(I - \sum_{j=1}^{k-1} d_j d_j'\right) \frac{1}{n}\sum_{i \in \mathbb{N}_n}(d'y_i)^2 y_i y_i'$ corresponding to the maximum eigen value of that matrix. The output is an orthonormal set of all vectors that maximize the kurtosis $d_1, d_2, \ldots, d_p$.
4. Find the projection $z_i = d'y$.

Kurtosis projection provides excellent results for detection of multivariate labeling outlier with very small and small contamination in the dataset, but it fails on a moderate percentage of data contamination. To improve the performance, the algorithm of robust kurtosis projection minimizing vector variance was proposed by [4].

Robust minimum vector variance was proposed by Herwindiati [3] for identifying multivariate outlier labeling. MVV estimator is the robust high breakdown point, i.e. $\frac{n-2(p-1)}{2n}$. Geometrically, vector variance (VV) is a square of length of parallelotope diagonal generated by all principal components of X [14].

Assume a random sample $X_1, X_2, \ldots, X_n$ of a p-variate, the estimator MVV is the pair (T_{MVV}, C_{MVV}) having minimum square of diagonal length of the parallelogram. The robust MVV algorithm was described by [3].

$$T_{MVV} = \frac{1}{n}\sum\nolimits_{i \in H} X_i \quad (10)$$

$$C_{MVV} = \frac{1}{n}\sum\nolimits_{i \in H} (X_i - T_{MVV})(X_i - T_{MVV})^T \quad (11)$$

Robust kurtosis projection minimizing vector variance is an effective method to identify the multivariate outliers in the high dimension. In the simulation experience, robust kurtosis projection using MVV has a breakdown point nearing 0.5. The measure indicates that the robust kurtosis projection method provides results that can be trusted until the half of the data is contaminated [5].

The algorithm of robust kurtosis method can be briefly explained as follows:

1. Find the orthonormal set of all vectors that maximizing kurtosis $\left\{\vec{d}_1, \vec{d}_2, \ldots, \vec{d}_p\right\}$.
2. Compute MVV robust estimators: the location and scale estimator.

The detailed computation for MVV robust estimator can be found in [3–5].

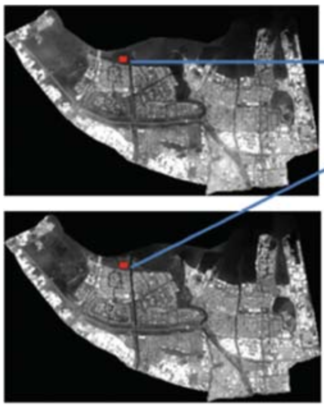
4 The Mangrove Classification

The supervised mangrove classification will be done in two processes: training and testing process. To conduct the training process, the algorithm of robust kurtosis projection is used for the estimation of mangrove and non-mangrove's spectral.

The mangrove and non-mangrove area for the training and testing purposes can be located visually from Google Earth; and by using the Global Mapper and ENVI software, the Landsat images can be cropped according to the coordinates. The data retrieved from the satellite images are the spectral values of each pxiel.

The mangrove vegetation is detected from the Landsat 8 satellite imagery which can be freely downloaded from http://glovis.usgs.gov. For the model training process, we use North Jakarta area which is cropped using the Global Mapper software. Subsequently, 300 points are selected by visual inspection of the area from Google Earth which proportionally represents mangrove, water area, and soil. Meanwhile, for testing and evaluating the trained model, we use the Greater Jakarta area. Therefore, the advantage of our model is that it can learn from a small training dataset size of 300 locations to detect much larger area (more than a million pixels in the testing data). The illustration of the training data can be seen in Fig. 4.

The classification step is conducted by using the spectral reference in the training step. For each satellite image pixels from the training data, our model learns the characteristics of mangrove vegetation, water, and soil.



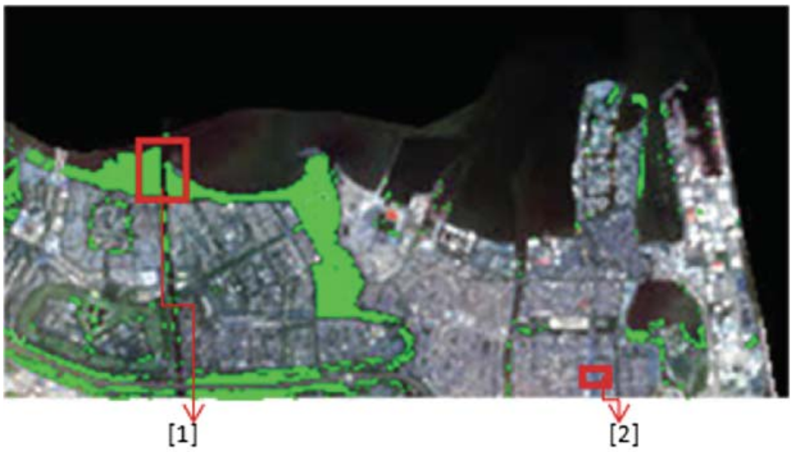
ID	X	Y	MapX	MapY	Lat_1	Lon_1	B1_1	B2_1	B3_1	...
1	136	61	693405	9325225	-6.101833	106.74765	355	...	364	...
2	137	61	693435	9325225	-6.101832	106.74792	358	...	361	...
3	138	61	693465	9325225	-6.101831	106.74819	359	...	363	...
4	139	61	693495	9325225	-6.10183	106.74847	350	...	366	...
5	140	61	693525	9325225	-6.101829	106.74874	351	...	361	...
...	...	...	...	...	...	...	...	...	...	...
...	...	...	...	...	...	...	...	...	...	...
30	140	64	693525	9325135	-6.102643	106.74874	349	...	362	...
31	141	64	693555	9325135	-6.102642	106.74901	345	...	357	...
32	142	64	693585	9325135	-6.102641	106.74928	350	...	354	...
33	136	65	693405	9325105	-6.102918	106.74766	361	...	377	...
34	137	65	693435	9325105	-6.102917	106.74793	358	...	379	...
35	138	65	693465	9325105	-6.102916	106.7482	356	...	375	...
...	...	...	...	...	...	...	...	...	...	...
...	...	...	...	...	...	...	...	...	...	...

Fig. 4. Illustration of cropping data for training process from the Landsat 8 satellite imagery (band 1 and band 3)

The spectral references are very useful for mangrove classification process. Let $W_1, W_2, \ldots, W_n$ be the pixels of the North Jakarta area having p-variates. The mapping of mangrove is conducted by checking the similarity between each pixel W_k, for $k = 1, 2, \ldots, n$, and the spectral references. Each pixel is classified into one of the three classes based on the value of the smallest distance. The pixel of W_k is classified as mangrove if its distance with the mangrove spectral reference is the smallest one. Figure 5 shows the mapping result of mangrove detection in North Jakarta.

Fig. 5. The mapping of mangrove in the north of Jakarta on 2015

The classification result is evaluated in two experiments. Google Earth imagery and our ground truth are used as the evaluation data. In the first experiment, we choose two areas that are classified as mangrove and non-mangrove. We compare the results of our classification model to the actual land cover. The visualization of this experiments can be seen in Fig. 6.



Note:

Information	Coordinat	The Existing Condition
[1]: Mangrove Land	Lat : -6.102668 Lon : 106.749994	
[2]: Non Mangrove Land	Lat : -6.121816 Lon : 106.790116	

Fig. 6. Evaluation of the first experiments on the performance of mangrove classification using robust kurtosis projection

In the second experiment, we compare two results of classification, the classification based on the robust kurtosis projection and the classification using the classical method. Figure 7 illustrates the comparison. The failure of detection is found in the classical method; the existing mangrove land is detected as non mangrove land at the coordinates (Lat: 6.111449; Long: 106.768597). This tells us that robust approach has better performance than the classical method, see Fig. 7.

The arithmetic mean $\vec{\bar{X}}$ is often considered as a location estimator in the classical method. The arithmetic mean is the sum of a collection of numbers divided by the number of numbers in the collection. In this research we build the classical distance for classical detection of mangrove land. The distance measures the similarity of an every pixel to the arithmetic mean $\vec{\bar{X}}$. The classical distance is very sensitive to an anomolous observation or an outlier. The occurrence of one or more outliers shifts the mean vector toward outliers and the covariance matrix becomes to be inflated.

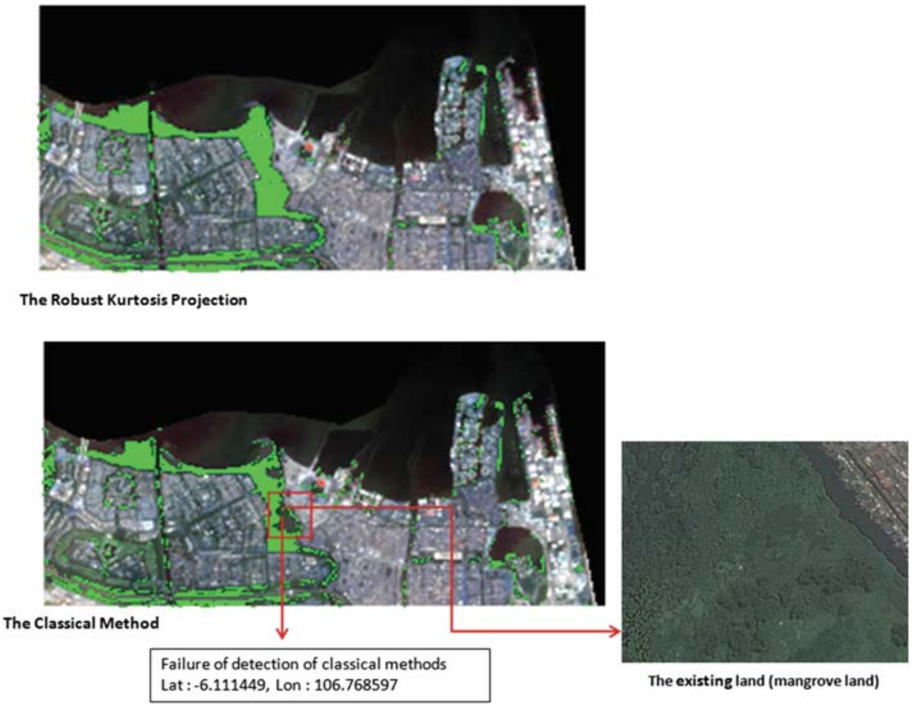


Fig. 7. The performance comparison of robust kurtosis projection performance and classical method for mangrove classification

5 Remark

The experiments and the evaluations prove that the robust kurtosis projection is an effective method that can be considered for mangrove classification. The process of mangrove land detection is not trivial. The mangrove land detection is different from the detection of green land. From the research experience, we need an advanced method that can confidently detect the mangrove ecosystem from satellite imagery. The special characteristics of mangrove is its growing location that can coincide with other green vegetation. This characteristic causes failure in mangrove detection. The empirical results provide strong evidence that the robust kurtosis projection has good performance for mangrove classification.

This study is our preliminary research. Regarding to the study results, we will use the robust kurtosis projection method for our further research; that is the mapping of mangrove land in the Central Java Province Indonesia.

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