Hasil Awal Analisis Citra Berbasis Objek pada Data TerraSAR-X Polarisasi Ganda dengan Menggunakan Algoritma *Fuzzy* untuk Deteksi Fase Pertumbuhan Padi

Initial Results of Geographic Object Based Image Analysis (GEOBIA) on Dual Polarization TerraSAR-X Data with Fuzzy Algorithm for Rice Crop Stages Detection

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ABSTRAK – Penelitian ini memberikan informasi awal hasil penggunaan metode GEOBIA dengan algoritma fuzzy pada data polarisasi ganda (HH dan VV) TerraSAR-X untuk mengidentifikasi tahap-tahap pertumbuhan padi di sebagian daerah Karawang, Jawa Barat. Dua jenis algoritma segmentasi yakni algoritma Multiresolution Segmentation dan Spectral Difference Segmentation kemudian digunakan secara berurutan dalam melakukan segmentasi citra ke dalam objek-objek primitif yang relatif homogen. Pengolahan data kemudian dilanjutkan ke dalam tahap klasifikasi dengan menggunakan skema fuzzy classification. Penelitian ini terdiri dari dua level segmentasi dan klasifikasi. Level 1 berfungsi untuk memisahkan semua objek selain lahan sawah seperti tubuh air, semak belukar, permukiman, dan pepohonan. Baru kemudian pada level 2, kelas lahan sawah diidentifikasi dan diklasifikasi menjadi 4 kelas yang lebih detil, terkait dengan fase pertumbuhan padi (pengairan, pertumbuhan awal, vegetatif, dan generatif). Sebagai informasi awal, performa algoritma klasifikasi fuzzy kemudian diuji dengan menggunakan informasi classification stability dan best classification results. Hasil awal menunjukkan bahwa penggunaan data polarisasi ganda data TerraSAR-X memberikan hasil yang cukup baik dalam mengidentifikasi fase pertumbuhan padi khususnya pada awal masa tanam. Masih belum tersedianya data lapangan membuat informasi akurasi hasil klasifikasi masih belum bisa disajikan. Untuk itu, analisis yang lebih lanjut dengan menyertakan informasi pengukuran lapangan dan data tambahan seperti peta lahan baku sawah masih diperlukan untuk memberikan informasi yang lebih lengkap lagi.

Kata kunci: GEOBIA, TerraSAR-X, Fuzzy, Padi, Polarisasi Ganda

ABSTRACT *-This study describes the initial results of GEOBIA method using fuzzy classification on single-date Dual Polarization (HH and VV) TerraSAR-X data to detect different rice crop development stage from flooding to late vegetative stage, in some part of Karawang, West Java, Indonesia. Multiresolution segmentation and spectral difference segmentation were then performed respectively to segment the relatively homogenous feature into primitive objects. It was then followed by a fuzzy classification scheme. At this stage, we created 2 levels of segmentation and classification schemes. The first level was to separate all non-rice crop objects (i.e. waterbody, trees, and settlements). The second level targeted specifically the rice-crop object of level 1. Afterwards the rice-crop of level 1 was classified into four different classes which represented four different rice crop development stages (flooding, transplanting, generative, and vegetative). As initial results, we then calculated the classification stability and its best classification results as the indicator how well the classification method performed within the classification scheme we built. The results indicated that the dual-pol information from TerraSAR-X information have a good performance on identifying different stages of rice crop especially for the early stages. The lack of field data measurement makes the assessment of mapping accuracy difficult. Thus, for more comprehensive results, further data analysis including field measurement data as well as another ancillary data are still needed.*

Keywords: *GEOBIA, TerraSAR-X, Fuzzy, Rice Crop, Dual Polarization*

1. INTRODUCTION

This paper described the initial results of GEOBIA method using fuzzy classification on single-date Dual Polarization (HH and VV) TerraSAR-X data to detect different rice crop development stage, in some part of Karawang, West Java, Indonesia. As the staple on some Asian countries, the study of the availability of rice becomes a matter of urgency related in terms of food security.SAR data, in general have been proven to be able to detect lowland rice system with its unique temporal signature of the backscatter coefficient (sigma naught or σ^0) (Nelson et al., 2014). A method using X-band HH SAR for monitoring rice crops area where monitoring is based on the analysis of temporal SAR data is proven suitable for multiple environments(Pazhanivelan et al., 2015).

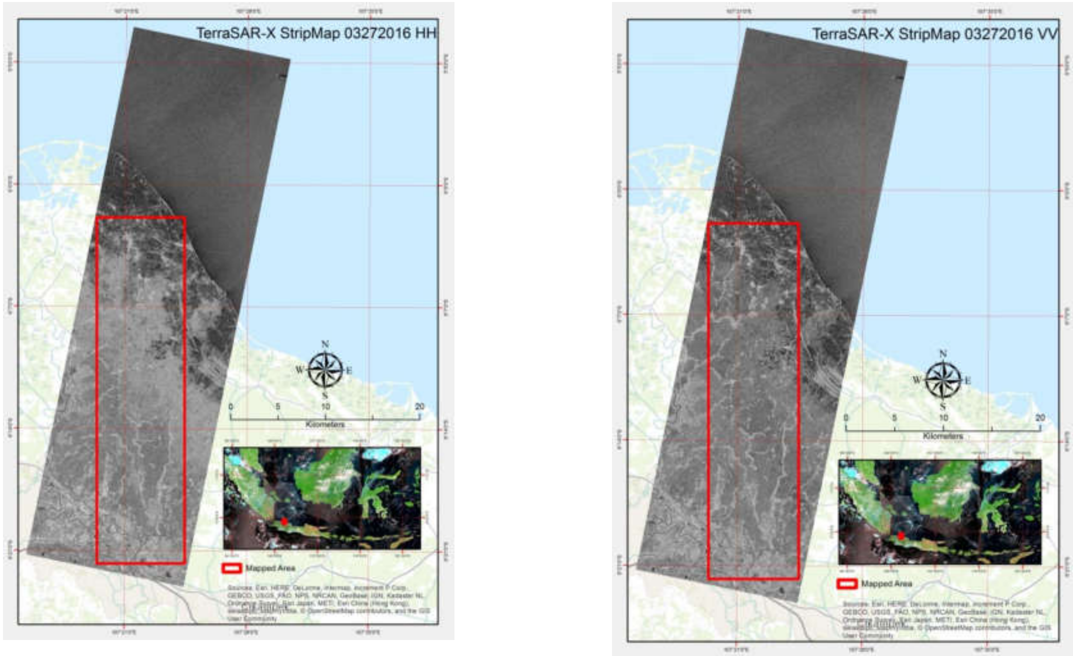
X-band SAR sensor has been proven to have high correlation with stem fresh weight, biomass panicles, and the amount of biomass. It also has high sensitivity for transplantation and will helps to create an accurate growth and harvest prediction (Inoue, Sakaiya, and Wang, 2014). The use of dual-pol TerraSAR-X image for rice crop monitoring has been done and proven to be successful by (Koppe et al., 2013; Lopez-Sanchez, Ballester-Berman, and Hajnsek, 2011).The problem was, these researches are all conducted outside Indonesia. Although the rain or heavy clouds would affect high frequency band SAR image data(Ka, Ku, or X), the certainty of data acquisition at the desired timing and the stability of data quality are superior than the optical sensors (Inoue et al., 2014).

The typical Indonesian rice-field with its small fragmented parcels considered well suited for the GEOBIA with the ability to focus on objects or parcel using segmentation process, and incorporate hierarchical features. On the parcel level, traditional pixel-based analysis of remotely sensed data results in inaccurate identification of some crops due to pixel heterogeneity, mixed pixels, spectral similarity, and crop pattern variability, since it is concentrate only on the properties of single pixels (Peña-Barragán, Ngugi, Plant, and Six, 2011; Singha, Wu, and Zhang, 2016). The transplanting time for each of these parcels, especially with the conventional type of rice-crop, usually have differences throughout the region. Therefore, we proposed to use multilevel fuzzy classification algorithm as it provide a more flexible results as opposed to the crisp classification algorithm, that hopefully able to give a better results. As of the time of this written, a specific use of GEOBIA with fuzzy classification on TerraSAR-X Dual-polarization data has not been done, especially in Karawang Region. Therefore, the aim of this paper is to attempt the use of GEOBIA on Dual-polarization TerraSAR-X data with fuzzy algorithm for Rice Crop Stages Detection in Karawang Region, West Java, Indonesia, and evaluate the result and its potential.

2. METHOD

2.1 Data

This study used two TerraSAR-X (TSX) data on StripMap mode with 6m spatial resolution, acquired on 27 March 2016.



(a) (b)

Figure 1.TSX data, StripMap Mode, Descending, 27˚. Red colored rectangle indicated the Area of Interest (AOI), (a) TerraSAR-X StripMap HH, (b) TerraSAR-X StripMap VV

2.2 Data Processing

These two data were HH and VV co-polarization with incident angle at 27˚. These data were processed as follow.

Preprocessing

TerraSAR-X Level 1b complex data were converted to intensity (squared amplitude) since polarimetric backscatter analysis was based on intensity values. In order to extract plot-level specific crop information, the images should be registered to each other and to the existing GIS data with high accuracy. Because SAR side-looking geometry causes geometric distortions when projecting slant range geometry on Earth a Digital Elevation Model (DEM) together with satellite orbit information was used in the orthorectification process. Due to high inherent slant range location accuracy up to 0.5 m (Eineder, Minet, Steigenberger, Cong, and Fritz, 2011) no ground control points are needed for orthorectification. With orthorectification, a radiometric calibration to sigma nought was also carried out using the following equation (Fritz and Eineder, 2010):

$$\sigma^0{}_{ij}\left[dB\right] = 10 * Log_{10}\left(K * DN^2{}_{ij}\sin\left(\alpha_{ij}\right)\right) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (1)$$

where, *DN* is the pixel amplitude of the *i, j* pixel, *K* the calibration factor, and *α* the local incidence angle of the *i, j* pixel. The equation was used to transform the amplitude of the backscattered signal (*DN*) into the backscattering coefficient ($\sigma^0{}_{ij}$) in decibel. The calibration factor for TerraSAR-X images varies between 10^{-6} and 10^{-4} depending on the incidence angle and polarization. The radiometric calibration is a requirement for multi-temporal analysis of different images. These data were then clipped with the AOI boundary shown in Figure 1, and then imported into Trimble® eCognition 9.2. An additional arithmetic layer of "HH-VV" were then created and exported as independent image layer, to be used as additional data to make an RGB composite.

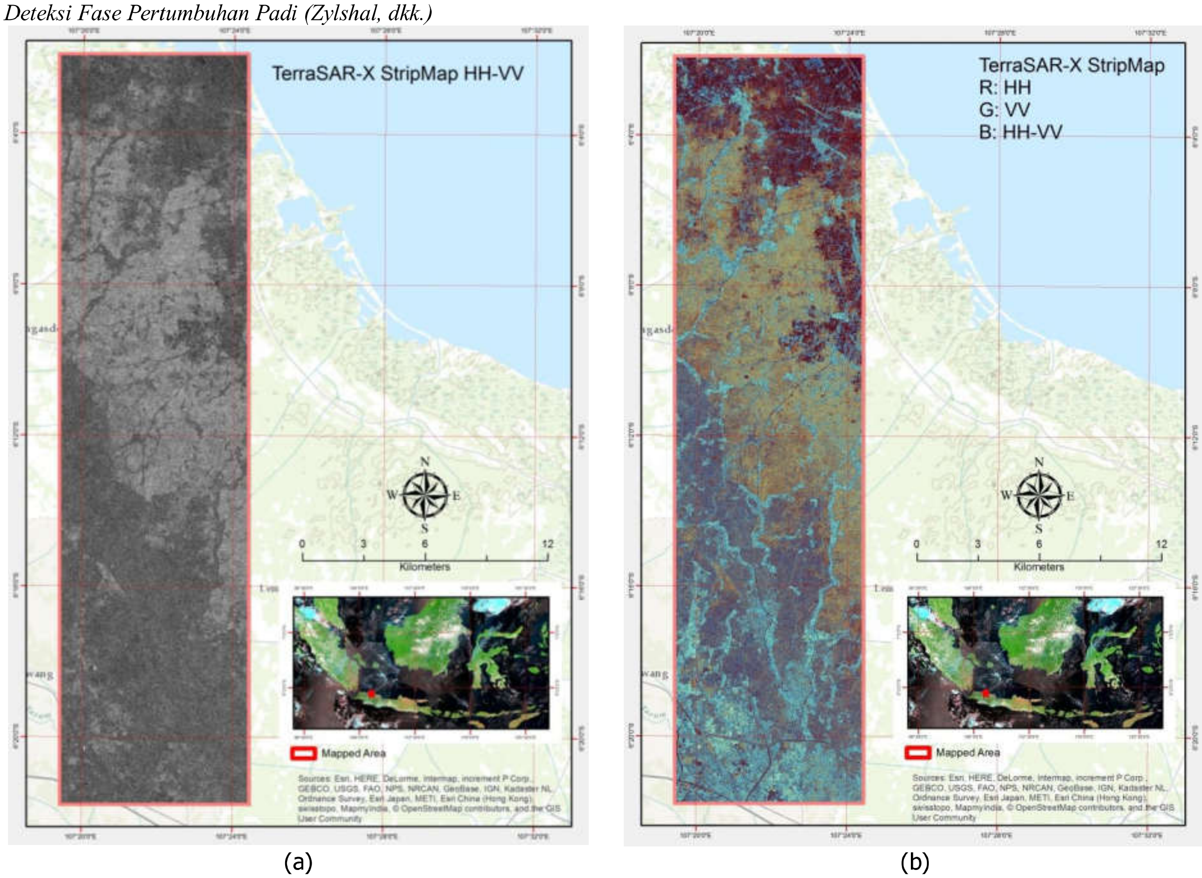


Figure 2. Cropped TSX data based on AOI, (a) Additional TSX Arithmetic layers (HH-VV), (b) TerraSAR-X RGB composite R: HH, G:VV, B:HH-VV

Segmentation

Multiresolution segmentation algorithm based on the Fractal Net Evolution Approach (Baatz and Schäpe, 2000) followed by Spectral difference Segmentation algorithm (Trimble, 2014) were conducted to the data, in the form of multilevel hierarchy approach with two different levels (Figure 3). The level 2 consist of bigger object size that level 1, and act as level 1's super object.Level 1, as the sub-objects of level 2, inherit the object parameters from level 2.

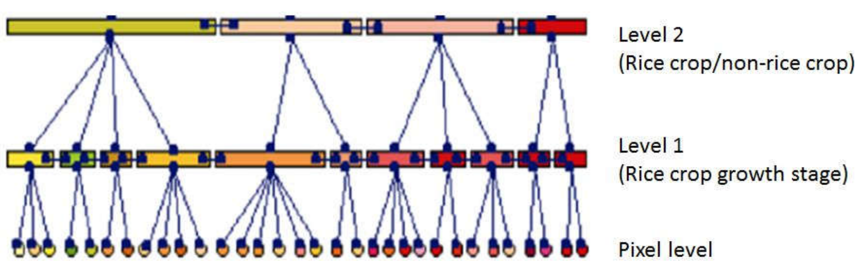
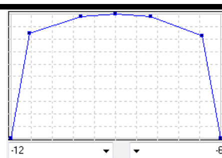
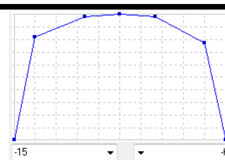
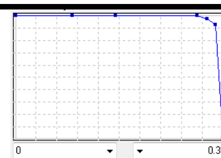
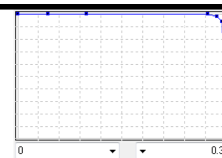
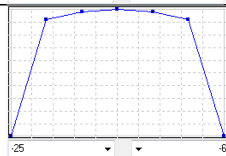
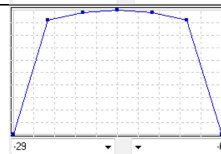
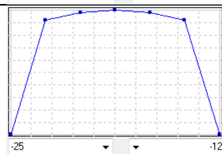
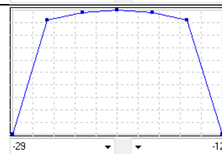


Figure 3.Multi-level hierarchical network of image objects used in this study

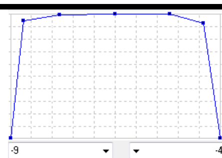
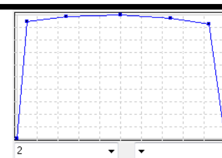
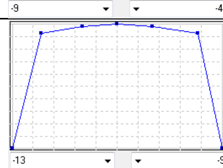
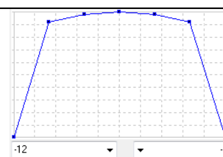
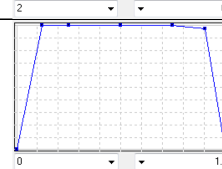
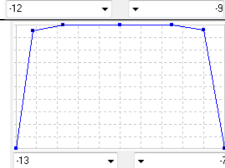
Classification

In this study, we conducted the classification stage using fuzzy logic. In fuzzy logic, the set membership values can range between 0 and 1 (inclusively), as opposed to crisp classification. The degree of truth of a statement can range between 0 and 1 and is not constrained to the two logical values 'true' (=1) and 'false' (=0) as in classical predicate logic(Hofmann, Blaschke, and Strobl, 2011). This procedure requests to define the membership functions. These functions calculate many parameters based both backscatter values and on the semantic relationships between the different objects and assign to each object a probabilistic value variable between 0 and 1. The classification process requests to define a class hierarchy(Emmolo, Orlando, and Villa, 2008). The hierarchy class contains the classification outline as shown in Figure 3. Table 1 and Table 2 show the fuzzy membership function used on level 2 and level 1, respectively.

Tabel 1. Fuzzy membership function used for describing rice and non-rice field landcover

Class Name	HH	VV	GLCM Homogeneity (HH)	GLCM Homogeneity (VV)
Rice				
Non-Rice				
Water				

Tabel 2. Fuzzy membership function used for detecting rice growth stage

Class Name	HH	VV	HH-VV
Stage1		-	
Stage2			
Stage3	-		-

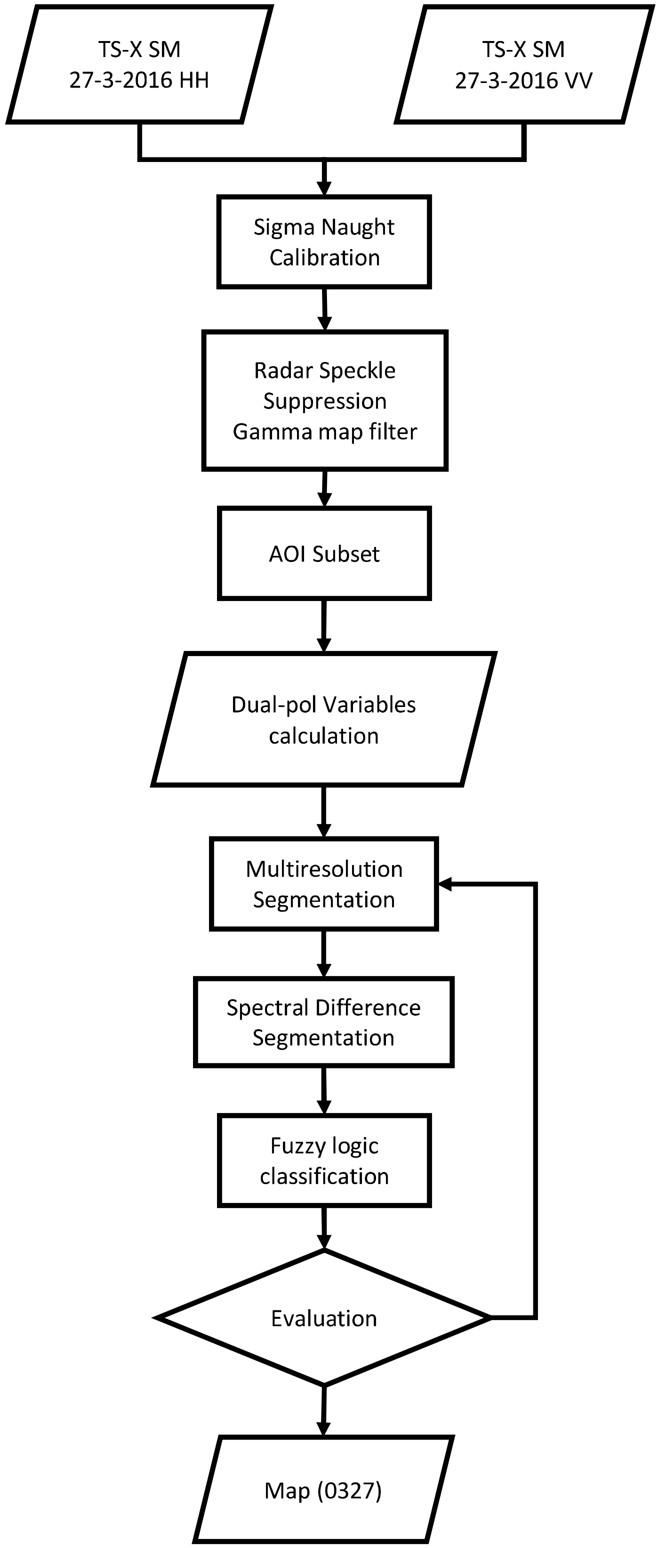


Figure 4. Data Processing Flowchart

2.3 Evaluation

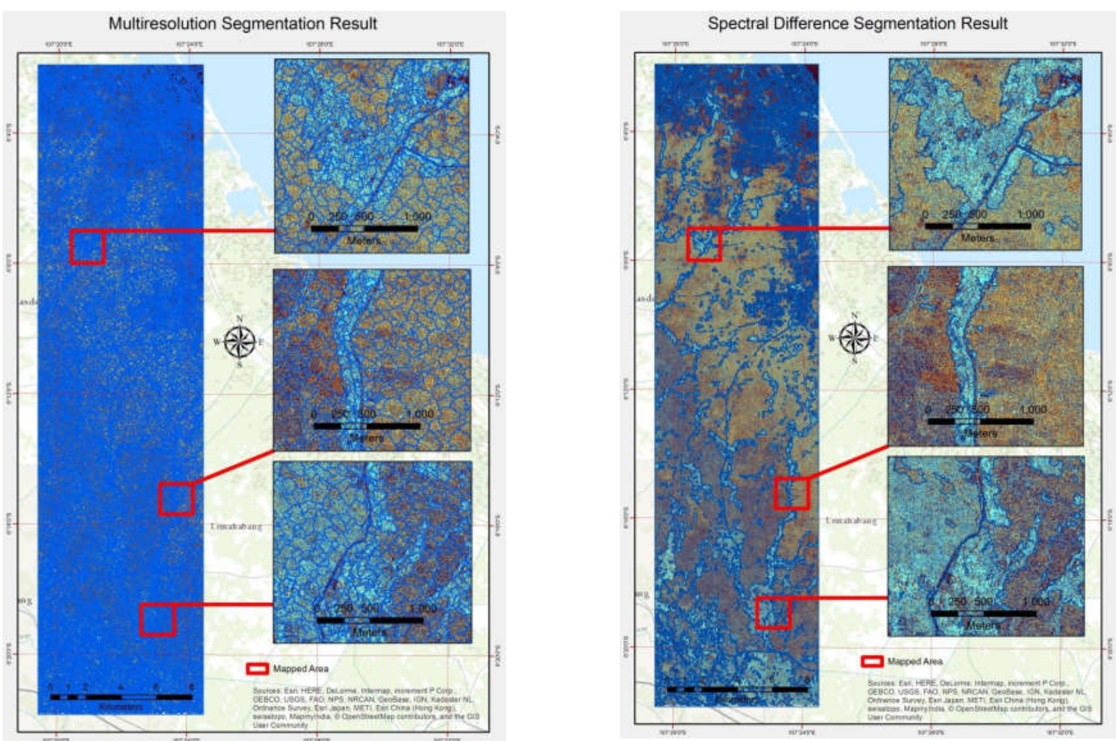
In this preliminary result, we deployed two evaluation techniques for the classified fuzzy classes. These evaluation techniques were ‘classification stability’ and ‘best classification result’. ‘Classification stability’ evaluates the differences in degrees of membership between the best classification result and the second best classification result for each object. The difference were then calculated as a percentage (Trimble, 2014). The small value indicated an ambiguous the classification. ‘Best classification result’ on the other hand assesses how high is the memberships of belonging to a class. This information indicates how good the objects of a class satisfy the class description(Gercek, 2010).

3. RESULTS AND DISCUSSION

In total, there are 52536 primitive object generated by the first segmentation process using multiresolution segmentation algorithm (Figure 5a). The result was deemed over-segmented in most of the areas. Further visual evaluation then showed that the over-segmented objects are able to represent its boundary quite well. The second segmentation process were then deployed and generated as the upper object level (super-object). With this step, the primitive object number was reduced to 7625. By merging the similar adjacent object to each other, we managed to get a more representative object boundary as shown in figure 5b. The complete segmentation parameters used is shown in Table 3.

Tabel 3. Segmentation parameters

Level	Segmentation Algorithm	Layer Input (weight)	Scale	Shape	Compactness
1	Multiresolution Segmentation	HH (3), VV (4), HH-VV(4), HH/VV(2)	20	0.2	0.4
Level	Segmentation Algorithm	Layer Input	Maximum Spectral Difference		
2	Spectral Difference Segmentation	HH (3), VV (4), HH-VV(4), HH/VV(2)	1		



(a) (b)

Figure 5. The segmentation results, (a) Multiresolution segmentation algorithm, (b) Spectral Difference Segmentation

Using the membership function in Table 1 and Table 2, we managed to create 6 different classes. These classes were put in a hierarchical manner as shown in Figure 6. Figure 7 shows the classification results.

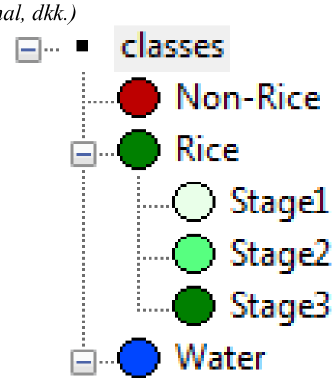


Figure 6.Class hierarchy

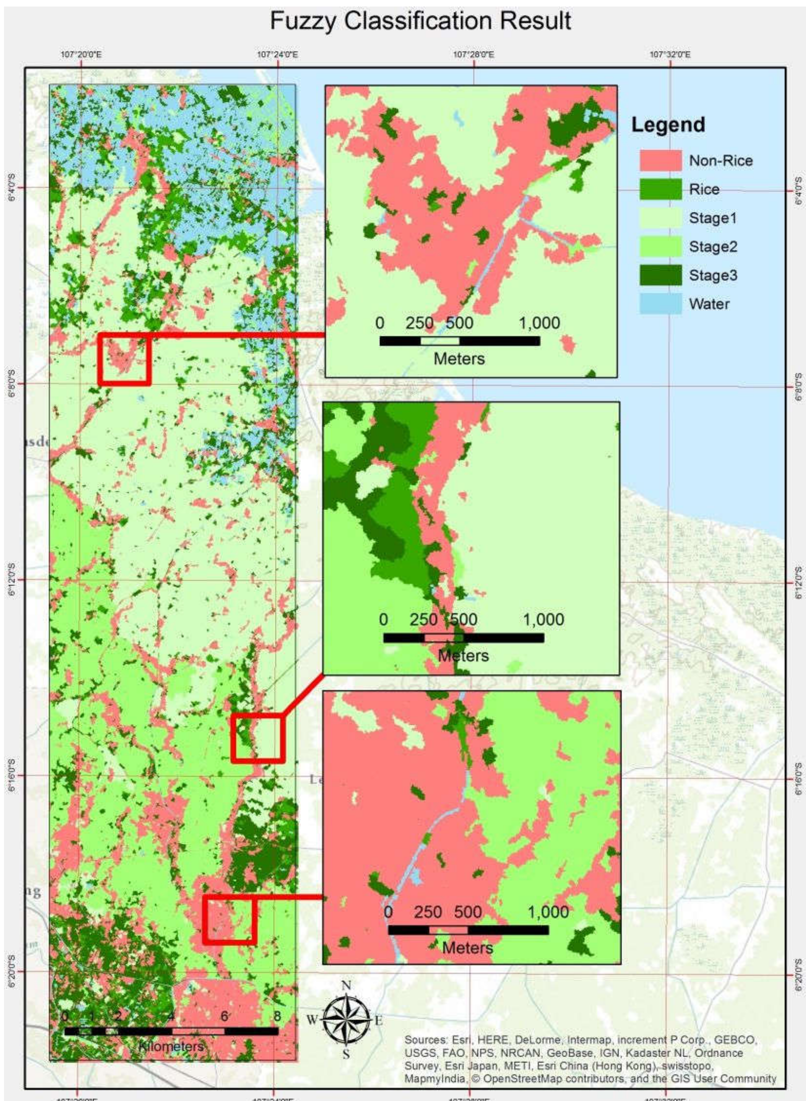
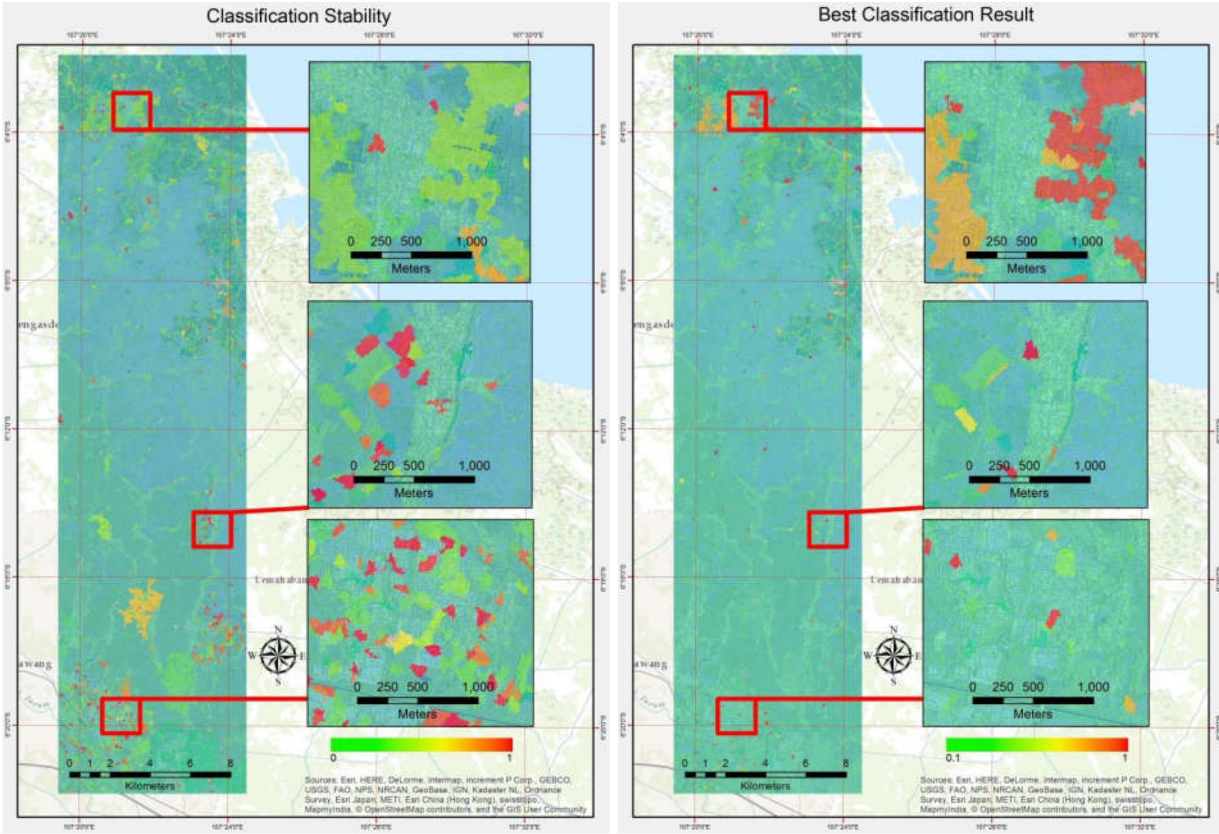


Figure 7. Classification Result

There are 6 classes in total what we were able to detect and extract. These classes were generally categorized into two type of classes. The first category was “water”, “rice”, and “Non-rice”, and acted as the first step in differentiating rice-crop field in the area. The second category was, “stage1”, “stage2”, and “stage3”. These classes fell specifically within the previous “rice” type, and therefore inherit all the object parameters from “rice” classes. We then evaluate these results by calculating the classification stability as well as the best classification result, as shown in Table 4.



(a) (b)

Figure 8. Fuzzy Classification evaluation, (a) classification stability, (b) best classification result

Tabel 4. Classification Stability and best classification results for 6 classes

	Classification Stability		Best Classification Result	
Class	Mean	StdDev	Mean	StdDev
Non-Rice	0.965529	0.134379	0.977146	0.089525
Water	0.840469	0.243987	0.840582	0.243818
Rice	0.607211	0.343288	0.838063	0.215461
Stage1	0.817832	0.281182	0.858219	0.234899
Stage2	0.714482	0.29157	0.714482	0.29157
Stage3	0.799886	0.329082	0.921799	0.192117

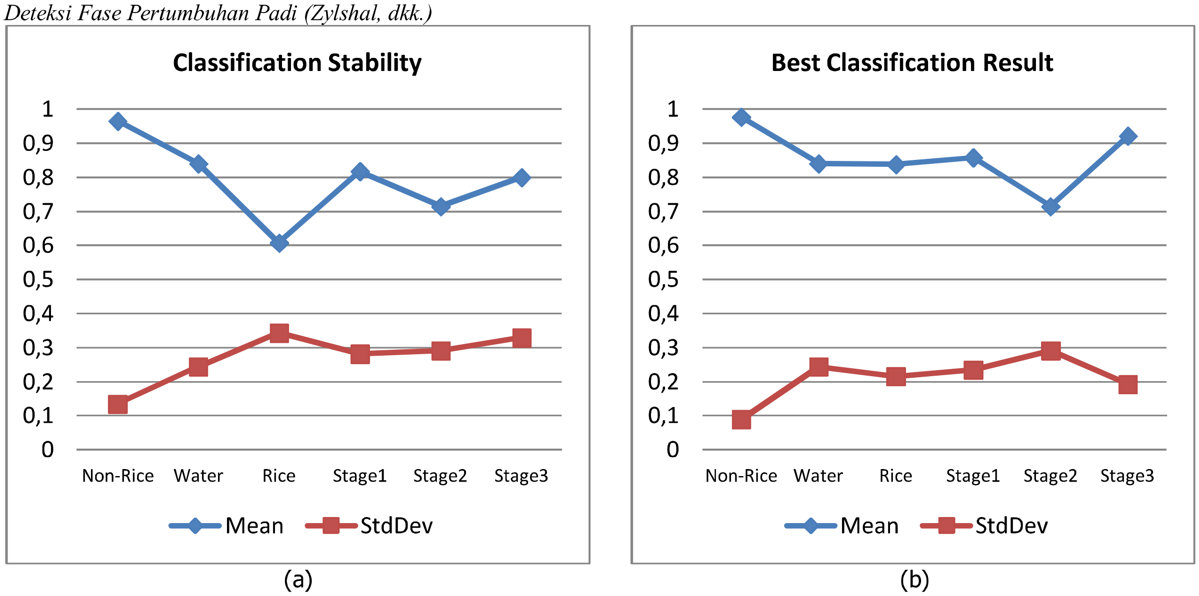


Figure 9.Classification Stability and best classification results for 6 classes

The evaluation of stability and efficiency showed that, the “non-rice” class pose a better results compared to the other classes, which means that this class was better separable from the similar classes given their class definition. With almost all classes were on above 0.7 on classification stability, it’s safely to say that for this particular purpose, the proposed method worked well in detect and separating different stages of rice crop growth. The lowest score on “rice” class, was an exception. Further investigation on this classes, were revealed that the proposed method seems unable to differentiate the “non-rice” feature that has similar leaf-structure as the paddy-rice, such as grass and shrubs. As an initial results, this was our first guess. As for detecting different rice growth stages, the proposed method were able to perform well, since the X-band and different growth stages of rice generate a distinctive backscattering signature that can be easily separated from other land use classes. This finding was also reported by (Koppe et al., 2013).

As for the exact stages these detected features further analysis as well as comprehensive field measurement are still needed, especially for the specific region of Karawang. Following the σ^0value on other region explained by (Koppe et al., 2013; Kucuk, Taskin, and Erten, 2016; Nelson et al., 2014; Pazhanivelan et al., 2015), we can roughly estimates the actual stages of our initial results. “Stage1” correspond to the transplanting, “stage2” correspond to vegetative, and “stage3” correspond to the generative stage.The use of multitemporal X-band SAR data, might also increase the change of better differentiating the rice-crop and non-rice-crop landuse, since the rice phenology has its own specific characteristic throughout the year, as well as identifying specifically which stages it was on the classified objects that we analyzed. The use of multitemporal SAR data, has been proved useful to get more detailed on rice phenology information, as reported by (Koppe et al., 2013; Kucuk et al., 2016; Nelson et al., 2014; Pazhanivelan et al., 2015).The further aim is to use a more complete multitemporal data for a year timeframe, to see the effect of seasonal dynamic of the crop.

4. CONCLUSION

This initial result showed that, the use of single date dual-polarization TerraSAR-X data combined with fuzzy classification using GEOBIA can be used as an indicator on detecting different stages of rice crop. However, forcing to only use a single date data, has its own limitation, such as identifying the exact growth stage of the rice crop. The use of TerraSAR-X StripMap data with it 2.5 meter spatial resolution, can give a better understanding on the rice phenology especially on the parcel level. Therefore, the dual-polarization TerraSAR-X data can be used as an alternative option on rice crop monitoring, given that we use several multitemporal dual-polarization data. The next step would be to conduct the analysis using multitemporal data, as well as, conducting a through field measurement that spanned for a year, to specifically identified theσ^0 characteristic in Karawang region, and to test the proposed method on different area in Indonesia.

5. ACKNOWLEDMENT

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PRESENTASI ILMIAH SINASINDERAJA 2016

Moderator : Dedi Irawadi
Judul Makalah : Hasil Awal Analisis Citra Berbasis Objek pada Data TerraSAR-X Polarisasi Ganda (Dual Polarization) dengan Menggunakan Algoritma Fuzzy untuk Identifikasi Fase Pertumbuhan Padi
Pemakalah : Zylshal (LAPAN)
Diskusi :

Pertanyaan: Kadarsah (BMKG)

1. Apa manfaat langsung yang dirasakan petani dari teknologi ini.

Jawaban:

TerraSARX dapat menghasilkan resolusi yang detail sehingga dapat menjadi masukan dalam pengambilan keputusan.

Pertanyaan: Laode (Univ. Haluoleo)

2. Kenapa tidak menggunakan citra ALOS dan bagaimana validasinya?

Jawaban:

Penggunaan X-band pada TerraSAR-X untuk identifikasi padi adalah hal baru, dan sudah terbukti bisa digunakan untuk identifikasi padi, khususnya di awal-awal pertumbuhan.Data ini dianggap paling sesuai dengan pendekatan yang dibangun pada makalah ini, dibandingkan dengan data ALOS-2 PALSAR yang menggunakan gelombang L. Validasi yang dilakukan untuk membedakan padi dan non padi.

Saran: Dr. Dede Dirgahayu (LAPAN)

Kenapa menggunakan data TerraSAR-X harus diberi alasannya. Penggunaan single date sangat susah untuk melihat perubahan fase sehingga perlu adanya penggantian judul menjadi identifikasi padi dan non padi saja, tidak sampai pada fase pertumbuhan.

Jawaban:

Penggunaan data *single date* TerraSAR-X memang memiliki kekurangan dalam hal keterbatasan informasi temporal ketika harus melakukan studi terkait *rice phenology*. Untuk itu, penulis telah menyesuaikan judul redaksi makalah dari “identifikasi” ke “deteksi” fase pertumbuhan padi.