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CAPABILITY ASSESSMENT OF ALOS DATA TO SUPPORT VARIOUS MAPPING ACTIVITIES

Working Group 4

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Abstract

This paper discusses the capability assessment of ALOS data, particularly the AVNIR-2 and PRISM images to support various mapping activities. The studies were carried out with the support from The Remote Sensing Technology Center of Japan (RESTEC), and coordinated by LAPAN Indonesia. In order to assess the ALOS data capability, several image processing and visual interpretation techniques were applied, including radiometric and geometric corrections, image fusion, visual interpretability for morphological/fisiographic features, vegetation index transformation, multispectral classification for land-cover/land-use mapping, image segmentation, and critical land assessment. The results show that ALOS data is very supportive in both digital and visual image-based mapping at local up to sub-regional scale .

1. Introduction

ALOS gives relatively wide range of spectral bands, starts from blue, green, red to near infrared and microwave region. In addition, a higher spatial resolution image in panchromatic mode is also available, making the produced images ready for various applications using both visual and digital interpretations, and using both optical and microwave analyses. The availability of those types of imagery requires a more comprehensive assessment on their advantages and disadvantages, particularly for mapping and updating of maps at corresponding scales in Indonesia.

The aims of this study was to assess the capability of ALOS data in supporting mapping and map updating activities at 2.5 – 15 m spatial resolutions, which are more or less equal to 1:10,000 up to 1:100,000 optimal scales.

2. Materials and Methods

In order to obtain a better understanding of the advantages and disadvantegs of ALOS data , a series of image processing and visual interpretation activities were carried out, and some of them involved GIS processing as well. Geometric and radiometric corrections were applied as prerequisite processing. Visualisation in terms of image fusion were applied to produce images, which would be used as a basis for visual interpretation. Spectral analyses using multispectral classification and vegetation index transformations were carried out in order to generate land-cover and vegetation maps. Object-oriented image classification was also run in order to compare the result with the pixel based classification. Furthermore, two methods of critical land mapping were applied in order to demonstrate the capability of the data in environmental applications.

2.1. Materials

Several sets of ALOS imagery covering Central Java and Yogyakarta Special Province were chosen. The ALOS data consists of PRISM and AVNIR-2. In addition to the ALOS image datasets, this study also made use of SRTM data (90 m spatial resolution), Landsat ETM+ (30 m spatial resolution), and topographic maps at 1:25,000 scale.

2.2. Methods

The following paragraphs briefly describe each method employed in this study.

2.2.1. Radiometric Correction

Radiometric correction focused on the conversion of pixel values (digital numbers/DN) to at sensor radiance. In some instances, at surface reflectance was needed. (Chander & Markham, 2003). By this method, the unitless DN was transformed into values in Wm^{-2} μm^{-1}. The radiometric correction is necessary for image analyses involving spectral transformation and multitemporal/multisensor analyses. However, such correction is not compulsory for multispectral classification of a single scene (Mather, 2004; Jensen, 2005). The correction was also used to observe the consistence in spectral patterns.

2.2.2. Geometric Correction

Geometric correction was performed using standard procedure involving ground control points for image-to-map and image-to-image correction. The transformation polynomial order could be first, second or third, depending on the terrain roughness of the study area, by which the higher order applies for rougher terrain. In line with the radiometric correction purposes, a nearest neighbour interpolation was mostly used in order to keep the pixel values as close as possible to the original data. However, a cubic convolution might also be used for generating smoother image, which was used as basis for visual interpretation. Bakosurtanal topographic map (RBI) at scale of 1:25,000 was used as a reference.

2.2.3. Image Fusion

Image fusion involved all-optical image fusion (ALOS AVNIR-2 + PRISM; ALOS AVNIR-2 + Landsat ETM+), ALOS AVNIR-2 + SRTM fusion, and ALOS AVNIR-2 + PALSAR fusion. The image fusion made use of multiresolution merging methods involving PCA and Brovey transformation. The results were then compared to each other by using physiographic or morphological features interpretability as a main criterion.

2.2.4. Multispectral Classification

This study used multispectral classification as a method for generating land-cover map. Supervised classification approach using maximum likehood algorithm was chosen since many studies reported its accuracy in comparison with other spectral classification techniques (Mather, 2004). The result was then compared with non-standard classification method (e.g. object-based image analysis/OBIA and neural network classifier) with respect to their accuracies (see 2.2.6 and 2.2.7).

2.2.6. Vegetation Index Transformation

Spectral transformation in terms of vegetation indices were used to transform the image DN to values, which can be correlated to various vegetation phenomena, such as biomass and stand volume. This study tried to transform the ALOS AVNIR-2 data to vegetation index maps based on several transformations including RVI (near infrared/red) and NDVI (near infrared-red/near infrared + red). Stand volumes of teak plantation forest were obtained from field measurement using Breast Height Diameter (BHD) approach. The best correlation coefficient obtained from various pairs of vegetation index and stand volumes dataset were then inversed in order to predict the stand volume throughout the study area.

2.2.6. Object-based Image Analysis using Image Segmentation

Besides standard multispectral classification using maximum likelihood algorithm, OBIA was also carried out by combining image segmentation and classification (Baatz and Schappe, 2000). The image segment-ation technique used in this study was region growing, which involves area and similarity thresholds in defining the segments. Bhattacharya distance was then used to classify the segments.

2.2.7. Artificial Neural Network (ANN) Classification

An ANN classifier with back propagation (Yuan *et al*., 2009) method was used in order to integrate spectral data (i.e. spectral bands of ALOS AVNIR-2) and other spatial data such as elevation, slope and NDVI. The choice of this classification method lies on the fact that the ANN can accomodate integration of multisource spatial datasets, which cannot be performed by any standard classification algorithm. A critical land mapping application was selected as a case.

In the analysis process, the parameters involving the number of iteration, the hidden layer, momentum, learning rate and RMS error were run in order to obtain the best result. A field reference in terms of location of critical land areas were used for accuracy assessment.

2.2.7. GIS Integration

GIS Integration implies the use of various spatial data coming from various sources (Longley *et al*., 2008). In this study, a parametric method for critical land assessment using vector data model, so that map overlays involving deducted attributes with scores from dif-ferent maps with different spatial units were performed.

3. Results and Discussion

3.1. The Effect of Radiometric Correction

Based on radiometric correction performed on two different dates of recording (3 September and 18 October 2009), it was found that :

- Differences in pixel value on multitemporal images due to atmospheric variation has been normalized via radiometric and atmospheric corrections
- It is recommended to perform atmospheric correction prior to performing multitemporal analysis.

The following pictures and tables explained the conclusions mentioned above.

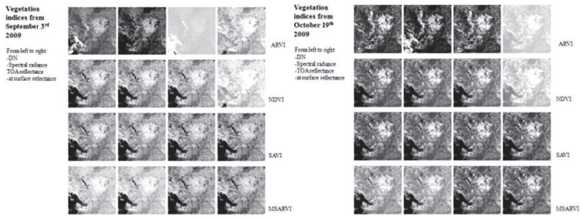

Image of 3 September 2011 **Image of 18 October 2011**

Figure 1. Comparison between vegetation indices applied to different dates usisng different level of processing (from left to right: original DN, spectral radiance, TOA reflectance, at surface reflectance).

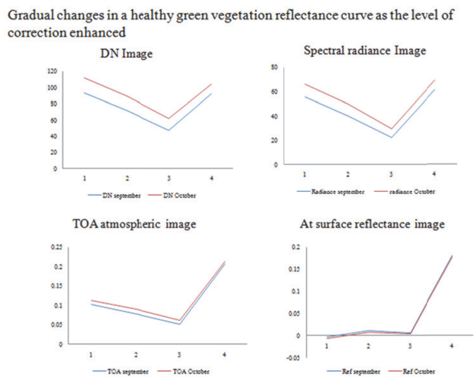

Figure 2. The effect of radiometric corrections on the spectral pattern of healthy vegetation. The right-bottom picture shows an idealised pattern according to the theory so that it confirms the importance of atmospheric correction.

3.2. Image Fusion as a Basis for Visual Interpretation

This study shows that ALOS AVNIR can be merged with other imagery in order to provide new images, which are more interpretable for phyisiographic/morphological analysis purposes.

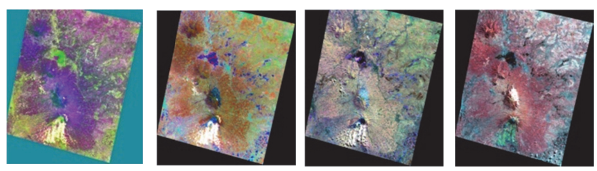

Figure 3. From left to right: Colour composite of AVNIR-2 PCA1 up to 3, ETM 451+ AVNIR-2 Band 1(Brovey); ETM 451+ AVNIR-2 Band 4(Brovey); ETM 451 + AVNIR-2 Band 1 (RGB-to-HSI).

Table 1. Comparison between fusion methods' performance as a source of visual interpretation.

Object	Fusion Method						
	FCC 431	FCC 421	PCA FCC	Landsat 451 + ALOS Band 1 (Brovey)	Landsat 451 + ALOS Band 1 (HSV to RGB)	Landsat 451 + ALOS band 4 (Brovey)	Landsat 451 + ALOS band 4 (HSV to RGB)
Linear Features	++	++	+++	++++	++++	+++++	+++++
Vegetation	+++	+++	++	++++	++++	+++++	+++++
Infrastructures	++	++	++	++++	++++	++++	++++
Physiography	++	++	+++	++++	++++	+++++	+++++

3.3. Comparison between Standard Multispectral Classification and Object-based Image Analysis

The availability of PRISM (panchromatic) and AVNIR-2 (multispectral) data attracts attention to compare their performances in both multispectral and object-based classification. To do the comparison, the image datasets were treated in two ways, i.e. using the original AVNIR-2 multispectral, and using the pan-sharpened AVNIR-2 datasets (Figure 4) . Each dataset was then classified using maximum likelihood and and object-based classifications (Figure 5 and 6).

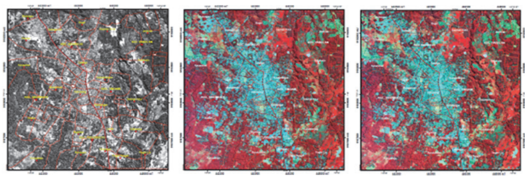

Figure 3. From left to right: PRISM, AVNIR-2, and pan-sharpened multispectral images of ALOS covering Salatiga, Central Java.

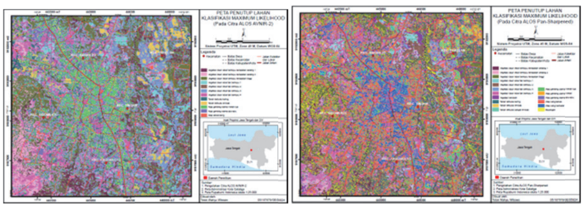

Figure 4. Classification result using maximum likelihood algorithm: AVNIR-2 (left), and pan-sharpened (right)

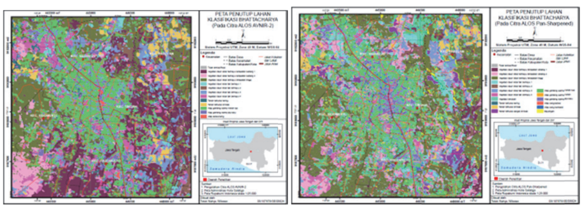

Figure 5. Classification result using OBIA (region growing image segmentation and bhattacharya distance algorithm): AVNIR-2 (left), and pan-sharpened (right)

The results shows that multispectral classification could give 91.25% overall accuracy (Kappa=0.9046) for original the AVNIR-2 and 92,73% overall accuracy (Kappa=0.92) for the pan-sharpened image. These values are higher than those of object-based classification results (87.86% overall accuracy and Kappa=0.8679 for original AVNIR-2 image; 89.29% overall accuracy and Kappa=0.88 for pan-sharpened image). The use of spectral-related land-cover classification scheme played an important role in making the maximum likelihood (spectral) classification, since it is not too suitable for spatial-context classification like object-based image analysis.

3.4. Teak Stand Volume Estimates using Vegetation Index Tranformation

Teak stand volume estimates were undertaken by correlating field volume measurement (using breast-height-diameter/BHD method) and vegetation indices obtained from AVNIR-2 image covering Karangmojo Forest, Gunung Kidul Regency, Yogyakarta Special Province. The vegetation indices used were NDVI (normalised difference vegetation index), RVI (ratio vegetation index) and SAVI (soil adjusted vegetation index). The NDVI was found as the most accurate predictor with R^2=0.555 (R=0.745); while the regression-based stand volume estimate map shows an accuracy level of 87%.

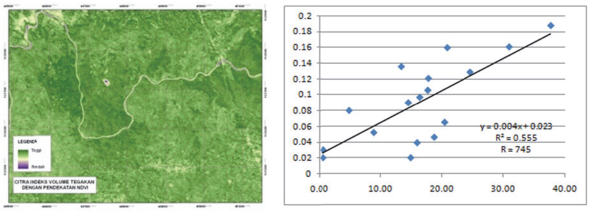

Figure 6. NDVI image (left) and the regression line of field stand volume and the NDVI

3.5. Mapping of Critical Land using GIS

A land-cover map consisting of water bodies, built up areas, barren land, and vegetation classes was geenrated using visual interpretation of AVNIR-2 image of Sleman Regency, Yogyakarta Special Region. This map was then integrated with other thematic data such as rainfall intensity, slope steepness, soil types and land-use to derive critical land map (Figure 7).

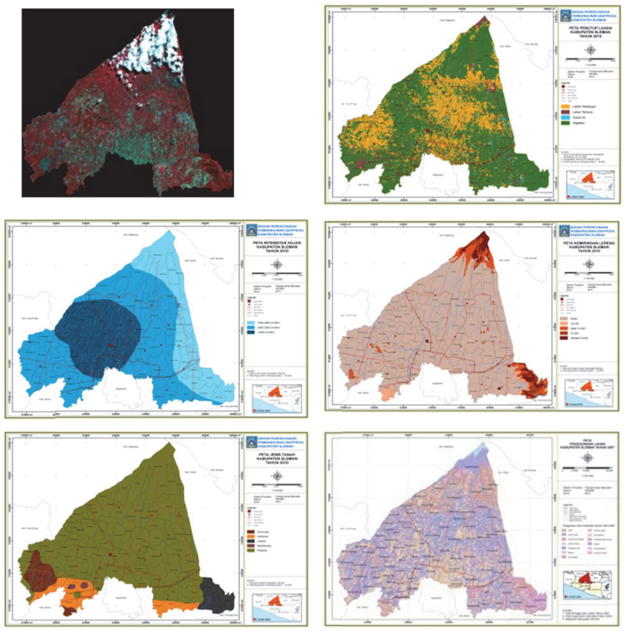

Figure 7. From top left to bottom right, clockwise: the original image, land cover map, and rainfall intensity, slope steepness, soil types and land-use maps.

Based on the spatial analysis of those maps, critical land map was delivered and presented in the folowing figure (Figure 8).

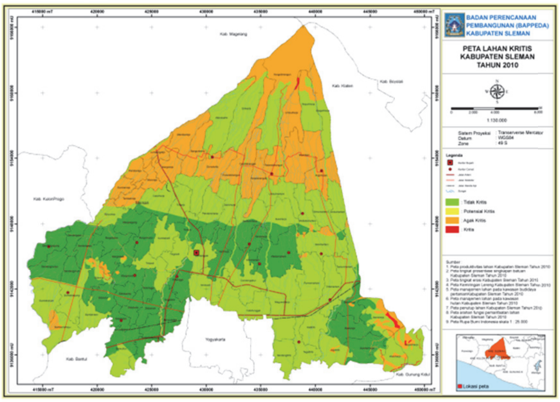

Figure 8. Critical land map generated using AVNIR-2 and GIS.

3.6. Artificial Neural Network Classification for Critical Land Mapping of Dlingo District, Bantul Regency

ANN Classification was performed to map critical land in Dlingo District, Bantul Regency. The mapping process involved original AVNIR-2 bands, slope, soil depth, and vegetation density maps. The non-spectral data were prepared in raster (pixel-based) data model in terms of DEM-derived, NDVI-based, and spatially-interpolated (Kriging) maps. Field measurement for critical land samples were used as reference, and the classification processes run using various ANN parameters, i.e. using different number of input 'bands' and different values for iteration, the hidden layer, momentum, learning rate and RMS error.

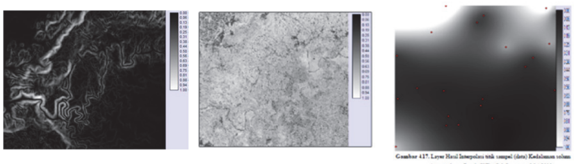

Figure 9. Non-spectral data involved in the ANN classification. From left to right: slope steepness, vegetation density, and soil depth

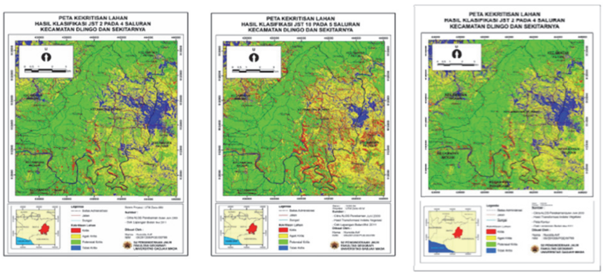

Figure 10. Critical land maps generated using different ANN simulations. From left to right: four original bands, five spectral bands (original plus NDVI-based vegetation density), and all spectral+non-spectral bands.

The study showed that the highest accuracy (83.33%) was achieved by a simulation using seven input bands, which integrate spectral and all non-spectral bands. It was performed using single hidden layer, momentum 0.04, learning frate 0.01, RMS eror 0.001 and the number of iteration 19,000. Lower accuracies involving four original bands and five spectral bands (original + NDVI) achieved 54.17% and 62.50% respectively.

4. Conclusions

All aforementioned studies show that ALOS data very supportive for various mapping activities. Generally speaking, the spatial resolutions of the PRISM and AVNIR-2 are adequate to support mapping at local – regional level (1:25,000 – 1:100,000). The use of pan-sharpened image can improve digital mapping capability at optimal scale of 1:10,000. However, it was also found that a combination between ALOS and Landsat may improve the image interpretability, particularly for visual interpretation of physiographic/ morphological features. This was due to the availability of Landsat middle and far infrared bands, which are sensitive to soil and rock reflectance, and was due to the Landsat's time of recording that gives effect on the better relief impression. An additional spectral bands covering middle and/or far infrared would be advantageous for the next ALOS missions.

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