IJCSI International Journal of Computer Science Issues, Vol. 10, Issue 2, No 2, March 2013
ISSN (Print): 1694-0814 | ISSN (Online): 1694-0784
www.IJCSI.org

Fusion of Physical Extraction Parameter Model Optical and SAR Data for Flood Detection

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Abstract

The limitations of classification results, interpretation, and detection of the optical data can be helped by using Synthetic Aperture Radar (SAR) data, in order to obtain a sama area with actual conditions. The combination/fusion is an effort to combine information from a number of sources to produce a single data entity in the form of specific and kompehensif. Image representation with modes fusion will improve different multi-sensory than conventional. In fusion performed 4 (four) steps of modeling, estimation, combination and decision-making. Modeling the physical parameter extraction resulted from optical and SAR data for flood detection to do with pixels, features, and decisions. The cost of using SAR imagery is a problem but, this may be compensation to get the good quality and low cost when compared with the survey directly. The finding that variable texture image provide valuable quantitative information to support and differentiate water bodies of other types of land cover classes.

***Keywords**: Optical Image, SAR Image, Features Extraction, Physical Parameters, and Flood.*

1. Introduction

In the twenty years of this decade, fusion of multi-source remote sensing data have made a real contribution in extracting and exploring physical parameters. The combination of spectral, spatial, and temporal different can be a complement and supplements (optional) to optimize the classification results. As an illustration of the penetration of the SAR data can penetrate cloud cover objects [1].

The limitations of classification results, interpretation, and detection of the optical data can be helped by using SAR data, in order to obtain a same area with actual conditions. Owned single polarization of SAR data can be integrated in a multi spectral using fusion/combination model, hope to obtain a better classification accuracy.

The strategy by performing a combination of feature extraction derived from both types of data. The logic of combination/fusion that combine information from a number of sources to produce a single data entity in the form of specific and kompehensif. Representation of images with fusion modal will enhance multi-sensory different than conventional. The approach can be done with the information fusion/extract features from digital imagery, determine the feature representation in limited domains, and perform fusion and classification feature code. In appliying fusion performed 4 (four) steps : modeling, combination estimation, and decision making.

To modeling the physical parameter of extraction results of optical and SAR data for flood detection can be done by pixel, feature, and decision. In principle, the formula for deriving fusion models can be expressed by the statement:

(physical parameters)= mf($x_1,x_2,\ldots,x_n$) .... (1)

where : x_n = variable

2. Basic Theory

Suppouse images with low spatial resolution B_l and high-resolution imagery A_h, resampling results expressed by B_h^{interp} form resolution l to h, so that the geometricaly the image in the same pixel size and straight [14]. In principle, if the spectral bands are related to k, the expression became B_{kl}. The general relations of original image from a variety of high and low spatial resolution of the image of the new B * as follows.

B*=f(A,B) .... (2)

The first property, a synthetic image B_h^* being degradation from native resolution 1, the expression of the equation becomes:

$D_1(B_{kl}B_{kl}^*)<\varepsilon l_k$ .... (3)

where:

D = distance between B_{kl} $dan\ B_{kl}^*$,

εl_k = degree of accuracy.

The second property, a synthetic image B_h^* which is identical to the image B_h sensor connected observed

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with the highest spatial resolution h, then the equation becomes:

$$D_2(B_{kh}B^*_{kh}) < \varepsilon 2_k \text{ ....} (4)$$

where
D = distance between B_{kh} $dan\ B^*_{kh}$,
$\varepsilon 2_k$ = degree of accuracy.

The fusin general step of optical and SAR can be represented with a flow chart as Figure 1 below [4] that is to pretreatment/preprocessing image to remove noise/speckle/salt & pepper, whose activities include geometric / geocoding / geometric correction superposition, filtering, and classification single image. In geometric correcting always keep the criteria no change in terms of attributes, similarity, deformation and optimization strategies.

The noise/speckel on SAR data must be removed in order image classification no trouble. Speckel caused by the mean value and variance of the backscatter signals from different targets interfered that reduce the correlation. The method to eliminate speckel can be used adaptive filters such as Lee, Frost and Gamma Maximum A posteriori (GMAP). The approach can be used for classification is a neural network, SVM, ISODATA, Fuzzy logic and genetic algorithms [5].

To exploit and combine spatial information from a variety of sources in the different levels, can be used Probabilistic Markov Random Field (MRF), conceptually the following formula.

$$U(x) = \sum_{s\in S} \emptyset_1(x_s) + \sum_{(s,r)\in C_2} \emptyset_2(x_s, x_r) \text{ ....} (5)$$

where:
$U(x)$ = MRF models
x_s = current pixel
S = the set of all pixels in an image
C_2 = the set of all possible sequences of order 2
x_r = the second pixel in the x_s squence
$\emptyset_1(x_s)$ = potential data descriptions
$\emptyset_2(x_s, x_r)$ =interaction potential between x_s and x_r

The device to describe the texture can be used auto models approach such as contrast, homogeneity, isotropy, entropy, and the texture coefficients. The auto models approach above can be divided into 4 (four) models types namely auto-logistics, auto-binomial, auto-normal, and auto-gamma. In this study represented two models of auto-normal and auto-gamma models.

Auto Normal Model:

$$U(x) = \alpha \sum_{s\in S} \|x_s - \mu_s\|^2 + \beta \sum_{(s,r)\in C} \|x_s - x_r\|^2 \text{ ....} (6)$$

where :
C = himpunan seluruh piiksel
$\alpha \sum_{s\in S} \|x_s - \mu_s\|^2$ =potential to describe the data
$\beta \sum_{(s,r)\in C} \|x_s - x_r\|^2$ = a term describing the interaction between the pixels

Probability density function becomes:

$$P(X_s = x_s / X_r = x_r,, r \in V_s) = N((\mu_s, \sigma_s^2) \text{ ....} (7)$$

$$\mu_s = E\{x_s / x_r, r \in V_s\} = m_s + \sum_{r\in V_s} \beta_{sr}(x_r - m_r) \text{ ....} (8)$$

$$\sigma_s^2 = E\{x_s / x_r, r \in V_s\} \text{......................................} (9)$$

where:
m_s = The average location of s
m_r = The average location of r
β_{sr} = interaction parameter of locations s and r

$$P(X_s = x_s / X_r = x_r,, r \in V_s) = \frac{\exp(-\frac{1}{2\sigma^2}(x_s - m_s - \sum_{r\in V_s} \beta_{sr}(x_r - m_r))^2}{\sum_{s\in S} exp\,(-\frac{1}{2\sigma^2}(x_s - m_s - \sum_{r\in V_s} \beta_{sr}(x_r - m_r))^2)} \text{ ....} (10)$$

where:
μ_s = average normal automodel s parameters are estimated
μ_r = average normal automodel parameter r estimated
β_{sr} = parameter normal automodel between locations s and r are estimated

Auto Gamma Model:

$$P(X_s = x_s / X_r = x_r,, r \in V_s) = \gamma(a_r(\alpha_s + \sum_{r\in V_s} \beta_{sr} x_r)) \text{ ....} (11)$$

where:
a = parameter model auto-gamma
α_s = auto-gamma model parameters s

Local Probability expressed to be:

$$\sum P(X_s = x_s / X_r = x_r,, r \in V_s) = \frac{x_s^{a-1} \exp(-x_s(\alpha_s - \sum_{r\in V_s} \beta_{sr}(x_r))^2}{\sum_{s\in S} x_s^{a-1} \exp(-x_s(\alpha_s - \sum_{r\in V_s} \beta_{sr}(x_r))^2} \text{ ....} (12)$$

where:
α = auto-gamma model parameters were estimated
α_s = auto-gamma model parameters are estimated s
β_{sr} = auto-gamma model parameters s and r are estimated

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Bayesian classification with the maximum likelihood method can be used algorithms expectation_maximum, steps expectation and to produce convergence [8].

3. Probabilistic Fusion Model

Fusion of various sources of image can be defined as the process combination of spatial k-information $S_1,S_2, \ldots,S_k$ heterogeneous character to produce increase of N-possible decisions $d_1,d_2,..,d_N$. The steps to fusion are the modeling, estimation, combination, and decision making. Modeling is choosing formalism and mathematical associated with its formalism.

For example one source image S_j generate information with *Mij* model, *Mij* the form of formula as in Table 1, depending on the chosen formalism. Estimates are as the most often modeling techniques required parameter estimation phase, and use additional information. The combination was associated with a compatible operators choice for modeling formalism. Decision fusion is an important step, which makes it possible to change the information (which is provided by other sources) for the selection decision.

Table 1 : The Formula in Fusion Steps for Varietly Sources Image

Fusion Steps	Formula	Note
1. Modeling	$M_i^j(x)=p(x\varepsilon C_i/I_j)$	x=pixels C_i= Blood of Class Object I_j= Remote Sensing Image
2. Estimate	$M_i^j(x)=p(I_j/x\varepsilon C_i)$	
3.Combination	$p(x\varepsilon C_i/I_1,\ldots,I_l)=\frac{p(I_1,\ldots,I_l/x\varepsilon C_i)p(x\varepsilon C_i)}{p(I_1,\ldots,I_l)}$	
4.Decision	$x\varepsilon C_i\ si\ p(x\varepsilon C_i/I_1,\ldots,I_l)=$ $max\{p(x\varepsilon C_i/I_1,\ldots,I_l), 1\leq k\leq N\}$	

4. Methodology

The data used in this research is the SPOT 2, SPOT 4, ALOS PALSAR and SRTM. SRTM used for ortho rectification, SPOT detailed descriptions of data as show in table 2. Ortho rectification using ENVI 4.8 software.

Table 2 : Technical Parameter of SPOT 2, SPOT 4 and ALOS PALSAR

Technical Parameter	SPOT 2	SPOT 4	ALOS PALSAR
Product Mode	Standard Image	Standard Image	
Sensor	HRV	HRV	
Orbit	Sun-Synchronus	Sun-Synchronus	Sun-Synchronus
Aquisition Time	26 days	26 days	46 days
Elevation Angle	±31,06'	±31,06'	8^o
Polarisation			HH/VV
Bit per piksel	8 bit	8 bit	5 bit

To make a proper description of the data must be able to extract the kind of special features. For example, a multispectral images can be used for the extraction of spectral , information difference vegetation index (DVI), while data ALOS PALSAR more suitable for texture feature extraction (Co-occurance, Gabor, Laws, etc.). For some data sources (eg DEM) feature extraction do not represented and data directly in the domain. The cardinality of domain should be appropriate for different feature (multispectral, texture, DEM, etc.).

ALOS PALSAR imagery is used to characterize the structure and properties of the surface texture of objects (eg. grass football ground, open areas, etc.). ALOS PALSAR data can also be used for texture feature extraction and to provide spectral information about the object of a coverage area. Fusion and classification strategy, which is particularly interesting in this study to compare the effects of data fusion on the classification accuracy and to compare the results of the classification fusion with a single sensor. Availability of data in this study is SPOT 2 (XS1, XS2, XS3, XS4), SPOT 4 (XS1, XS2, XS3, XS4), and ALOS PALSAR, and the possibility of multisensor combinations and single sensor data as follows:

1. SPOT 2 (single-sensor, 4 bands)
2. SPOT 4 (single-sensor, 4 bands)
3. ALOS PALSAR (single-sensor, 1 bands)
4. SPOT 2 VNIR+ Texture ALOS PALSAR +SPOT 4 VNIR
5. SPOT 2 VNIR+ Texture ALOS PALSAR + Texture SPOT 4

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6. Texture SPOT 2 + Texture ALOS PALSAR + Texture SPOT 4
7. Texture SPOT 2 + Texture ALOS PALSAR + Texture SPOT 4 +DTM

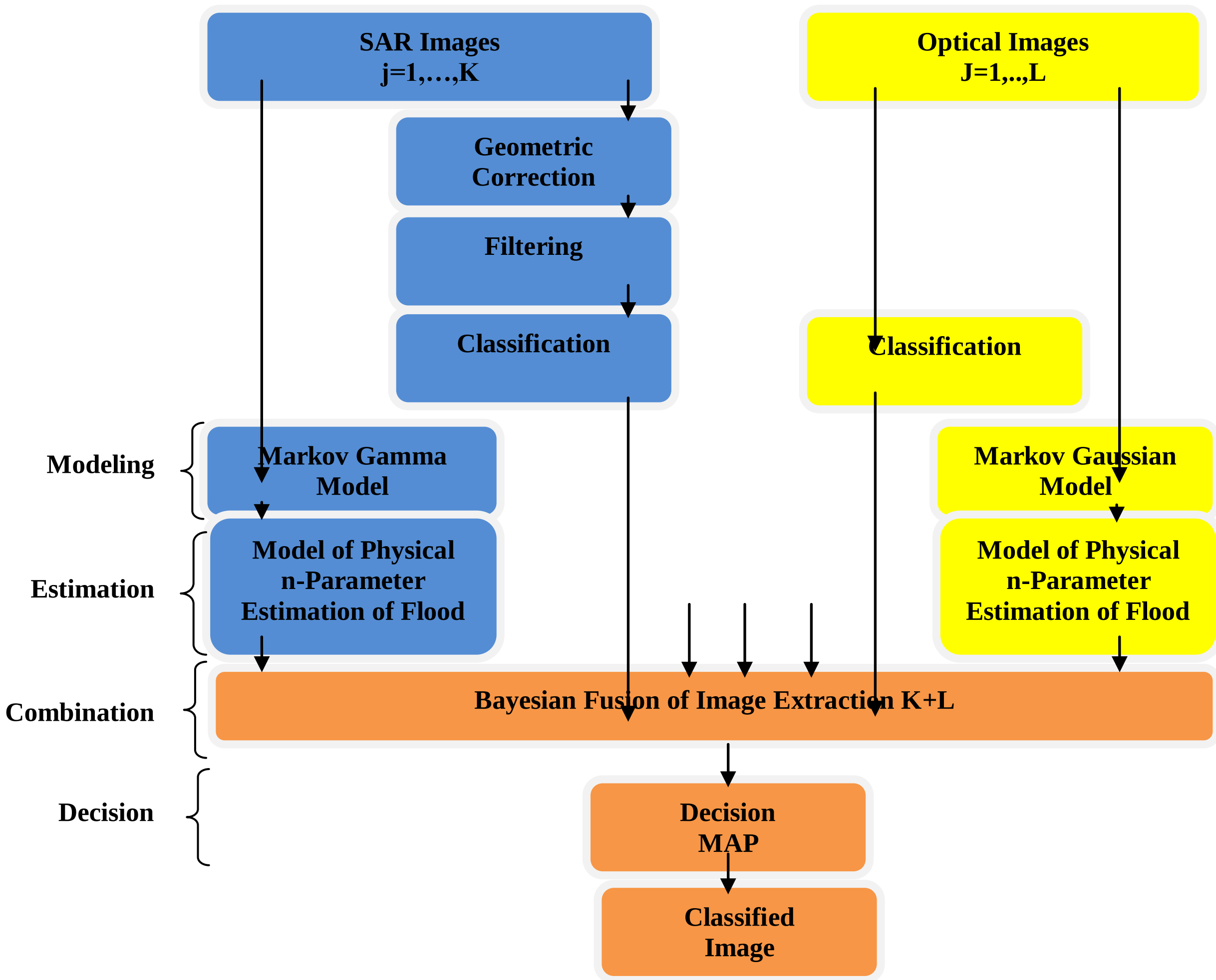

Figure 1 The Approach of Probabilistik Multisource Fusion for Flood Detection

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Table 3 : The Formula of Change Counting

Root mean Square difference	C_{RMSE}	$r_{xx}{}^{h} = \frac{\sum_{t=1}^{T-h}(x_t - \bar{x}_1)(x_{t+h} - \bar{x}_2)}{\sqrt{\sum_{t=1}^{T-h}(x_t - \bar{x}_1)^2}\sqrt{\sum_{t=1}^{T-h}(x_{t+h} - \bar{x}_2)^2}}$ $\bar{x}_1 = \sum_{t=1}^{T-h} x_t/(T-h)$ $\bar{x}_2 = \sum_{t=1}^{T-h} x_{t+h}/(T-h)$ $r_{xy}{}^{h} = \frac{\sum_{t=1}^{T-h}(x_t - \bar{x})(y_{t+h} - \bar{y})}{\sqrt{\sum_{t=1}^{T-h}(x_t - \bar{x})^2}\sqrt{\sum_{t=1}^{T-h}(y_{t+h} - \bar{y})^2}}$ $\bar{x} = \sum_{t=1}^{T-h} x_t/(T-h)$ $\bar{y} = \sum_{t=1}^{T-h} y_{t+h}/(T-h)$
Maximum value of a cross-corregram	I_{CC}	$r_{xy}{}^{h} = \frac{\sum_{t=1}^{T-h}(x_t - \bar{x})(y_{t+h} - \bar{y})}{\sqrt{\sum_{t=1}^{T-h}(x_t - \bar{x})^2}\sqrt{\sum_{t=1}^{T-h}(y_{t+h} - \bar{y})^2}}$ $\bar{x} = \sum_{t=1}^{T-h} x_t/(T-h)$ $\bar{y} = \sum_{t=1}^{T-h} y_{t+h}/(T-h)$
Root mean square difference	I_{RMSE}	$I_{RMSE} = \sqrt{\frac{\sum_{t=1}^{T}(x_t - y_t)^2}{T}}$
Mean Difference	I_{MBE}	$I_{MBE} = \frac{\sum_{t=1}^{T}(x_t - y_t)}{T}$

5. The Use of Water Spectral Index to Medelineasi Water Feature

Spectral index of water is a single value derived from mathematical operations (ratio, difference and mormalized difference) from two or more spectral bands. The corresponding threshold of an index then set out to separate the water body from the features of another cover based on the spectral features. Designing a spectral index of water is based on the fact that water absorbs the near infrared (NIR) energy and short-wavelength infrared (SWIR).

Arithmetic operations not only improves the signal of spectral with contrasts reflectance between different wavelengths, but canceling most common noise components in different regions wavelength (ie, sensor calibration and changing conditions of radiation caused by illumination, soil, topography, and atmospheric conditions, etc.).

Adopting the format of NDVI, Feeters MC (1996) developed the NDWI, defined by the formula: NDWI=(ρ_{green}-ρ_{NIR})(ρ_{green}+ρ_{NIR}) .... (13)

where:
ρgreen, ρNIR = reflectance of green and NIR bands, NDWI = ranges from -1 to 1, McFeeters (1996) sets the number 0 as the threshold. It can be stated that this type of water if NDVI> 0 and it is not water if the NDWI ≤ 0.

But Gao, the formula for SPOT:
NDWI=(ρ_{NIR}-ρ_{SWIR})(ρ_{NIR}+ρ_{SWIR}) .... (14)

Roger and Kearney, NDWI the formula for Landsat:

NDWI=(ρ_{RED}-ρ_{SWIR})(ρ_{RED}+ρ_{SWIR}) .... (15)

Due to the imperfection of human made characteristics separating similar to water, because the lower NIR reflekstance than green reflekstance. The compensation for modified Landsat become :
MNDWI=(ρ_{GREEN}-$_{SWIR}$)(ρ_{GREEN}+ρ_{SWIR}) ....(16)

SPOT can be modified to be:
NDPI=(ρ_{SWIR}-ρ_{GREEN})(ρ_{GREEN}+ρ_{SWIR}) ....(17)

NDWI equation identical to NDPI.

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Table 4 : Index Derived from SPOT to Temporal Distribution Detect and Flood Spacial

Index	Formula
Land Surface Water Index (LSWI)	$LSWI = \frac{NIR - SWIR}{NIR + SWIR}$
Enhanced Vegetation Index (EVI)	$EVI = 2{,}5x \frac{NIR - RED}{NIR + 6xRED - 7{,}5xBLUE + 1}$
Normalized Difference Water Index (NDWI)	$NDWI = \frac{RED - SWIR}{RED + SWIR}$
Normalized Difference Vegetation Index (NDVI)	$NDVI = \frac{NIR - RED}{NIR + RED}$
Difference Value (DVEL)	*EVI-LSWI*

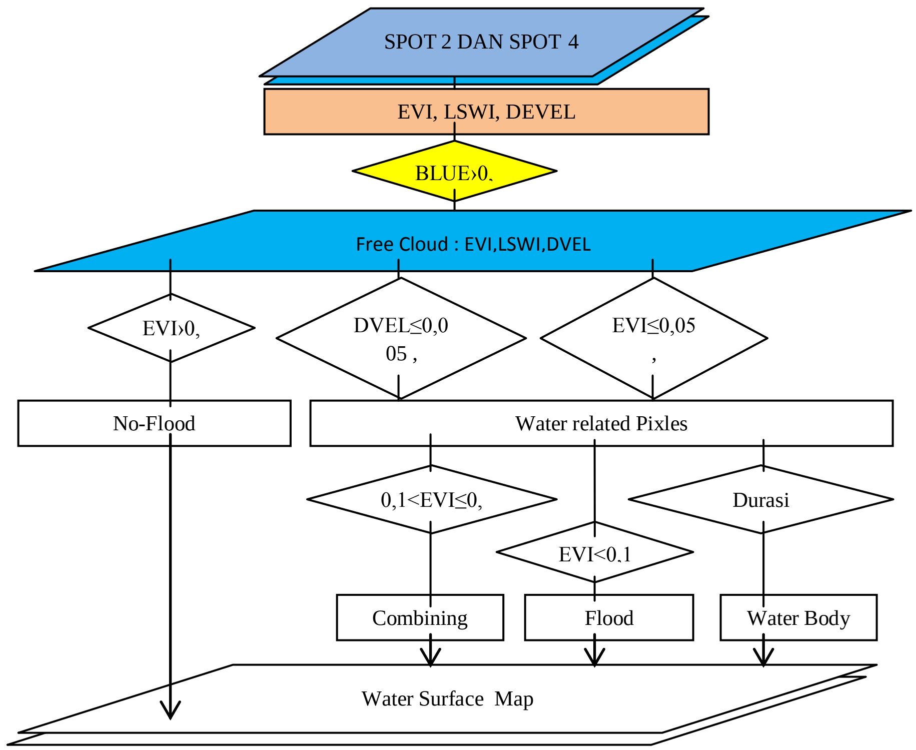

Figure 2 Flowchart of Optical Image Segmentation by EVI and LSWI

6. Results and Discussion

Indexing, used Normalized Difference Vegetation Index (NDVI) and Normalized Difference Water Index (NDWI) to identify surface water related. The main reason for using NDWI is that the short wave infrared (SWIR) is very sensitive to the water content in the soil and vegetation canopy.

In this study has been conducted in the use of spectroscopic characterization of SWIR to detect water levels indicates that NDVI in the fields more than NDWI derived from SPOT for the same period flooded and planting of rice in Wasior used anomaly between the Land Surface Water Index (LSWI) and Vegetation Index (NDVI or EVI).

Figure 2 is a form of an algorithm to estimate the distribution of paddy fields. The results of the combination of textures Cooccurance (Figure 3) and the occurance texture (Figure 4). The next step is to estimate the difference EVI, LSWI and DVEL for each type of land cover classes. In this study, water discrimination related to pixel and Non-Flood pixel is carried out in accordance with the methods of pioneers before. EVI, LSWI and DVEL specifically used to distinguish Flood, Mixed, Non-Flood and Water-related pixels. The changes of EVI, LSI and DVEL for different types of land use since 2007 is presented in Figure 4.

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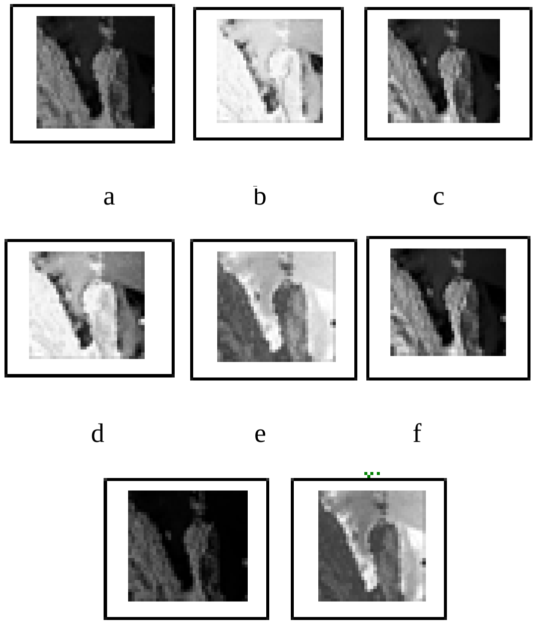
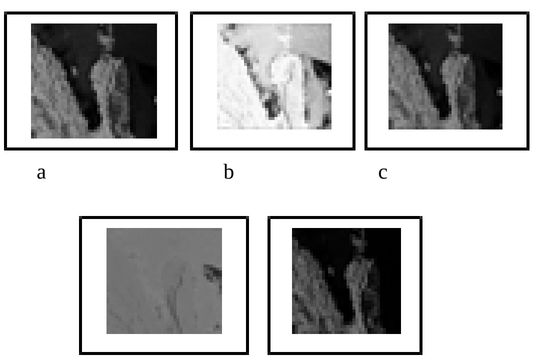


a b c

d e f

g h

Figure 3 Result of Texture Proces with Cooccurance
a. Contrast, b. Correlation, c. Dissimilarity, d. Entropy,
e. Homogenity, f. Mean, g. Second Moment, h. Variance



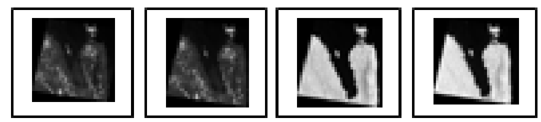
a b c

e f

Figure 4 Result of Texture Proces with Occurance
a. Data range b. Entropi c.Mean d.Entropi e,Skewness f. Variance

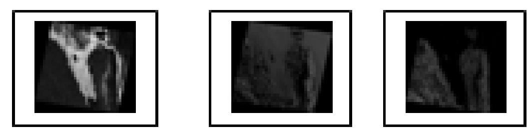
If EVI is greater than 0.3, can be classified as Non-Flood related pixel. EVI curve of the "Forest land the use type shows the value of more than 0.3 the year long except for the flood season. The EVI permanent of water bodies such as the" river "and" sea " type of land use value of less than 0.05 or even negative as the year long. DVEL from "The River" and "Sea" type of land use DVEL value less than 0.05.

It can be associated pixel infrared that water must have DVEL less than 0.05. But for this type of land use "lakes", DVEL value is not always less than 0.05. To overcome this problem, other criteria setted to identify the pixels associated water. In such cases, if the EVI is less than or equal to 0.05 and LSWI less than or equal to 0, the pixel will be identified as related to water pixels. The results combined with texture derived from ALOS PALSAR showed changes in flood area, is an indication that the texture information very dominan give impact to the results.



a b c d

Figure 5 SPOT after Flood
a.XS1 b.XS2, c.XS3, d.XS4.



a b c

Figure 6 Result of Physical Parameter Extract
a.LSWI b.NDVI, c.NDWI

7. Conclusion

The finding in this study that SAR images adds to the effectiveness and new information if it is not available or not possible to get the optically data complete. The cost of using SAR imagery for routine (not a disaster situation) is a problem, but this cost can be compensation to get a good mapping quality and low cost when compared with the survey directly to the field.

Texture variable of image of ALOS PALSAR provide valuable quantitative information to support and differentiate water bodies from other types of land cover classes.

Image texture achieve higher accuracy than the images without texture variables (increased from 85.6% to 91.7%) ALOS PALSAR. Application of median filter with 3 × 3 window to identify the better for the body of water. Thus, the water body can be easily identified higher with textured images. The use of supervised classification based on variable texture and HH polarization, resulting in the separation of the land cover class of homogeneous land classification with the prevalence of water from ALOS PALSAR image of 96.42%.

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Need to study the sensitivity of the texture of the sensitivity of water to clarify the boundary delineation of flood extents, so it can be set as the main element of physical parameters.

Acknowledgements

This study is a research assignment for university and done a good help and cooperation of parties. For that we thanks to the leader Indonesia University of Education, Chairman of the Institute for Community Research and Service UPI, Dean of the Faculty of Mathematics and Sciences Education of UPI, Chief Educational Technology Laboratory, and the Academic Civitas of Study Program of Computer Science of Education, especially team who have supported on this research. Hopefully the results of research through which it has established good cooperation has been the contributions together in an effort to build the Indonesian.

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