GEOSTATISTICAL TEXTURE CLASSIFICATION OF TROPICAL RAINFOREST IN INDONESIA

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ABSTRACT:

Traditional spectral classification of remote sensing data applied on per pixel basis ignores the potentially useful spatial information between the values of proximate pixels. Although spatial information extraction has been greatly explored, there have been limited attempts to enhance classification by combining spectral and spatial information. This improvement would arise from the hypothesis that a pixel is not independent of its neighbors and, furthermore, that its dependence can be quantified and incorporated into the classifier.
This study aims to explore the potential of utilizing texture spatial variability using geostatistics and Grey Level Co-occurrence Matrix (GLCM) texture measures. Different texture layers derived from geostatistics method, namely fractal dimension, semivariogram, madogram, rodogram, pseudo-cross variogram and pseudo-cross madogram, were incorporated for the land cover classification of tropical rainforests in East Kalimantan, Indonesia. Texture layers of grey level co-occurrence matrix (GLCM) channels, i.e. variance, contrast, dissimilarity, and homogeinity, were also used for the classification. Two classification methods, using Support Vector Machine and Minimum distance were applied for image classification.
Landsat 7 ETM images combined with textural information is used for land cover classification of tropical rainforest area. Band 5 of Landsat data was used to compute texture layers using the GLCM and geostatistics methods. This band was chosen because it has the highest variance of training data compared to other spectral bands.
The results were compared to find out how the extra information given by the texture enhances the classification. According to the accuracy assessment using error matrix, combinations of image and texture data performed better with 81% of accuracy compared to those of image data only with 76% of accuracy.

1 INTRODUCTION

Mapping of forest cover is an ultimate way to assess forest cover changes and to study forest resource within a period of time. On the other hand, forest encroachment is hardly stopped recently due to excessive human exploitation on forest resources. The forest encroachment is even worse in the tropical forest, which is mostly located in developing countries, where forest timber is a very valuable resource. The needs for the updated and accurate mapping of forest cover is an urgent requirement in order to monitor and to properly manage the forest area.

Remote sensing is a promising tool for mapping and classification of forest cover. A huge area can be monitored efficiently at a very high speed and relatively low cost using remote sensing data. Interpretation of satellite image data mostly applies a per pixel classification rather than the correlation with neighboring pixels. Geostatistics is a method, that may be used for image classification, as we can consider spatial variability among neighboring pixels (Jakomulska and Clarke, 2001). Geostatistics and the theory of regionalized variables have already been introduced to remote sensing (Woodcock et al., 1988).

This work attempts to carry out image classification by incorporating texture information. Texture represents the variation of grey values in an image, which provides important information about the structural arrangements of the image objects and their relationship to the environment (Chica-Olmo and Abarca-Hernandez, 2000). The work aims to explore the potential of pixel classification by measuring texture spatial variability using geostatistics, fractal dimension, and conventional GLCM methods. This is encouraged by several factors, like: *(1)* texture features can improve image classification results, as we include extra information; *(2)* image classification on forest area, where visually there are no apparent distinct objects to be discriminated (e.g. shape, boundary) can take into benefit the use of texture variation to carry out the classification; and *(3)* texture features of land cover classes in forest area, as depicted on Figure 1 are quite different visually even if the spectral values are similar; therefore the use of texture features may improve the classification accuracy.

2 STUDY AREA

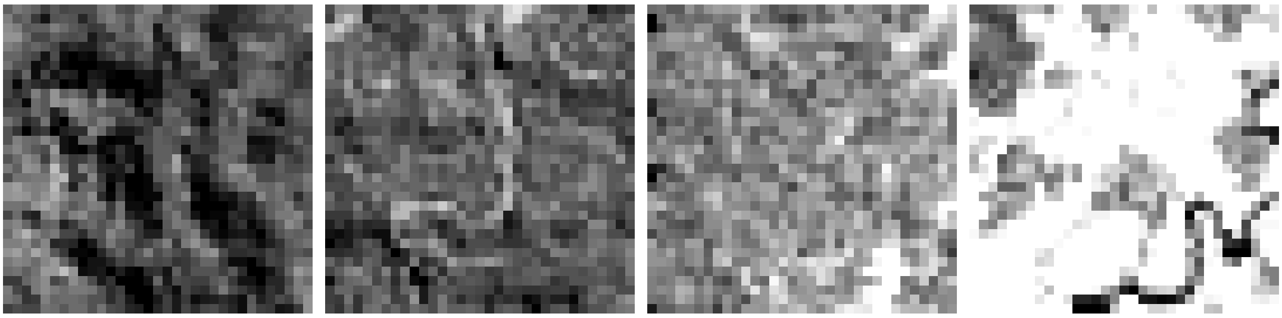
The study focuses on a forest area located in Labanan concession forest, Berau municipality, East Kalimantan Province, Indonesia as described on Figure 2. This area geographically lies between 1° 45' to 2° 10' N, and 116° 55 and 117° 20' E.

The forest area belongs to a state owned timber concession-holder company where timber harvesting activity is carried out, and the area mainly situated on inland of coastal swamps and formed by undulating to rolling plains with isolated masses of high hills and mountains. The variation in topography is a consequence of folding and uplift of rocks, resulting from tension in the earth crust. The landscape of Labanan is classified into flat land, sloping land, steep land, and complex landforms, while the forest type is often called as lowland mixed dipterocarp forest.

3 DATA AND METHOD

3.1 Data

Landsat 7 ETM of path 117 and row 59 acquired on May 31, 2003 with 30 m resolution was used in this study. The data were geometrically corrected using WGS 84 datum and UTM projection



(a) Dense Forest (b) Logged Over Forest (c) Burnt Area/Open Forest (d) Clear Cut Forest/Bare Land

Figure 1: Different texture of land cover classes represented on the study area

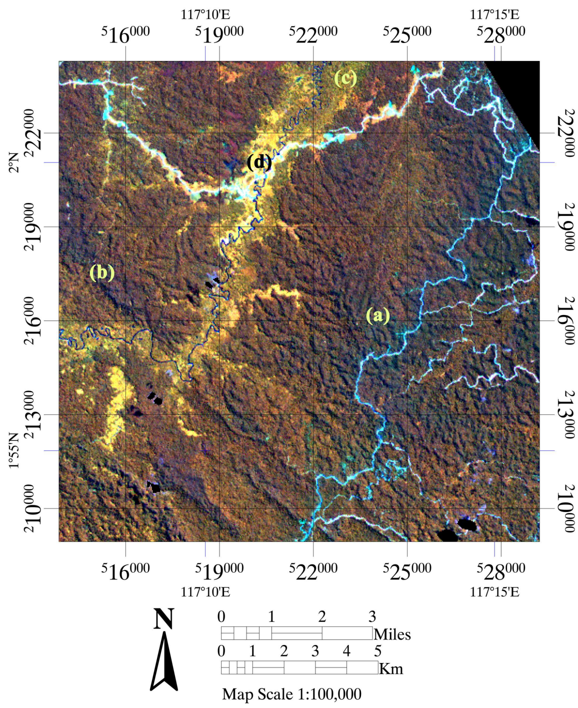


Figure 2: Study area represented using combination of Band 453 in RGB channel. Important land cover classes are marked here, namely Logged over Forest (a), Dense Forest (b), Burnt Area/Open Forest (c), and Clear Cut Forest/Bare Land(d)

with an RMS error of less than 1.0 pixel. Subsequently, atmospherically corrections on the satellite data were conducted using ATCOR module (Richter, 1996). A subset of the Labanan concession area (512×512 pixels) was used for the classification in order to optimize effort and time for forest cover classification and validation.

During dry season 531 sampling units collected on September 2004, 364 units were used to train the classification and 167 units were used as test dataset. Five forest cover classes were identified, namely logged over forest, clear cut forest/bare land, dense forest, and burnt areas/open forest.

3.2 Method

Grey Level Co-Occurrence Matrix. The grey-level co-occur rence matrix (GLCM) is a spatial dependence matrix of relative frequencies in which two neighboring pixels that have certain grey tones and are separated by a given distance and a given angle, occur within a moving window (Haralick et al., 1973).

The GLCM texture layers could be computed from each band of Landsat data. To provide the largest amount of texture information, the following strategy was adapted in selecting the satellite band for computing the GLCM texture layers. Covariance matrix showing the variance of each land cover class for each band was computed and the band corresponds to the highest mean variance of forest classes was selected. Compared to other spectral bands, Band 5 of Landsat ETM has the highest mean variance value as summarized on Table 1. Using a window size of 5×5 at every pixel and grayscale quantization level of 64, four GLCM layers were derived from the Landsat image, using variance, homogeneity, contrast, and dissimilarity as defined by Haralick et al. (1973).

Geostatistics Features. To incorporate Geostatistical texture features in the classification, semivariogram was computed in the neighborhood of every pixel. Generally, spatial variability $\gamma_{(h)}$ increases gradually with distance separating the observations up to a maximum value (the sill) representing the maximum spatial variance. The distance at which the sill is reached represents the range of variation, i.e., the distance within which observations are spatially dependent. Respectively, the size of moving window used to extract texture information of spectral data has an important role to provide an accurate estimation of semivariance, which eventually effects the classification accuracy. This work uses 5×5 and 7×7 moving windows to derive geostatistics texture layers.

Semivariogram is an univariate estimator, which describes the relationship between similarity and distance in the pixel neighbourhood. $Z(x)$ and $Z(x+h)$ are two values of the variable Z located at points x and $x + h$. The two locations are separated by the lag of h. The semivariogram values are calculated as the mean sum of squares of all differences between pairs of values with a given distance divided by two as described in the following equation (Carr, 1995).

$$\gamma(h) = \frac{1}{2n} \sum_{i=1}^{n} (Z(x_i) - Z(x_i + h))^2 \tag{1}$$

where n is number of pairs of data.

Another spatial variability measure is the madogram, which instead of measuring squares of all differences takes the absolute values (Deutsch and Journel, 1998; Chica-Olmo and Abarca-Hernandez, 2000).

$$\gamma(h) = \frac{1}{2n} \sum_{i=1}^{n} |Z(x_i) - Z(x_i + h)| \tag{2}$$

Land Cover Class	Band 1	Band 2	Band 3	Band 4	Band 5	Band 6	Band 7
Logged Over Forest	3.49	3.03	8.46	23.56	50.98	0.70	15.46
Burnt Areas/Open Forest	2.59	1.76	2.59	24.19	18.46	0.46	5.04
Road Network	65.68	165.39	332.63	74.12	386.45	1.91	294.98
Clear Cut Forest/Bare Land	2.70	5.20	2.90	33.52	32.49	0.83	8.70
Dense Forest	2.92	1.56	1.49	1.82	11.08	0.49	4.73
Hill Shadow	2.62	2.78	2.58	40.28	30.32	0.57	6.63
Mean Variance of total classes	13.33	29.95	58.44	32.91	88.30	0.83	55.92

Table 1: Variance matrix of forest cover classes training data

By calculating square root of absolute differences, we can derive a spatial variability measure called rodogram as shown in the following formula (Lloyd et al., 2004).

$$\gamma(h) = \frac{1}{2n}\sum_{i=1}^{n}|Z(x_i) - Z(x_i + h)|^{\frac{1}{2}} \tag{3}$$

Alternatively, three multivariate estimators quantify the joint spatial variability (cross correlation) between two bands, namely pseudo cross variogram, and pseudo cross madogram were also computed. The pseudo-cross variogram represents the semivariance of the cross increments, and calculated as follows.

$$\gamma(h) = \frac{1}{2n}\sum_{i=1}^{n}(Y(x_i) - Z(x_i + h))^2 \tag{4}$$

The pseudo-cross madogram is similar of the pseudo-cross variogram, but again, instead of squaring the differences, the absolute values of the differences area taken, which leads to a more generous behavior toward outliers (Buddenbaum et al., 2005).

$$\gamma(h) = \frac{1}{2n}\sum_{i=1}^{n}|Y(x_i) - Z(x_i + h)| \tag{5}$$

Using Band 5 of Satellite data, the spatial variability measures were computed and median values of semivariance at each computed lag distance were taken, resulted in the full texture layers for each calculated spatial variability measure. These texture layers were then put as additional input for the classification.

Fractal Dimension. Fractal is defined as an object which are self-similar and show scale invariance (Carr, 1995). Fractal distribution requires that the number of objects larger than a specified size has a power law dependence on the size. Every fractal is characterized by a fractal dimension (Carr, 1995).

Given the semivariogram of any spatial distribution, fractal dimension (D) is commonly estimated using the relationship between the fractal dimension of a series and the slope of the corresponding log-log semivariogram (m) plot (Burrough, 1983; Carr, 1995).

$$D = 2 - \frac{m}{2} \tag{6}$$

4 RESULTS & DISCUSSION

4.1 Results

Before Geostatistics texture layers were derived, we observed whether there is textural variation among different classes. Using training data, semivariogram of land cover classes on the study area was sequentially computed for lag distance (range) of 30 pixels, as presented on Figure 3.

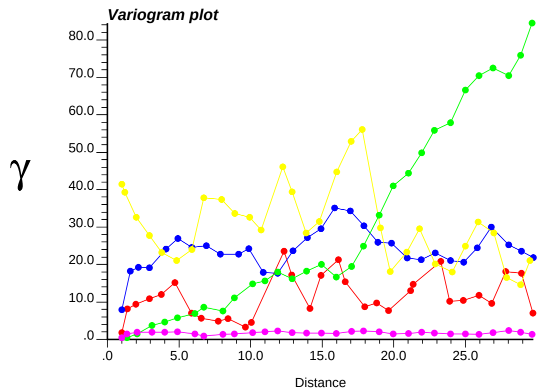
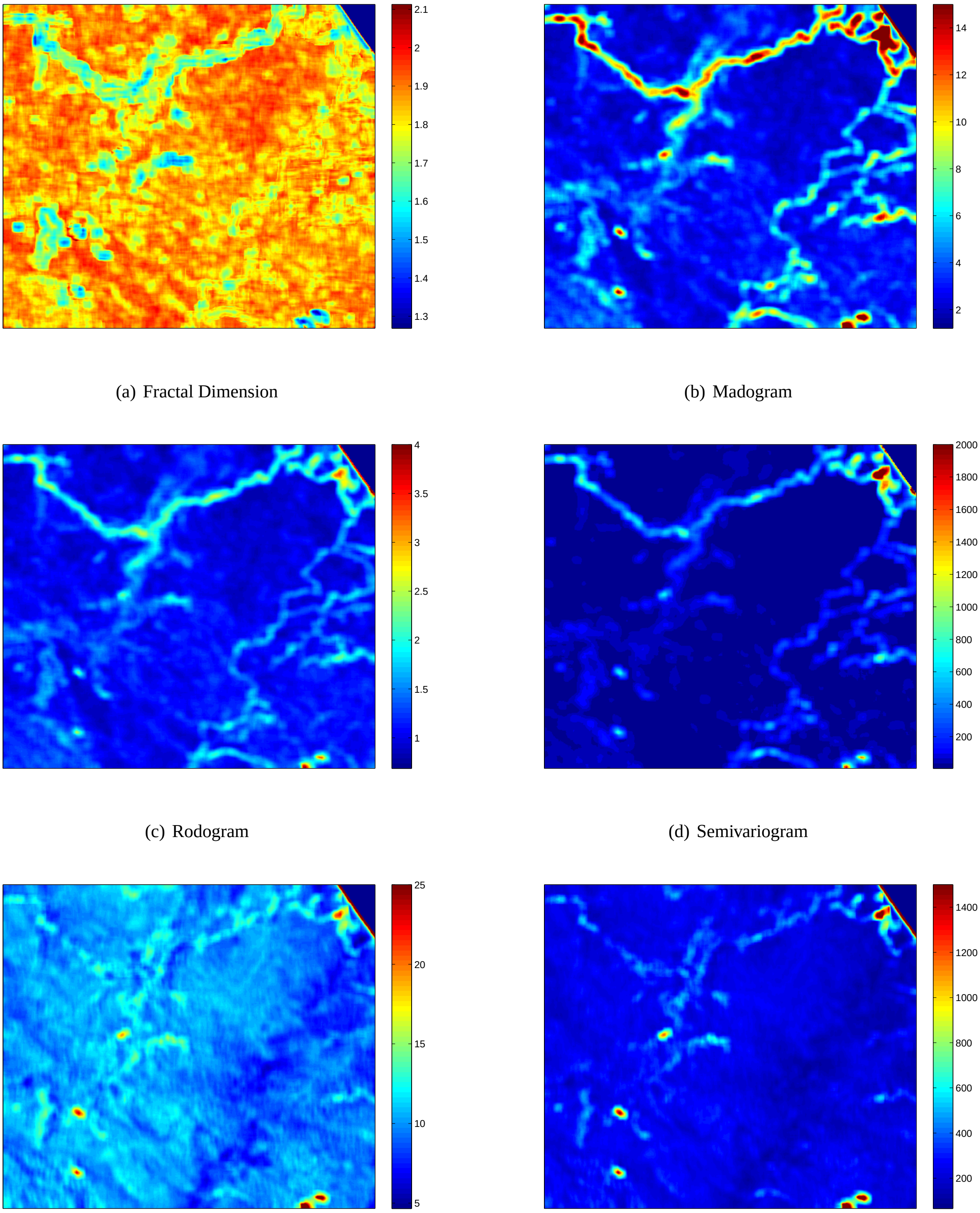


Figure 3: Variogram plot of training data shows the spatial variability of land cover classes on the study area, i.e. logged over forest (red), burnt areas/open forest (blue), clear cut forest/bare land (yellow), dense forest (green), hill shadow (purple)

As shown in Figure 3, semivariance computed for every lag distance may provide useful information for data classification as those values of each forest class revealed spatial correlation for lag distance of less than 10 pixels. However, there is an exceptional case for dense forest class, which shows spatial variability on larger lag. This may be a problem for computing semivariance for this particular class as the calculation of per pixel semivariance on large lag distance is computationally expensive. Compromising with other forest classes, texture layers were computed using 5×5 and 7×7 moving windows. Using different spatial variability measures explained before, semivariance values for each pixel were calculated and median of these values was used, resulting in texture information of the study area. The results of Geostatistics texture layers are described on Figure 4.

Classification of satellite image was done using following data combinations: *(1)* ETM data; *(2)* ETM data and GLCM texture, and; *(3)* ETM data and Geostatistics texture. Two classification methods, using minimum distance algorithm and Support Vector Machine (SVM) method were applied for the purpose of the study.

The SVM method is originally a binary classifier, that is based on statistical learning theory (Vapnik, 1999). Multi-class image classification using the SVM method is conducted by combining several binary classification to segmenting data with the support of optimum hyperplane. The optimum performance of this method mainly affected by a proper set up of some parameters involved in the algorithm. This study, however, was not trying to optimize the SVM classification, therefore those parameters were arbitrarily determined. For the classification, Radial Basis



(a) Fractal Dimension

(b) Madogram

(c) Rodogram

(d) Semivariogram

(e) Pseudo-Cross Madogram

(f) Pseudo-Cross Semivariogram

Figure 4: Different texture layers derived from spatial variability measures of Geostatistics Method

Function kernel was used, γ in kernel and classification probability threshold were respectively, 0.143 and 0.0, while penalty parameter was 100.

The motivation of using those two methods for classifying spatial and texture data was in order to study the performance of texture data given two completely different algorithms in the classification. The classification results are summarized on Table 2.

Applying the SVM and Minimum Distance in the classification, the results showed that 74% and 76% of accuracies were achieved when Band 3,4,5 of Landsat image and multipectral Landsat data (i.e. Band 1-5,7) were used in the classification, respectively. Furthermore, multispectral bands of Landsat data were used to perform classification using texture data.

The GLCM texture layers have slightly improved the classification accuracies, when variance, contrast, and dissimilarity were used in the classification. The GLCM texture classification performed by the SVM resulted in 81% of accuracy when combination of ETM data and all the GLCM texture layers were applied.

Geostatistics texture layers, on the other hand, performed quite satisfactorily, resulting more than 80% of accuracies when fractal dimension, madogram, rodogram and combination of those texture layers were used in the classification. The classification resulted in 81.44% of accuracy and kappa of 0.78 when image data, fractal dimension, madogram and rodogram were classified by the SVM method, the results were depicted on Figure 5.

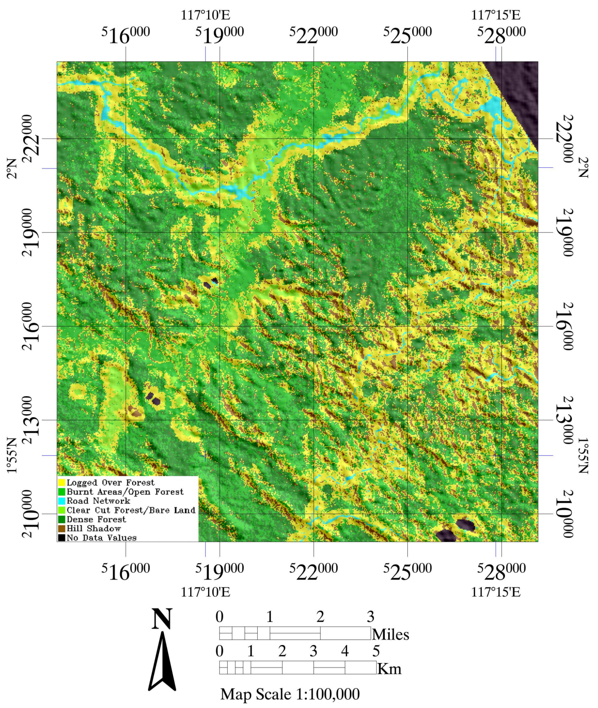


Figure 5: The final classification result image

Indeed, the SVM performed better than Minimum Distance, when texture data was used, it has already been proven that the SVM performed well dealing with large spectral data resolution, such as hyperspectral, as reported by several recent studies (Gualtieri and Cromp, 1999; Pal and Mather, 2004, 2005).

4.2 Discussion

Geostatistics texture layers performed quite well in the classification. However, semivariogram and pseudo-cross semivariogram texture layers were not giving satisfactory classification results when those layers were classified by Minimum Distance method. This is due the nature of semivariogram and pseudo-cross semivariogram, which calculate the mean square of semivariance for all observed lag distance, either using monovariate or multivariate estimators. This, eventually may reduce the classification accuracy because of the presence of data outliers.

Combined with madogram and rodogram, the classification resulted in higher accuracies with the SVM and Minimum Distance method methods. This is obvious as madogram, calculating the sum of absolute value of semivariance for all observed lag distance, and rodogram, computing the sum of square root of those semivariance, have 'softer' effect to the presence of outliers compared to those of semivariogram.

This study observed that by changing the size of moving window from 5×5 into 7×7 has slightly improved the classification accuracy. This is because the scale of land cover texture is similar with the the 7×7 window size; therefore, this window size provides more texture information than the other. However, computation of texture layer using larger size of moving window is absolutely not efficient in terms of time, thus to initially find the optimum size of moving window may be an alternative to reduce efforts and time for the computation of geostatistics texture layers. Selection of proper size of moving window will provide better texture information resulted from spectral image data.

In general, additional texture layers for image classification, either derived from the GLCM or Geostatistics, have effectively improved the classification accuracy. Although, this study found that by applying different GLCM texture layers as well as Geostatistics layers in a single classification process considerably improved classification accuracy, one should be very careful to apply the same method for different types of data. The selection of classification algorithm depends on the data distribution.

5 CONCLUSIONS AND FUTURE WORK

This study found that texture layers derived from the GLCM and Geostatistics methods have improved classification of spatial data of Landsat image. Texture layers are computed using the moving window method. Selection of the moving window size is very important since extraction of texture information from spectral data is more useful when texture characteristics corresponds to the observed land cover classes are already known.

Support Vector Machine as well as Minimum Distance algorithm were performed well in the classification elaborating texture data as additional input of Landsat ETM data. Moreover, the SVM resulted on average higher accuracies compared to those of Minimum Distance Method.

The authors observed that for future work, it is also possible to compute Geostatistics texture layer with adjustable moving window size, depending on the size of texture polygon for certain land cover class being observed. This may be an alternative to extract better texture information from spectral data.

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	Min. Distance		SVM	
	OAA (%)	**Kappa**	**OAA (%)**	**Kappa**
ETM Data				
ETM 6 Bands	76%	0.71	76%	0.71
ETM Band 3,4,5	74%	0.69	74%	0.71
ETM 6 Bands, Geo-Texture Windows 5×5				
ETM 6 Bands, Fractal	76%	0.71	81%	0.77
ETM 6 Bands, Madogram	77%	0.72	78%	0.74
ETM 6 Bands, Rodogram	76%	0.71	80%	0.76
ETM 6 Bands, Semivariogram	57%	0.48	77%	0.72
ETM 6 Bands, Pseudo-Cross Semivariogram	47%	0.36	77%	0.72
ETM 6 Bands, Pseudo-Cross Madogram	76%	0.71	75%	0.71
ETM 6 Bands, Fractal, Madogram, Rodogram	77%	0.72	81%	0.77
ETM 6 Bands, Geo-Texture Windows 7×7				
ETM 6 Bands, Fractal	76%	0.71	79%	0.75
ETM 6 Bands, Madogram	78%	0.73	80%	0.76
ETM 6 Bands, Rodogram	76%	0.71	81%	0.77
ETM 6 Bands, Semivariogram	50%	0.39	77%	0.73
ETM 6 Bands, Pseudo-Cross Semivariogram	47%	0.37	76%	0.71
ETM 6 Bands, Pseudo-Cross Madogram	76%	0.71	76%	0.71
ETM 6 Bands, Fractal, Madogram, Rodogram	78%	0.73	81%	0.78
ETM 6 Bands, GLCM				
ETM 6 Bands, Variance	77%	0.72	77%	0.72
ETM 6 Bands, Contrast	77%	0.72	75%	0.70
ETM 6 Bands, Dissimilarity	72%	0.67	77%	0.73
ETM 6 Bands, Homogeinity	62%	0.54	77%	0.72
ETM 6 Bands, Variance, Contrast, Dissimilarity, Homogeinity	63%	0.55	81%	0.77

Table 2: Overall Accuracy Assessment (OAA) of the Classification

studying in the International Institute for Geo-Information Science and Earth Observation the Netherlands. Therefore, the first author would like to thanks to Dr. Ali Sharifi and Dr. Yousif Ali Hussein, who make possible of data collection used for the purpose of this study.

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