EVALUATION OF INCORPORATING TEXTURE INTO WETLAND MAPPING FROM MULTISPECTRAL IMAGES

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ABSTRACT

Multispectral images have been transformed into Tasseled Cap features to characterize the wetland properties for mapping purpose. The texture derivatives were applied to the brightness, greenness, and wetness using three texture measures based on the grey-level co-occurrence matrix method. In this study, the data-driven window size over which texture measures are derived will be determined based on the experimental semivariograms instead of a trial-and-error method. Eight combinations of window sizes have been analyzed to evaluate the benefit of the proposed strategy. A supervised classification based on the maximum likelihood algorithm was applied to the three Tasseled Cap features and to their combination with each texture inputs under different window sizes. Classification accuracy is measured by the overall accuracy for the whole set of classification. User's accuracy and kappa coefficient are used to estimate individual class accuracy. The combination of multiple window sizes from the Tasseled Cap features to derive texture measures for classification purposes is proposed according to the semivariograms. The overall accuracy of the spectral-textural classification shows a 95.5% accuracy, higher than the multispectral classification alone. For the purpose of wetland mapping of the study site, the proposed combinations of multiple window sizes provide wetland class 92.6% accuracy higher than randomly selected identical window sizes.

Keywords: Texture analysis, semivariograms, grey-level co-occurrence matrix (GLCM), Tasseled Cap features, wetland.

INTRODUCTION

Information about land cover is essential for environmental monitoring. Remotely sensed data supply a current and important source of data for wetland mapping. Image texture quantifies the spatial variation of tone that is related to the distributions of different land cover types on the ground surface. However classical classification algorithms ignore the potential of the spatial information existing between a pixel and its neighbours when applied on a pixel-by-pixel basis. To achieve reliable and accurate results in mapping applications, image attributes within a land cover type over its neighbourhood should be characterized. Texture, the intrinsic spatial variability of radiometric data, is a valuable feature to discriminate the different land cover types.

Many approaches were developed for texture analysis. According to the processing algorithms, three major categories, namely, structural, spectral, and statistical methods, are common ways for texture analysis. Grey-level co-occurrence matrix (GLCM), one of the most widely used methods, contains the relative frequencies of the two neighbouring pixels separated by a distance on the image. Several statistical measures (1) such as homogeneity, contrast, and entropy can be computed from the matrix to describe specific textural characteristics. Each texture measure can create a new channel that can be incorporated with spectral features for classification purposes. However, a certain number of parameters directly associated with the GLCM method should be considered before computing texture measures. Two important factors, the combinations of texture features and the window size selection, have been examined according to their benefits on the classification accuracy.

Various combinations of texture measures have been tested for different applications such as crop classification in agriculture (2) and forest species classification (3) in nature resources management. Results showed that incorporating texture features in classification was superior to the classification of the original image. A combination of three or four texture features performs better than the combinations of one or two texture features. But no rules have been recommended for the texture measures selection. The most appropriate combination of texture features depends strongly on the surface properties of the land cover types of interest. Since unique texture patterns were hypothesized to discriminate different land cover types, a proper window size that matches the patch size can extract the textural pattern of this particular landscape. Large window size can capture the spatial patterns of each land cover type better, but may contain more than one land category, which could introduce systematic errors. The window should then be small enough to keep the variance low and to maximize the potential for class separability. Previous studies have been performed to examine several different window sizes (4,5). These trial-and-error methods are time intensive and the window size strongly depends on the attributes of the radiometric data for each particular case.

Geospatial techniques utilize spatial information that considers the spectral dependence existing between a pixel and its neighbour. Radiometric data that are highly correlated within a range can be indicated through the semivariogram function (6). The digital number (DN) value of each pixel can be interpreted as a regionalized variable. Meanwhile, a data-driven semivariogram provides a method of measuring the spatial dependency of continuously varying phenomena. Recently, some techniques have involved geostatistical parameters deduced from the semivariogram function for image classification (7, 8, 9). Although suggestions have been made that the window size should be defined for each particular case, identical windows as fixed square pixel arrays were used for all input channels. The approach of this paper intends to analyze the spatial dependence of radiometric data by geostatistical methods to obtain the suitable window size for the landcover type of interest from data-driven semivariograms. For this purpose multiple window sizes will be used to derive texture measurements from the Tasseled Cap features – brightness, greenness, and wetness - for wetland mapping. The objective of this paper is to assess the benefit of incorporating texture for classification by the proposed methodology.

METHODS

The study site is located within the boundaries of Prince Albert National Park in Northern Saskatchewan, Canada. Approximate coordinates of the study are as follows: 53°45’00’’N to 54°00’00’’N and 106°00’00’’W to 106°25’00’’W. The elevation in the area generally decreases from west to east, varying from 501 to 747 m above sea level. The lowest elevation is Waskesiu Lake (elevation 501 m), while the highest (about 747 m) is in the western part of the site. According to the 7-year Meteorological Service of Canada (MSC) normals for 1996-2002, the mean monthly temperatures range from approximately -17.2°C in January to 17.5°C in July and the mean monthly precipitation varies significantly from 80.2 mm in July to only 14.7 mm in November.

Multispectral data were obtained from the Landsat ETM+ sensor. The multispectral image was acquired in August 1999 and processed at level 1G (standard geocoded image resampled to UTM projection). The scene was resampled to 25 m resolution by cubic convolution and a 1086×1086 pixels sub-image was extracted for this study (Figure 1).

Image pre-processing

According to the definition given by the National Wetlands Working Group (1988), wetlands are characterized by three components: soil, vegetation, and water. A Tasseled Cap transformation utilizes a canonical component analysis to decompose multispectral image into three dimensions: brightness, greenness, and wetness. Wetland pixels can be extracted by using Tasseled Cap transformed images (10) since the brightness channel highlights areas of high reflectance; the greenness channel represents vegetated areas and the wetness channel marks areas that have a high water or moisture content. A Tasseled Cap transformation based on at-satellite reflectance is more appropriate for regional applications where atmospheric correction is not feasible (11). Thus, the six cloud-free multispectral bands were chosen which did not require atmospheric correction, because atmospheric data necessary for running the atmospheric correction algorithm were not available. Raw digital numbers were converted to radiance and at-satellite reflectances were calculated according to Landsat 7 Science Data Users Handbook (12).

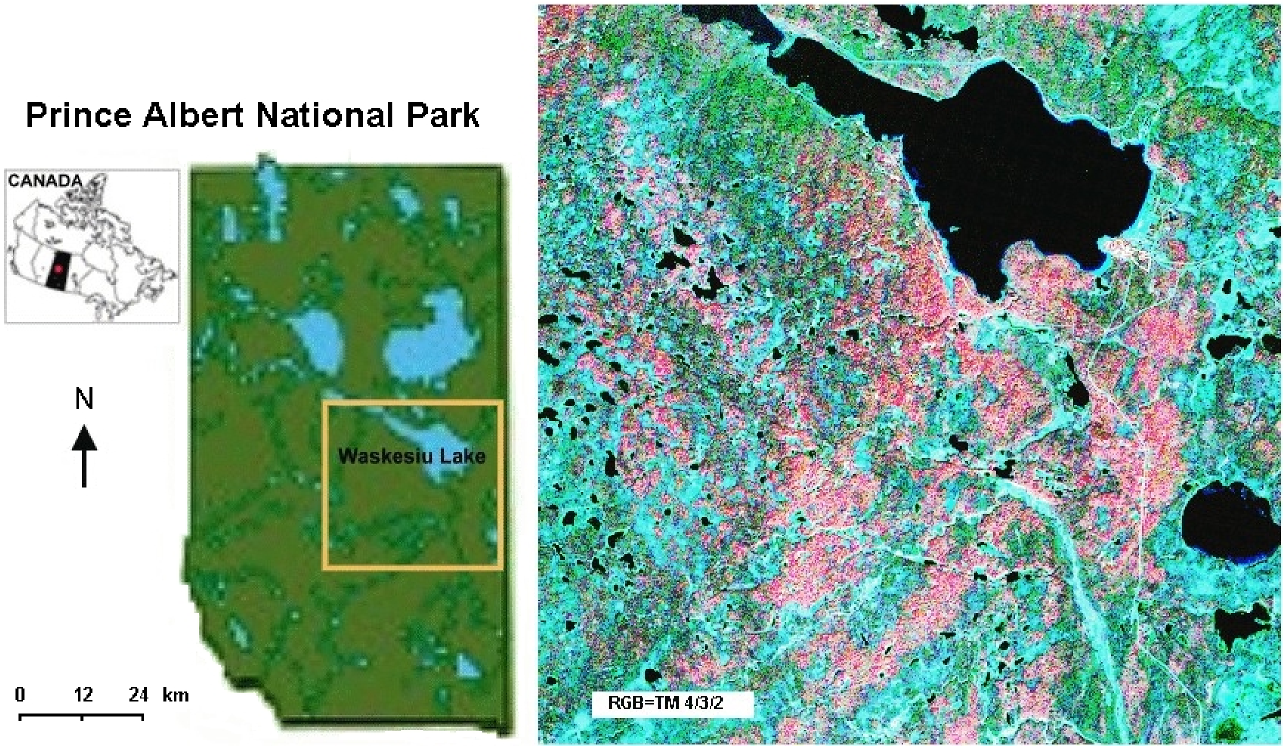

Figure 1: Location map of study area and Landsat-7 composite image (RGB=TM 4/3/2)

Semivariogram

The semivariogram was employed as a tool to model the spatially varying phenomenon of natural objects. The average change of a property is illustrated by a changing lag and the classical equation can be expressed as follows:

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

The experimental semivariance $\gamma(h)$ is defined as half the average squared difference between values separated by a given lag h, where h is a vector in both distance and direction. While $Z(x_i)$ represents the DN value at a pixel location x_i, $N(h)$ means the total number of pairs. Semivariogram interpretation is usually focused on relating nugget, sill, and range parameters (Figure 2). In this study, lag h increased by one pixel instead of a real measurement in length unit. Pixels separated within the range are highly correlated with each other. Range can be used as a measure of homogeneity. Automatic fitting of models to semivariograms is the main problem (13) with variogram model-based approaches for texture classification. Since the choice of model may be restricted to certain regions or classes, the coefficient of the model fitting the local variogram may be misleading and unreliable. Modelling was not used to fit the semivariance curves in this study; only experimental values of the semivariograms were used. Semivariograms of four land cover types (wetland, water, dense vegetation, and open vegetation) were examined.

Image textural channels and classification

Texture analysis, which provides a complementary tool to multispectral studies, has received great attention in image processing. The grey level is assumed not to be randomly distributed within an image, but to be associated with structures of land cover types. Texture reflects the local variability of grey levels in the spatial domain and reveals the information about the object structures in the natural environment. In this study, texture features are computed over a moving window determined by semivariograms. Odd numbers of pixels from 5 to 11 were employed as window size for the three Tasseled Cap features to derive texture measures. In addition, combinations of multiple window sizes were also evaluated. The following texture measures were computed from the Tasseled Cap features: mean, variance, and angular second moment (ASM). To evaluate the effects of the proposed window sizes, data were subjected to a maximum likelihood classification algorithm. Accuracy was assessed for wetland mapping.

Although open water can be classified very accurately from the image, some misclassified errors did result from water pixels. Water bodies in the study area varied from few pixels to thousands of pixels due to the natural geographic conditions. A pixel-based image classification algorithm may eliminate small size water bodies. To minimize the errors from misclassification of the water body, the normalized difference vegetation index (NDVI) was employed to develop an upper threshold, which would identify pixels likely to be open water. One binary map highlighting all pixels within the image being considered open water was created according to this threshold. The map masked out the water-likely pixels to eliminate those pixels during the classification procedure. Therefore, only three classes were considered in the classification process: dense vegetation, open vegetation, and wetland.

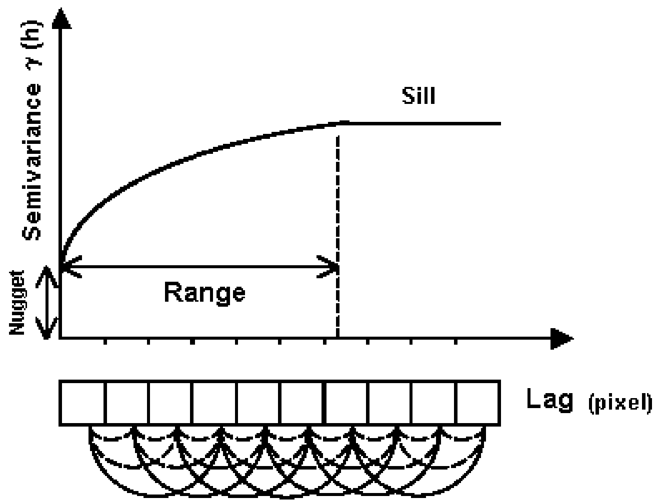

Figure 2: Example semivariogram showing nugget, sill, and range in image application.

RESULTS

Analysis of semivariogram behavior

Semivariogram behaviours of four classes, water, wetland, dense vegetation, and open vegetation were examined in the study. An arbitrary size (34x34 pixels) was selected for each training site (Figure 3). The DN statistics (mean ± standard deviation) within the geometric size are presented in Table 1.

While dense vegetation has higher brightness and greenness values, its wetness value is lower than for any of the other three classes. On the other hand, wetland and open vegetation have similar values in brightness and greenness. Although open vegetation has slightly higher vegetation density than wetland, these similarities are factors that decrease the signature separability of the two landcover types. In this study of spatial autocorrelation, experimental semivariograms of the three Tasseled Cap features were computed within the selected training areas for four directions (*i.e.* NS, EW, NNE, SSE) and for one isotropic curve. The semivariograms have different behaviours due to variations in the correlation patterns of the DN values. Only omnidirectional semivariograms are analyzed to extract the optimum lag distance for deriving texture features in the study.

Table 1: DN statistics (mean ± standard deviation) of Tasseled Cap features for four training sites.

Class	Brightness	Greenness	Wetness
Water	50.41± 1.64	-38.30± 2.39	-65.95 ± 5.22
Wetland	155.95±12.78	-50.50± 2.77	-271.82 ± 25.19
Dense Vegetation	180.56± 4.13	-24.79± 2.61	-283.03 ± 7.62
Open Vegetation	134.47±13.62	-47.60± 4.90	-230.665± 23.66

Semivariograms computed for each class are unique (Figure 4) and have the following characteristics.

(1) Water: The semivariograms calculated from brightness, greenness, and wetness are essentially flat, exhibiting little or no spatial correlation for lag distances greater than one pixel. Although the nugget and sill values may vary with the DN data, the analogous curve behaviours can be observed from the semivariograms for the three different data features.

(2) Wetland: Directional and isotropic semivariograms have similar behaviours either for brightness or wetness features. They rose smoothly and reached the sill at a lag of 7 pixels. Semivariogram of greenness feature showed the /weakest variances among the training classes of the study area but the greatest variance in wetness. The curve of greenness rose steadily up to a local peak at a lag distance of 5 pixels and waved a little bit until it reached the sill at a lag of 11 pixels.

(3) Dense vegetation: The semivariograms of dense vegetation calculated either from brightness, greenness or wetness features showed periodic forms in four directions. For the isotropic curves of the three Tasseled Cap features, the semivariograms reached a limiting value at a lag of 5, 9, and 5 pixels, respectively.

(4) Open vegetation: Although open vegetation showed the greatest variances among the training classes in brightness and wetness features, the range was slightly larger than that of the wetland class. The semivariograms for both brightness and wetness features rose to a lag distance of 11 pixels, curving to a flat level fairly coincident to the DN variance of the training site. One significant difference should be noticed: Although wetland and open vegetation have similar spectral DN values in greenness feature, their semivariograms showed the difference in variance.

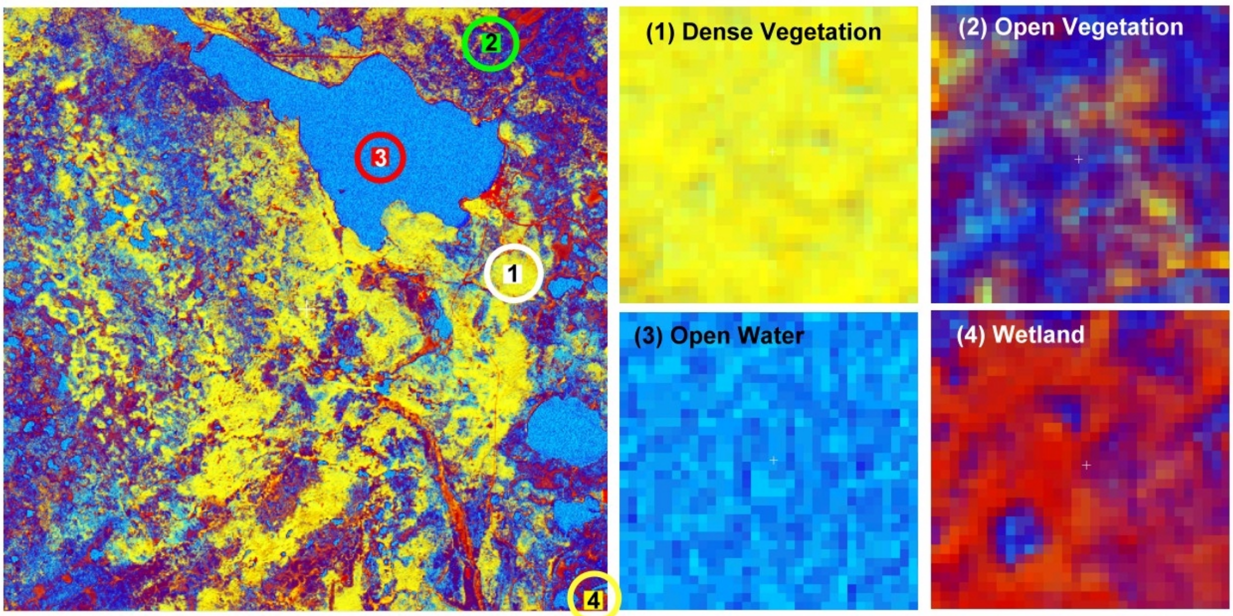

Figure 3: Selected training sites for semivariance calculation. (1) Dense vegetation; (2) open vegetation; (3) open water; and (4) wetland. Composite image is illustrated by Tasseled Cap features in RGB=Brightness/ Greenness/ Wetness.

The semivariograms of the three Tasseled Cap features are used as criteria to determine the optimal window size for deriving texture measurements. A window size for each brightness, greenness, and wetness feature was determined according to the experimental semivariogram signatures of wetland class presented in Figures 4. Therefore, the window size used to derive texture features from the three Tasseled Cap features were 7×7, 11×11, and 7×7 pixels, respectively.

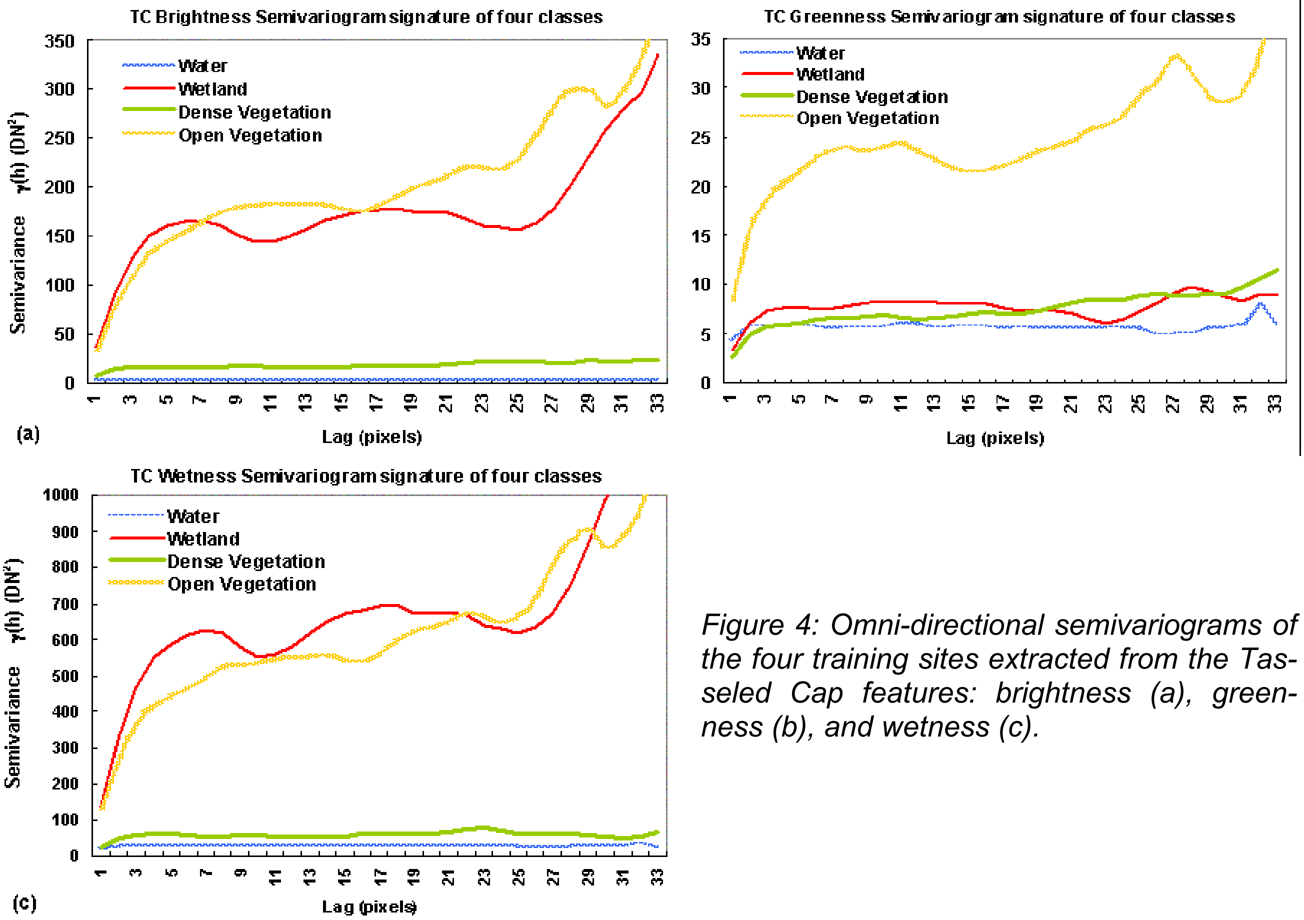

Figure 4: Omni-directional semivariograms of the four training sites extracted from the Tasseled Cap features: brightness (a), greenness (b), and wetness (c).

Classification

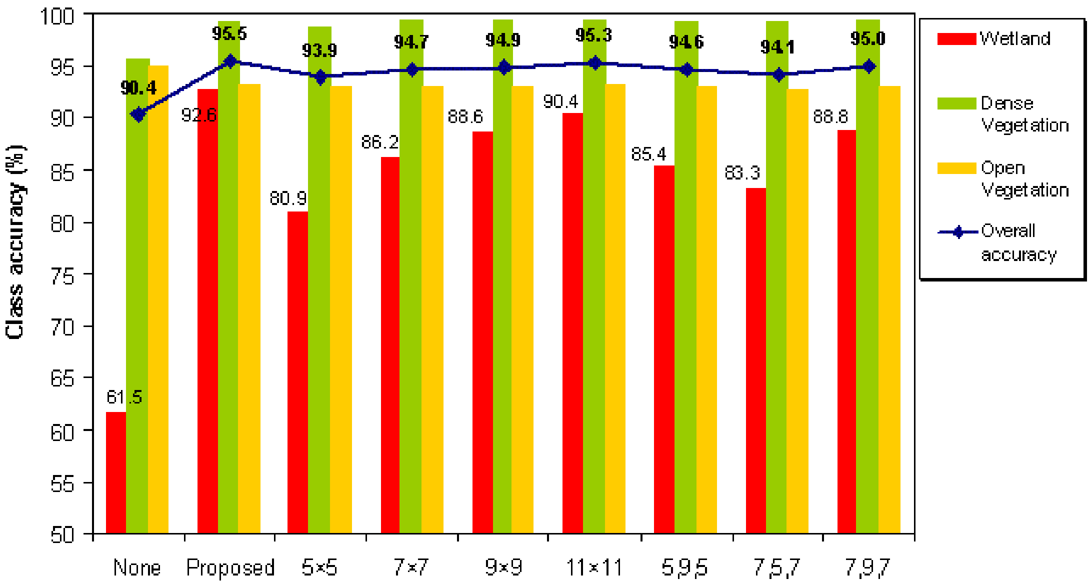

Figure 5: Graph illustrating comparison for classification accuracy for three classes based on the Tasseled Cap features and on different window sizes for texture measures.

The overall accuracy and accuracies of the three classes are illustrated in Figure 5. The three Tasseled Cap features were always used as the input channels for the classification. Texture features derived from different window sizes were compared to assess their influence on wetland mapping. Consequently, the strategy utilizing semivariograms to determine the optimal window size was also evaluated. For this purpose, four identical window sizes from 5×5 to 11×11 and four combinations of multiple sizes were investigated.

The comparison of spectral and spectral-textural classification accuracies indicates that introducing texture features into classification could provide a better result than spectral data alone. The overall accuracy increases by 4% at least (Figure 5). The proposed method predicting the preferred window sizes for deriving texture features as 7×7 for brightness, 11×11 for greenness, and 7×7 for wetness shows a highest overall accuracy of 95.5%. Incorporation of the texture features into the classification of the Landsat TM data improved the accuracy of the wetland class. The accuracy of the wetland class improved from 61.5% using spectral bands to 92.6% using a combination of spectral bands and texture features. Wetlands in the study area are fragmentary and distributed around small water bodies or in the river riparian. Nearly identical spectral reflectances between vegetation types cause the low signature separability between the wetland and open vegetation classes. Texture features therefore provide additional information that is used to distinguish the insignificant differences in the spectral signature.

Table 2: Summary results of accuracy assessment of spectral and textural classification.

Band combination [a]	**Overall accuracy**	**User's accuracy (%)**			**Kappa coefficient**		
		Wetland	Dense Vegetation	Open Vegetation	Wetland	Dense Vegetation	Open Vegetation
Spectral alone	90.4	61.5	95.7	95.0	0.56	0.93	0.90
Spectral-textural							
Proposed size	95.5	92.6	99.4	93.3	0.92	0.99	0.86
5×5	93.9	80.9	98.8	93.1	0.78	0.98	0.86
7×7	94.7	86.2	99.4	92.9	0.84	0.99	0.86
9×9	94.9	88.6	99.4	92.9	0.87	0.99	0.86
11×11	95.3	90.4	99.4	93.3	0.89	0.99	0.86
5,9,5	94.6	85.4	99.2	93.1	0.83	0.99	0.86
7,5,7	94.1	83.3	99.2	92.7	0.81	0.99	0.85
7,9,7	95.0	88.8	99.4	93.0	0.87	0.99	0.86

[a] The window sizes used to derive the texture features from Tasseled Cap transformations are represented by numbers.

User's accuracy and kappa coefficients for spectral and spectral-textural classifications are computed to estimate the accuracy of individual classes in Table 2. The table also illustrates the comparison between randomly selected window size and the one predicted by the semivariogram analysis. The window size is responsible for most of the variability in the classification, because a significant correlation is observed between class accuracy and selected window sizes used to derive texture features. However, this trend was not found in dense vegetation and open vegetation classes. The accuracies of these two classes do not show much variation between different combinations of textural classification. Since the wetlands in the study area are fragmentary and vary in different sizes, the semivariogram captures the spatial correlation by predicting an appropriate lag distance for deriving texture measures. The kappa coefficient of the wetland class evaluated by adding proposed texture channels is 0.92, which is higher than the other randomly selected 5×5 window to 11×11 window sizes. When examining the semivariogram of the greenness feature (Figure 4.b), the variance reached a local peak at a lag of 5 pixels. By using a 5×5 window for greenness, it shows a lower kappa coefficient for the wetland class. The result indicates that a small window size may lose some spatial information of the specific class. However template window size at 11 pixels, which is the range value related to the sill of the semivariogram, can provide a better classification result. Utilization of multiple window sizes (*i.e*. 7×7 for brightness, 11×11 for greenness, and 7×7 for wetness) is proposed in the classification. Multiple window sizes can retain the integrity of the small windows while reducing the effects of noise encountered with large windows. The result also illustrates the capability of improving the accuracy by applying this concept.

CONCLUSIONS

The overall accuracy indicated that the incorporation of texture measures into multispectral data could improve the classification result by 5% for this case study. Window size for deriving texture features is a factor contributing to classification accuracy. The study addresses the need to determine the data-driven window size predicted by the range of semivariogram for specific class inspection. According to the semivariograms of the target class, the resulting range parameter can provide superior discrimination and correlation results compared to those obtained using randomly selected identical windows. The proposed method shows the capability of increasing wetland class discrimination from 61.5% to 92.6%. This is a time-effective strategy that can be used to optimize texture derivations of remotely sensed imagery. Future studies will be performed to examine, if the pixels of these fragmentary classes can be grouped as segments and then take the advantage of texture analysis for identification of land cover units.

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