EVALUATION OF SPECTRAL AND TEXTURE FEATURES FOR OBJECT-BASED VEGETATION SPECIES CLASSIFICATION USING SUPPORT VECTOR MACHINES

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ABSTRACT:

The use of appropriate features to characterize an output class or object is critical for all classification problems. This paper evaluates the capability of several spectral and texture features for object-based vegetation classification at the species level using airborne high resolution multispectral imagery. Image-objects as the basic classification unit were generated through image segmentation. Statistical moments extracted from original spectral bands and vegetation index image are used as feature descriptors for image objects (i.e. tree crowns). Several state-of-art texture descriptors such as Gray-Level Co-Occurrence Matrix (GLCM), Local Binary Patterns (LBP) and its extensions are also extracted for comparison purpose. Support Vector Machine (SVM) is employed for classification in the object-feature space. The experimental results showed that incorporating spectral vegetation indices can improve the classification accuracy and obtained better results than in original spectral bands, and using moments of Ratio Vegetation Index obtained the highest average classification accuracy in our experiment. The experiments also indicate that the spectral moment features also outperform or can at least compare with the state-of-art texture descriptors in terms of classification accuracy.

1. INTRODUCTION

Interpretation of remotely sensed images has played an important role in vegetation mapping in the past decades, however the use of coarser spatial resolution satellite imagery have proven insufficient or inadequate for discriminating species-level vegetation in detailed vegetation studies (Yu et al., 2006). Airborne high spatial resolution imagery provides more information for detailed observation of vegetation. However, traditional classification algorithms based on single pixel analysis are often not capable of extracting the information we desire from high spatial resolution images. In recent years, object-based approaches become popular in high spatial resolution image classification, which has proven to be an alternative to the pixel-based image analysis and a number of publications suggest that better results can be expected (Blaschke, 2010). When applying object-based method to vegetation species classification, individual trees are expected to be segmented as image-objects and after that classification will be conducted in object-feature space.

The use of appropriate features to characterize an output class or object is fundamental for all classification problems. How to extract representative object-features in arbitrary-shaped regions is still an open issue for object-based image classification. Texture is a fundamental feature to describe image, but most texture descriptors are based on regular images or regular regions (e.g. small blocks) and do not consider the color information (Liu et al., 2006). Shape features are very significant features which are very close to human perception. However due to the inaccuracy of image segmentation and view angle variations, shape features are not widely used in natural image analysis. We believe that statistical measurement is a better way to summarize arbitrary-shaped image regions in object-based image classification. Color histograms are the most widely used statistical features in computer vision. They are often used for the illumination independent characterization of the color distribution of the pattern. However, color histograms do not exploit the spatial layout of the colors. A good way to include such lost information is to use statistical moments as features. Color moments improve the characterization the shape and color distribution of the pattern and have proven to be effective features under changing viewpoint and illumination (Moons, 2004).

Most previous feature extraction methods were conducted in original spectral bands (e.g. RGB color space), which were often fragile in visually complex environments. Incorporating domain knowledge might be a better way in real-world image analysis projects. From the literature review, the dominant method for interpreting vegetation biophysical properties from optical remote sensing data is through spectral vegetation indices. Plants have distinctive spectral signatures which is often modelled by combinations of reflectance measured in two or more spectral bands (Myneni et al., 1995). To our knowledge, little work has been done on utilizing vegetation indices as visual feature descriptors to combine multiple spectral bands for vegetation species classification from remote sensing images.

In this paper, we take the advantage of vegetation spectral properties and use spectral moment features for object-based vegetation species classification. To evaluate the usefulness of spectral moment features, the state-of-art texture features such as Gray-Level Co-Occurrence Matrix (GLCM) and Local Binary Patterns (LBP) are also extracted for comparison purpose. Different feature descriptors were compared by means of classification accuracy. A Support Vector Machines (SVM) classifier is employed for the classification in object-feature space. Multispectral images are collected in a power line

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corridor for vegetation management purposes and an extensive experiment on this dataset is conducted.

2. STUDY AREA AND DATA

The data used in this research were collected in rural Queensland Australia in October 2008 for research into vegetation management in power line corridors. The reason why we need species information of individual trees is that vegetation management in power line corridors is based on their potential risks to power lines. Some tree species are of particular interest and are generally categorized as undesirable and desirable species. For example, species with fast growing rates and that also have the potential to reach a mature height of more than four meters are defined as undesirable species. These undesirable species often pose high risks to power lines and therefore should be identified and removed.
The images were captured in a 1.5 kilometres corridor by a high resolution 3-CCD digital multi-spectral camera mounted on fixed wing aircraft. Figure 1 shows a mosaic of the test area generated from aerial images acquired from the trial. The four spectral bands of the camera are: NIR (800-966 nm), red (670-840 nm), green (540-640 nm), and blue (460-545 nm). The spatial resolution of the captured images is about 15 cm. The ground truth data of vegetation species were obtained from a field survey with domain experts' participation.

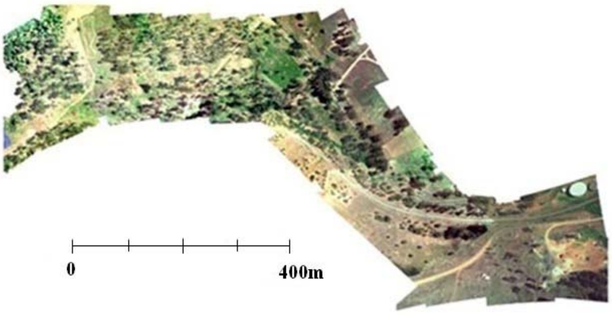


Figure 1. Experiment test site

It should be noted that classifying all types of species in power line corridors requires significantly more resources than are currently available, however, classifying species in a given test area as a proof of concept is possible. In this research, we focus on three dominant species in our test field: *Eucalyptus tereticornis*, *Eucalyptus melanophloia*, and *Corymbia tesselaris*. These three species Here we abbreviate the species names to *Euc_Ter, Euc_Mel* and *Cor_Tes*. According to the field survey, these three species account for over 80% of all the trees in the test corridor.

3. METHODS

In this research, object-based image analysis is adopted which consists of a three-stage processing: image segmentation, spectral and texture feature extraction, and supervised classification employing SVM.

3.1 Image Segmentation

Successful object-based image analysis results largely depend on the performance of image segmentation. Since we are going to classify the species among trees, tree crowns are the only image-objects of interest in our research. The aim of segmentation is, therefore, to detect and delineate all trees from images while eliminating other image regions. We have developed an automatic tree crown detection and delineation algorithm by utilizing spectral features (i.e. band ratio of near-infrared and red) in a pulse coupled neural network (PCNN) followed by post-processing using morphological reconstruction (Li et al., 2009). Since PCNN is capable to capture the proximity of image structure and texture, this method can automatically detect and delineate tree crowns from multi-spectral images and has been proved to be superior to some classic segmentation algorithms. Figure 2 shows an example of the segmentation results generated by our automatic segmentation algorithm.
Although the automatic segmentation is satisfied from visual assessment, decomposition of tree clusters is occasionally poor. Since the main aim of this research is evaluate the effectiveness of different feature descriptors for detailed vegetation species classification, manual segmentation is used to minimize the influence of inaccuracy in segmentation. The background is removed and each tree crown is labelled with a unique label to identify the tree which is paired against individual tree species obtained from field surveys. After segmentation, different feature descriptors are extracted from the segments (i.e. tree crowns) and used for training classifiers.

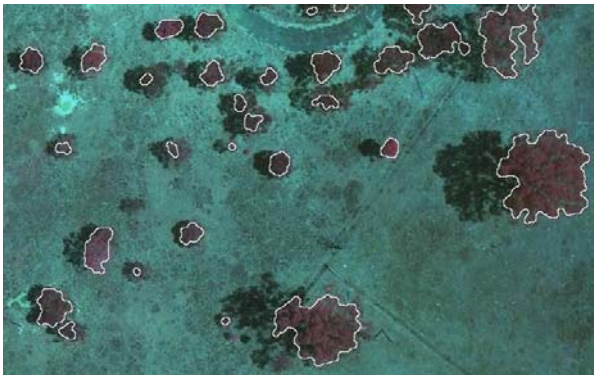


Figure 2. Example of automatic segmentation results

3.2 Spectral and Texture Feature Extraction

The object-based classification is substantially different from a per-pixel classification as it is done in object-feature space. Once the image-objects are segmented, both spectral and spatial attributes of each image-object (polygon) are extracted and used as input to a variety of classification algorithms for analysis. The basic approach to compute object-features from a multi-spectral image is to calculate separately the derivatives of the spectral channels. However, to generate features which could have high discriminative power among tree species is difficult as they all look green from visual spectrum. In addition, there can be large variations in lighting and viewing conditions for remotely sensed images, which may greatly affect the classification results if the feature descriptors used are not robust to these changes.

3.2.1 Spectral Moment Features: Color histograms are often used for the illumination independent characterization of the color distribution of the pattern. However, color histograms do not exploit the spatial layout of the colors. A good way to include such lost information is to use moments. Probability theory identifies that a probability distribution is uniquely characterized by its moments. Based on this idea, moment features have been proposed for color indexing (Stricker et al., 1995). However, moment features are mostly extracted from image as global features for image retrieval purpose, few work has been done on trying to represent image-object using moment features in object based image classification.

Since most information is concentrated on the low-order moments, only four central moments are considered as feature vectors in this research. They are defined as (Weinbach et al., 2007):

$$\mu = \frac{1}{\mathrm{N}}\sum_{i=1}^{N} s_i \tag{1}$$

$$\sigma = \sqrt{\frac{1}{\mathrm{N}}\sum_{i=1}^{N}(s_i-\mu)^2} \tag{2}$$

$$sk = \left(\frac{1}{N\times\sigma^3}\times\sum_{i=1}^{N}(s_i-\mu)^3\right)^{1/3} \tag{3}$$

$$ku = \left(\frac{1}{N\times\sigma^4}\times\sum_{i=1}^{N}(s_i-\mu)^4\right)^{1/4} \tag{4}$$

where in equations (1-4) N is total number of pixels within the image-object (i.e. tree crown), μ is the arithmetic mean, and σ represents the standard deviation, sk stands for the third moment skewness, and ku indicate the fourth moment kurtosis.

Plants have distinctive spectral properties. In the past decades, many spectral vegetation indices have been developed as measurements of relative abundance and activity of green vegetation. These vegetation indices are developed for purposes such as to estimate vegetation biophysical properties, to normalize or model external effects like viewing and sun angle variations and internal effects like background and soil variations (Jensen, 2000). Most of these vegetation indices are calculated from the near-infrared and red band of the spectrum. These vegetation indices have been successfully applied to measure biophysics of green vegetation. However, there has been very limited work on using these vegetation indices as feature descriptors for detailed vegetation species mapping, especially from the individual tree perspective.

In this paper, moments extracted from three widely used vegetation indices maps are evaluated: Ratio Vegetation Index (RVI) (Jordan, 1969), Normalized Difference Vegetation Index (NDVI) (Rouse et al., 1973) and Perpendicular Vegetation Index (PVI) (Richardson et al., 1977). They are defined as:

$$RVI = \frac{\rho_{NIR}}{\rho_{red}} \tag{5}$$

$$NDVI = \frac{\rho_{NIR}-\rho_{red}}{\rho_{NIR}+\rho_{red}} \tag{6}$$

$$PVI = \frac{\rho_{NIR}-a\rho_{red}-b}{\sqrt{1+a^2}} \tag{7}$$

where ρ_{NIR} and ρ_{red} are the spectral reflectance of near-infrared and red band respectively. The parameters of PVI are set to be a=0.96916,b=0.084726 according to literature (Seo et al., 1998).

3.2.2 Texture Features: Texture contains important information in image classification, as it represents the content of many real-world images. Textures are characteristic intensity (or color) variations that typically originate from roughness of object surfaces (Davies, 2008). As a powerful source of information, texture features have been intensively studied in remote sensing image classification (Zhang et al., 2004, Franklin et al., 2000, Reulke et al., 2005, Samal et al., 2006). There are many different methods used to extract model texture from images. In this paper, we evaluated the widely used GLCM texture measures and state-of-art texture descriptor Local Binary Patterns (LBP) and its extensions: uniform LBP, rotation-invariant LBP, dominant local binary patterns (DLBP). In this section, an overview of these texture descriptors is given.

The image-objects generated from segmentation is arbitrary-shaped, however, texture measurements are usually extracted based on the texture property of pixels or small blocks within the rectangular shaped region. Therefore, in this paper, the arbitrary-shaped objects are extended to a rectangular area for texture extraction. This can be achieved by padding zero or mean value outside the object boundary, or obtaining the inner rectangle from the object. Zero padding introduces spurious high frequency components leading to degrading the performance of the texture feature, while the inner rectangle cannot usually represent the property of the entire object well. Mean-intensity padding has shown better performance than the other two approaches (Liu et al., 2006) and thus is adopted in this paper. Firstly, the minimum bounding rectangle is obtained from the image segment, and then the area which is outside of the segment and inside of the minimum bounding rectangle is padded using the mean value of pixels in the region.

Grey-level co-occurrence matrices (GLCM) have been successfully used for deriving texture measures from images. This technique uses a spatial co-occurrence matrix that computes the relationships of pixel values and uses these values to compute the second-order statistics (Haralick et al., 1973). The GLCM approach assumes that the texture information in an image is constrained in the overall or “average” spatial relationships between pixels of different grey level. In this paper, we use mean and standard deviation of four measures from the grey-level co-occurrence matrices: energy, entropy, contrast, and homogeneity.

LBP is first proposed by Ojala et al. to encode the pixel-wise information in the texture images (Ojala et al., 2002). The LBP method attempts to decompose the texture into small texture units and the texture features are defined by the distribution (histogram) of the LBP code calculated for each pixel in the region under analysis. Figure 3 gives an example of binary code in a 3×3 neighbourhood which generates 2^8 possible standard texture units. The LBP value for the centre pixel is calculated using the following equation:

$$LBP_{P,R} = \sum_{i=0}^{p-1} u(\mathrm{t}_i - t_c)\times 2^i \tag{8}$$

where P is the total number of neighbouring pixels, R is the radius used to form circularly symmetric set of neighbours. In this paper, we use $P=8, \mathrm{R}=1$.

Although LBP has proven to be a powerful texture descriptor, a number of extensions have been proposed to improve or supplement the classic LBP operators. We also evaluated several extensions to the conventional LBP operator including: uniform LBP, rotation-invariant LBP, and dominant LBP (DLBP) (Ojala et al., 2002, Liao et al., 2009). The uniform LBP is used to represent the most important microstructures, which contain at most two bitwise (0 to 1 or 1 to 0) transitions. The rotation-variant LBP is produced by circularly rotating the original the original LBP code until its minimum value is attained, making LBP code invariant with respect to rotation of the image domain. DLBP only considers the most frequently occurred patterns, and try to avoid the information loss caused by just considering the uniform LBP and the unreliability by considering all possible patterns.

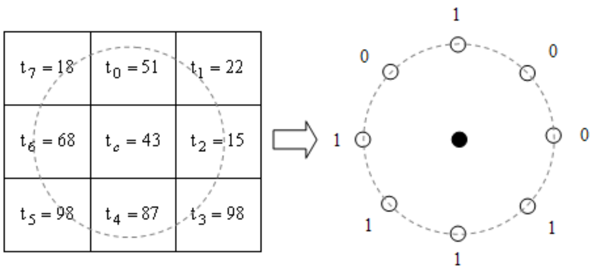


Figure 3. Example of binary code calculation in a 3×3 neighbourhood. The binary labels of the neighbouring pixels is obtained by applying a simple threshold operation with respect to the centre pixel t_c. $u(t_i - t_c)$ represents a step function, where $u(x) = 1$ when $x \geq 0$; else, $u(x) = 0$.

3.3 Supervised Classification Using SVM

In this research, the species distribution in the test area is known a priori through the field survey and thus supervised classification is adopted to evaluate the discriminative power of different features in vegetation species classification. From our field survey, a vegetation database has been generated by giving each tree in the test field a unique ID and recording several attributes of each tree (e.g. species name and values of all extracted object-features).

In our research, Support Vector Machines (SVMs) are employed as the classification methodology. SVM is an machine learning technology which has been successfully used in a variety of pattern recognition tasks and often outperforming other classification methodologies (e.g. Artificial Neural Networks) (Mills, 2008). The basic idea of SVM is to find an optimal decision function (a hyperplane) with the largest margin to separate the training data $\{x_1, x_2, ..., x_n\}$ with a label $y_i \in \{-1, +1\}$ into the positive (+1) or negative (-1) classes. The decision function is described as equation (9), and decision could be made according to that when $f(x) = 0$, x is classified as +1, otherwise, x is classified as -1. Figure 4 illustrates a simple linear separable case.

$$f(x) = w \cdot x + b \tag{9}$$

For data not linearly separable in the input space, SVM would map the data from the initial space to a (usually significantly higher dimensional) Euclidean space H by computation of inner-product kernels $K(x_i, x)$. After the mapping, the data, which is not linearly separable in the input space, become linearly separable in the H space. Thus, the SVM classifiers can be described as equation (10). Various classification methods are constructed by employing different kernel functions $K(x_i, x)$ (e.g., linear, polynomial, RBF, sigmoid, etc.). Radial basis function (RBF) is selected in this paper as it often suggested as the first choice since it has several advantages over other common kernel functions (Hsu et al., 2008): 1) unlike linear kernel, RBF nonlinearly maps samples into a high dimensional space, so it can handle the case when the relation between class labels and attributes is nonlinear; 2) RBF kernel has less hyperparameters than the polynomial kernel which make it less complex in model selection; 3)

$$f(x) = \sum_{i=1}^{n} y_i \alpha_i K(x_i, x) + b \tag{10}$$

$$\text{RBF kernel } K(x, y) = \exp(-\gamma \| \text{x - y} \|)^2 \tag{11}$$

where $0 \leq \alpha_i \leq C$ is the maximal margin hyperplane in the H space. When the maximal margin hyperplane is found, only those points that lie closest to the hyperplane have $0 \leq \alpha_i \leq C$, and these points are the *support vectors*.

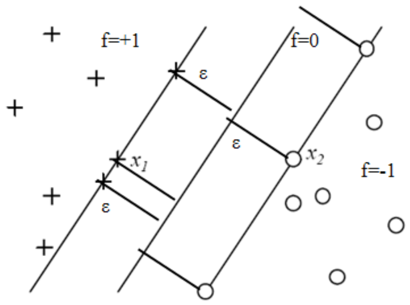
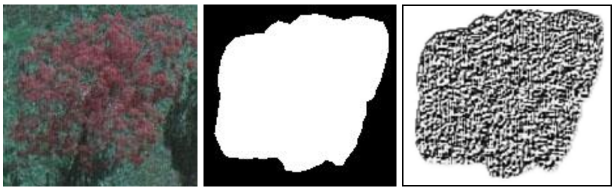


Figure 4. A linearly separable binary classification problem. The optimal hyperplane is with the maximum *margin* ε between the separating hyperplane and a hyperplane through the closest points of each of the two classes. These closest points are called the *support vectors* (x_1 and x_2 are examples of support vectors).

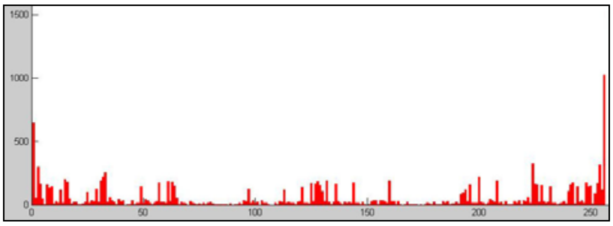
4. EXPERIMENT AND RESULT

4.1 Experiment Setup

The proposed spectral moment features are evaluated against the LBP and GLCM texture features on the multispectral data set discussed in section 2. The experiments are conducted in an open source SVM toolbox (SVMKM) (Rakotomamonjy et al., 2008). For the decision function of SVM, two parameters γ and C are specified using a grid search scheme. The 'one against one' strategy is employed for multi-class classification. The training samples include 75 trees with 25 for each species. Two testing datasets were used for evaluation with 60 samples in each dataset. Totally 10 region feature descriptors are extracted from the segments (polygons), of which LBPs and GLCM texture features are extracted from grey channel which is derived by averaging the four spectral bands. The LBP and its extensions are calculated in a 3×3 neighbourhood. All the feature descriptors are extracted from the regions of interest (segmented tree crowns). Figure 5 shows an example of LBP texture feature extraction from tree crowns. The extraction of other feature descriptors also follows the same procedure. Table 6 lists the evaluated features in the experiment, their abbreviations and feature dimensions.



(a) Original image (b) region of interest (c) LBP code image



(d) LBP histogram on the region of interest

Figure 5. Example of feature extraction from tree crowns

Feature	Abbr.	Dimension
Grey-level co-occurrence matrices	GLCM	8
Local Binary Pattern	LBP	256
Dominant Local Binary Patterns	DLBP	205
Uniform Local Binary Patterns	ULBP	59
Rotation-invariant Local Binary Patterns	ri_LBP	10
Spectral moments in RGB space	m_RGB	12
Spectral moments in CIR space	m_CIR	12
Spectral moments in RVI space	m_RVI	4
Spectral moments in NDVI space	m_NDVI	4
Spectral Moments in PVI space	m_PVI	4

Table 6. Evaluated features

4.2 Results and Discussion

The overall classification accuracy is obtained by comparing the classified data and the ground truth reference data. The overall accuracy is defined as:

$$Accuracy = \frac{Number\ of\ correct\ predictions}{Total\ number\ of\ samples} \qquad (12)$$

Figure 6 compares the average classification accuracies in two datasets by using different feature descriptors. Classification accuracies in testing dataset1 using four central moments of RGB, CIR, RVI, NDVI and PVI spectral sub-space, LBP, uniform LBP, rotation-invariant LBP, DLBP and GLCM are 0.5, 0.533, 0.65, 0.567, 0.533, 0.45, 0.45, 0.467, 0.383, and 0.5 respectively. From the results we can see that the use of moments in spectral vegetation indices indicate higher classification accuracy than using original spectral bands and the state-of-art texture descriptors. Similar results were obtained in dataset2 with the average classification accuracy of 0.683, 0.717, 0.733, 0.717, 0.683, 0.733, 0.75, 0.617, 0.717, and 0.717 respectively for the 10 feature descriptors. From the experiment, we can see that incorporating spectral vegetation index in moment feature extraction improved the classification accuracy and the spectral moments in RVI showed the best performance.

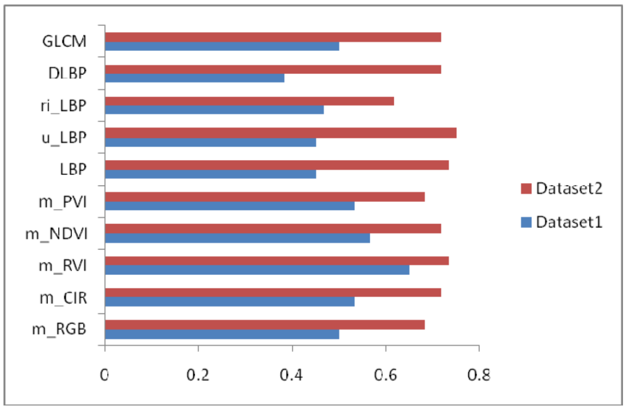


Figure 8. Evaluation of feature descriptors on two testing datasets. The horizontal axis indicates the average classification accuracy and the vertical axis compares different features descriptors.

Table 7 presents the average classification accuracies of the 10 features per category. It is noted that the evaluated features have different discriminative powers for different tree species. Therefore, it would be interesting to investigate whether the integration of multiple features will improve the classification result and how to select and fuse different features. A possible solution is to use feature subspace selection methods such as principal component analysis (Lu et al., 2007) and locally linear embedding (Roweis et al., 2001). These algorithms have been reported to be effective in reducing the dimensions of input space and achieving better performance which might be helpful when multiple features are used.

Trees can often show different appearances in different seasons and even the same tree species may vary due to the their health status. Nevertheless, from our experiment we can conclude that the spectral moment fetures derived from spectral index maps have the potential to improve the accuracy in detailed vegetation mapping tasks. Our future work is to fuse multiple spectral and texture features to further improve the classification accuracy.

Category	m_RGB	m_CIR	m_RVI	m_NDVI	m_PVI	LBP	ULBP	ri_LBP	DLBP	GLCM
Euc_Ter	0.725	0.675	0.65	0.8	0.65	0.375	0.375	0.325	0.35	0.4
Euc_Mel	0.6	0.6	0.675	0.625	0.575	0.65	0.475	0.425	0.45	0.475
Cor_Tes	0.45	0.6	0.75	0.5	0.6	0.75	0.95	0.875	0.85	0.95

Table 7. Overall classification accuracies of 10 features per category

5. CONCLUSION

This paper evaluates the capability of spectral moment and texture features for object-based vegetation species classification. Totally 10 spectral and texture feature descriptors were evaluated using SVM by means of classification accuracy. The experimental results showed that spectral moment features has the potential to improve the accuracy in individual tree species classification from high resolution multispectral images.

The use of spectral moment in RVI indicates the highest classification accuracy in our experiment.

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