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Analyzing fine-scale wetland composition using high resolution imagery and texture features

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ABSTRACT

In order to monitor natural and anthropogenic disturbance effects to wetland ecosystems, it is necessary to employ both accurate and rapid mapping of wet graminoid/sedge communities. Thus, it is desirable to utilize automated classification algorithms so that the monitoring can be done regularly and in an efficient manner. This study developed a classification and accuracy assessment method for wetland mapping of at-risk plant communities in marl prairie and marsh areas of the Everglades National Park. Maximum likelihood (ML) and Support Vector Machine (SVM) classifiers were tested using 30.5 cm aerial imagery, the normalized difference vegetation index (NDVI), first and second order texture features and ancillary data. Additionally, appropriate window sizes for different texture features were estimated using semivariogram analysis. Findings show that the addition of NDVI and texture features increased classification accuracy from 66.2% using the ML classifier (spectral bands only) to 83.71% using the SVM classifier (spectral bands, NDVI and first order texture features).

1. Introduction

Wet graminoid communities such as marl prairies and marshes are being degraded and altered in the Florida Everglades due to encroachment from urban uses and land use changes. These communities cover substantial portions of the Florida Everglades ecosystem (Davis et al., 1994) and also provide key habitat and food for several wildlife species. Such changes in graminoid community distribution could be used as indicators to monitor and assess the effects of ecological and anthropogenic disturbance and other ecological shifts due to climate and/or land use changes (Goodin and Henebry, 1997; Pearlstine et al., 2010). Indeed, Olmsted and Armentano (1997) stressed the importance of monitoring wetland vegetation and confirmed that accurate spatial data on vegetation distributions is key to better understand and detect changes in ecosystem function at the local and landscape scales. In fact, rapid and accurate discrimination of wet graminoid communities using remote sensing technologies has been the most frequently cited challenge in past attempts at land cover classification in many areas worldwide including the Everglades (Ferguson, 1991; Gluck et al., 1996; Ozesmi and Bauer, 2002).

Remote sensing is regularly used to provide rapid and large scale discrimination of plant communities, including marsh and wet prairie (Smith et al., 1998; Belluco et al., 2006). However, spectral similarity and inter-digitations between these two previously mentioned communities prevents high classification accuracies using a single remote sensing data source (i.e. spectral bands only) or other standard classification approaches such as parallelepiped or maximum likelihood classification methods (Gluck et al., 1996; Ozesmi and Bauer, 2002; Schmidt and Skidmore, 2003). Also, coarse spatial resolutions can significantly affect image classification accuracy, especially in riparian and wetland areas as reported by Yang's (2007) and Maheu-Giroux and Blois' (2005) studies.

For example, Yang (2007) demonstrated the significance of high spatial resolution (2 m) scanned ortho-rectified color aerial images and ancillary data (e.g. digital elevation model and land use map) inclusion in accurately classifying riparian zone vegetation in the Hunter Region of Australia when compared to Satellite Pour l'Observation de la Terre (SPOT)-4 and Landsat-7 Enhanced Thematic Mapper (ETM+) imagery. The overall accuracy of the high resolution aerial imagery results was 81% while SPOT-4 and Landsat-7 provided 63% and 53% overall accuracy. Maheu-Giroux and Blois (2005) used scanned black and white (B&W) and color aerial photos (0.33 m ground resolution) to discriminate common reed (*Phragmites australis*), an invasive plant, from other types of

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vegetation and achieved an overall accuracy between 71 and 87% for panchromatic image analysis and 77–88% for color imagery in the South shore of Montreal, Quebec, Canada. However, differences were not statistically significant. Additionally, Dillabaugh and King (2008) used the spectral bands of IKONOS imagery (4 m spatial resolution) to discriminate wetland vegetation types near Ottawa, Ontario, Canada. The authors noted an increase in overall classification accuracy of 61–88% when the Normalized Difference Vegetation Index (NDVI) was included in the analysis; however wetland classes (i.e. emergent terrestrial, shrub and grass-sedges) were also merged, because of the high confusion rate between classes.

High resolution imagery also provide better discrimination through the extraction and use of first and second order texture features (Haralick et al., 1973; Wang et al., 2004). This sort of contextual identification can improve the classification accuracy of high-resolution images (Ge et al., 2006; Waser et al., 2008). Moreover, the spatial neighborhood of a pixel might provide additional information than the sole use of this individual pixel spectra (Dell'Acqua et al., 2006). Spectral features can also provide additional information as they describe the average tonal variations in various bands of the visible and infrared portions of the electromagnetic spectrum, whereas using textural features will provide information on the spatial distribution of tonal variations within a band (Haralick et al., 1973).

First (i.e. range, mean, standard deviation/variance and entropy) and second (i.e. angular second moment, contrast, correlation, entropy, homogeneity, dissimilarity) order texture features have also been commonly used in remote sensing studies (Haralick et al., 1973; Wulder et al., 1998; Baraldi and Parmiggiani, 1995; Clausi, 2002; Coburn and Roberts, 2004; Pearlstine et al., 2005; Puissant et al., 2005; St-Louis et al., 2006; Ashish et al., 2009). For example, Coburn and Roberts (2004) found that the inclusion of variance increased the classification accuracy of land cover classes by 9%. Also, Pearlstine et al. (2005) concluded that the mean and standard deviation features were very effective in discriminating Brazilian pepper (*Schinus terebinthifolius*) from other type of vegetation. Furthermore, St-Louis et al. (2006) used first order texture measures to predict bird species richness and reported that range and standard deviation were significant predictors and Ashish et al. (2009) observed that mean and standard deviation increased overall mapping accuracy.

Additionally, the inclusion of textural features has been assessed by other studies such as Gong et al. (1992) who compared several texture features in the land-use classification of SPOT HRV multispectral data at the rural-urban fringe of Metropolitan Toronto, Canada and concluded that the combined image using the standard deviation and the angular second moment (ASM) (5×5 pixel window size, GLCM method) produced the best classification results. Other studies by Baraldi and Parmiggiani (1995) found that ASM, contrast and correlation provided the best results when classifying an Advanced Very High Resolution Radiometer (AVHRR) image using cluster analysis. Also, Wulder et al. (1998) tested Haralick's texture features using Compact Airborne Spectrographic Imager (CASI) imagery and found that homogeneity, contrast, dissimilarity, and entropy were useful. Another study by Clausi (2002) recommended that contrast, correlation, and entropy extracted from Synthetic Aperture Radar (SAR) imagery and classified using maximum likelihood classifier were also useful, while Puissant et al. (2005) recommended the use of the homogeneity texture feature using SPOT-5 imagery. Since textural features are scale dependent, determining the optimal window size to extract these features is also of particular important (Puissant et al., 2005; Tso and Mather, 2009). In general, relatively large window sizes perform better for higher resolution images and spatially heterogeneous classes (Puissant et al., 2005; Murray et al., 2010). Conversely, small window sizes yield a higher accuracy for spatially homogeneous classes (Ashish et al., 2009). Tso and Mather (2009) noted that if the window size is too small, relative to the examined texture feature, the true properties of the texture feature may not be accurately depicted. That said, determining the appropriate window size for certain scales is difficult (Dell'Acqua et al., 2006). Semivariograms have been extensively used in remote sensing studies to calculate optimal neighborhood size (Franklin et al., 1996; Dell'Acqua et al., 2006; Johansen et al., 2007; Balaguer et al., 2010). For example, Franklin et al. (1996) used semivariogram range to estimate and select the appropriate and optimal window size for different vegetation classes in an image.

As demonstrated by Wang et al. (2004), the Maximum likelihood (ML) classifier delivered good overall classification results (75%) when using spectral bands and derived texture features using 1 m spatial resolution IKONOS imagery. The ML classifier assumes a normal distribution of the input data (Richards and Jia, 2006), despite the fact, that texture features do not generally have a normally distribution (Maillard, 2003). However, as Clark and Hosking (1986) pointed out, if the sample size is the same for all texture features and is reasonably large; the normal distribution assumption can be eased. In addition to the ML classifier, several other machine learning algorithms have been proposed recently such as the Support Vector Machine (SVM) algorithm (Tso and Mather, 2009) which can deliver promising classification results of remotely sensed data (Mountrakis et al., 2011).

Overall, these previously mentioned studies have documented the use and importance of remote sensing techniques to assess the effects of ecological disturbance to wetlands from climate and/or land use changes. In addition, studies show that inclusion of additional textural features and scale-specific window sizes improve classification accuracy (Franklin et al., 1996; Wang et al., 2004; Mountrakis et al., 2011). However, as Pearlstine et al. (2010) and Olmsted and Armentano (1997) noted, marl prairie and marsh plant communities are difficult to classify in a rapid, automated and accurate manner due to spectral similarities.

Therefore, the overall goal of this study is to develop a rapid and accurate classification methodology utilizing the spectral characteristics of very high resolution digital aerial imagery (30 cm), textural features, and ancillary data. More specifically, this study's hypothesis is to determine if incorporating first and second order textural features significantly improves the classification accuracy of highly heterogeneous plant communities in a wetland environment. This study builds on previous studies, however it uses multiple combinations of spectral and textural features and ancillary data as additional dimensions to improve classification accuracy in a challenging wetland landscape dominated by marl prairie and marsh plant communities. Multiple window sizes for first and second order texture features are also tested to identify optimal parameters for achieving the highest classification accuracy.

2. Methods

2.1. Study area and field data collection

We selected an 8.5 km^2 study area located in the south eastern portion of the Everglades National Park (ENP) in the United States (25°25′09.09″ to 25°24′15.16″N and 80°46′41.46″ to 80°45′41.00″W) as shown in Fig. 1. Similar to the overall characteristics of the ENP, our study area was flat with elevations ranging from 0 to 0.6 m above sea level. The major plant communities in the study area were defined by their dominant species and marsh types. The selected plant communities were dominated by fewer than 10 species (Kushlan, 1990; Craft et al., 1995; Olmsted and Armentano,