Texture Augmented Detection of Macrophyte Species Using Decision Trees

Cameron Proctor^{a*}, Yuhong He^b, Vincent Robinson^c

Department of Geography, University of Toronto Mississauga, 3359 Mississauga Road N,
William G. Davis Bldg, Mississauga, Ontario, CANADA L5L 1C6

Department Fax: (905) 828-5273

^acameron.proctor@utoronto.ca

3359 Mississauga Road N.

Mississauga, ON

L5L 1C6

(416) 792-4830

^byuhong.he@utoronto.ca

^cdoc.robinson@utoronto.ca

*Corresponding Author

Abstract. Image classification using multispectral sensors has shown good performance in detecting macrophytes at the species level. However, species level classification often does not utilize the texture information provided by high resolution images. This study investigated whether image texture provides useful vector(s) for the discrimination of monospecific stands of three floating macrophyte species in Quickbird imagery of the South Nation River. Semivariograms indicated that window sizes of 5x5 and 13x13 pixels were the most appropriate spatial scales for calculation of the grey level co-occurrence matrix and subsequent texture attributes from the multispectral and panchromatic bands. Of the 214 investigated vectors (13 Haralick texture attributes * 15 bands + 9 spectral bands + 10 transformations/indices), feature selection determined which combination of spectral and textural vectors had the greatest class separability based on the Mann-Whitney U-test and Jefferies-Matusita distance. While multispectral red and near infrared (NIR) performed satisfactorily, the addition of panchromatic-dissimilarity slightly improved class separability and the accuracy of a decision tree classifier (Kappa: red/NIR/panchromatic-dissimilarity - 93.2% versus red/NIR - 90.4%). Class separability

31 improved by incorporating a second texture attribute, but resulted in a decrease in classification
32 accuracy. The results suggest that incorporating image texture may be beneficial for separating
33 stands with high spatial heterogeneity. However, the benefits may be limited and must be
34 weighed against the increased complexity of the classifier.

1. Introduction.

Macrophytes play an important role in many biogeochemical processes such as the production of methane and the fixation of carbon and nitrogen (Matthews & Fung, 1987; Harden & Chanton, 1994). However, the services macrophytes perform are likely to change in the near future as climate change is predicted to cause a considerable shift in macrophyte community composition (Root et al., 2003). Specifically, global warming may increase the introduction of invasive species that can alter the physical and chemical characteristics of wetlands and cause significant disturbance that affects populations, communities and ecosystem processes (Benoit & Askins, 1999). In order to address the many questions regarding macrophyte community composition change and its effects, a reliable and detailed macrophyte monitoring methodology is needed. Field based surveys are often weak in this regard, as they are only practical on relatively small areas (Lee and Lunetta, 1996) and have limited ability to capture the distribution of macrophytes in an entire lake (Zhang, 1998).

As individuals or small macrophyte stands are often of sub-meter to meter extent, monitoring macrophyte via remote sensing can be challenging. Typically the spatial resolution of the sensor must match the size of the target species in order for the species to approach dominance per pixel (Jensen et al. 1993). Previous attempts at species discrimination indicate that the moderate spatial resolution of SPOT and Landsat imagery are insufficient for discrimination at the species level (Armstrong 1993; Zhang 1998; Laba et al., 2008). However, studies focusing on the utility of high spatial resolution (HSR) imagery for multispectral detection of macrophytes demonstrate that good classification accuracy is achievable. Sawaya et al., (2003) revealed that five classes of emergent and four classes of submerged macrophytes could be discriminated from IKONOS imagery with an overall accuracy of 79.5% and

producer's and user's accuracies from 36% to 100%. As to be expected, heterogeneous communities with sparse vegetation cover had lower classification accuracy than dense beds of cattail/arrowhead and lily/floating leaf pondweed. At the species level, Dogan et al., (2009) utilized Quickbird imagery to classify three submerged macrophyte classes and two water classes in Lake Mogan, Central Anatolia. Utilizing an unsupervised classification technique, an overall accuracy of 71.69% was achieved regardless of problems with mixed pixels due to the species being submerged in the water column. In addition, Laba et al., (2008) utilized Quickbird imagery to conduct a land cover classification involving nine species level classes of emergent or floating macrophytes in estuarine ecosystems and coastal watersheds. Classification accuracy ranged from 64.9% to 73.6% between four test areas with unique water chemistry (i.e., brackish, oligotrophic and fresh).

One of the challenges in utilizing HSR multispectral imagery is that floating macrophyte species have similar biochemical composition such that their spectral signatures may not be sufficiently unique to separate classes (Ge et al., 2006). To respond to the challenges posed by weak spectral variability, many techniques have been developed to utilize the information supplied by image texture. Image texture can be broadly defined as the visual patterns or spatial arrangements of pixels that may have statistical properties, structural properties or both (Haralick, et al., 1973; Borne 1994; Krishnamoorthi & Seetharaman, 2007). In terms of remotely sensed imagery, texture can be defined as the local brightness variation in a small neighborhood surrounding each pixel (Ross, 2011). Image texture has been associated with many vegetation parameters such as forest-structure variables (age, top height, circumference and basal area) (Kayitakire, et al., 2006; Vincent, et al., 2012), which are often unique to certain vegetation classes, but are not apparent by their spectral signatures.

The combination of spectral and texture information often outperforms spectral vectors alone (Johansen & Phinn, 2006). Rao et al., (2002) noted that classification of IRS-1D panchromatic band of the diverse land cover in the Prakasam District of India improved with the incorporation of texture derived using the Grey Level Co-occurrence Matrix (GLCM) approach. Eight popular texture measures derived from a 1-11 pixel window size were semi-qualitatively tested for their capability to discriminate different land cover classes. Utilizing GLCM derived entropy and correlation, an overall classification accuracy of 88.71% was achieved, which is considerable greater than the 62.89% achieved by the panchromatic band alone. However, a panchromatic and texture classification further improved the accuracies to 96.24%. Furthermore, textural attributes can be derived from non-optical remote sensing imagery. Arzandeh & Wang, (2003) derived texture from RADARSAT imagery in a spectral-textural classification monitoring the colonization the *Phragmites australis* in the cattail dominated Walpole Island in southern Ontario. Incorporation of RADARSAT texture improved the overall accuracy regardless of whether the imagery source was Landsat thematic mapper, Satellite pour l'Observation de la Terre (SPOT) or the Indian Remote Sensing Satellite. Yet the increase in accuracy was minor, with the highest overall accuracy increase only ~3.5% for the SPOT classification.

In terms of texture augmented classification of macrophytes, Laba et al., (2010) reported mixed results in a four species level and seven land cover classification of the Hudson River National Estuarine Research Reserve. A spectral-textural maximum-likelihood classification utilizing variance obtained from a moving window decreased the classification accuracy, often drastically, for the target invasive species classes. Reductions in accuracy were more likely from species that occurred in narrow strips or small patches, suggesting that texture is poorly

representative in these patches due to edge effects and the influence of neighboring patches. In contrast, the results from an object oriented spectral-textural classification were marginally better than a spectral only classification (77.7% versus 76.2%). Interestingly the improvement was not systematic, with increases and decreases between the user's and producer's accuracies fluctuating from the spectral classification baseline. For instance, producer's accuracy for *L. salicaria* decreased from 78 to 65% while user's accuracies increased from 75 to 83%. Moreover the object oriented approach accuracy decreased similarly to the initial moving window approach when a larger (5x5) window is used, suggesting that useful textures are locally defined.

However, textural variations between floating macrophyte species have not been examined and it remains in question whether morphological or colonization pattern differences manifest as unique image textures. The aim of this paper is to investigate the utility of a texture augmented classifier to differentiate between stands of three floating macrophyte species. As the texture attribute(s) that improve class separability are unknown, this paper conducts a thorough analysis on a wide range of attributes derived from multispectral, panchromatic, pansharpened, transformed imagery and vegetation indices. Good performing spectral and textural vectors are selected through feature selection that identifies the best combination(s) based on two test of class separability. Combinations of vectors are assessed for overall classification accuracy utilizing a standard training data set and supervised classifier. Since classification results can be affected by differences in scale among the variables, decisions tree classification is utilized as the statistical inferential technique. Decision tree classifiers are an appropriate choice as they are non-parametric rule-based classifiers that can handle nonlinear relations between classes, are easily translatable across scenes and are intuitive (Fayyad & Irani, 1992).

2. Methods and Approaches

2.1 Study area, imagery and field data

The study area is within a 6km section of the South Nation River downstream from the town of Spencerville in the Southeastern Ontario region (Figure 1). As the study area is near the headwaters of the South Nation River, the current is weak and water drains slowly throughout the study area. Bays or inlets off the main water course are partially sheltered, creating pools of water that are partially immobile and stagnant in certain sections. The study area is predominantly comprised of marshland and shallow open water wetlands (National Wetlands Working Group, 1987). Three species of floating macrophytes are present within the study area. The invasive European Frog-bit (*Hydrocharis morsus-ranae*) is the dominant floating macrophyte, established extensively throughout the study area. Native floating macrophytes Duckweed (*Lemna minor*) and Yellow Water-lily (*Nuphar lutea*) are present in limited patches and isolated bays near to shore. As the majority of the littoral zone is colonized by floating macrophytes, submerged macrophytes Coontail (*Ceratophyllum demersum*) and Floating-leaf Pondweed (*Potamogeton natans*) are often concealed from the canopy, occurring to a limited extent in stagnant water. Terrestrial species along the riparian zone are a mixture of Common Reed (*Phragmites australis*), Narrowleaf Cattail (*Typha angustifolia*) and other grasses and mixed forest predominantly comprised of deciduous species common to Southeastern Ontario such as Red Maple (*Acer rubrum*), Eastern White Cedar (*Thuja occidentalis*), Paper Birch (*Betula papyrifera*), etc. The classification schema (Table 1) is based upon the species noted during the field survey. Three classes are species level classes (contain a single vegetation species) and the remaining land cover types are comprised of multiple species or no vegetation.

Quickbird imagery of the study area was acquired from the Digital Globe archival collection (DigitalGlobe, 2005) dated September 5th 2007 15:33:44 local time. The standard product was purchased given the minimal elevation relief of the study area and limited potential for geometric distortions due to elevation change. Atmospheric correction was performed utilizing PCI Geomatica 10 ATCOR2 (PCI Geomatics, 2010) to remove the influence of atmospheric effects on the spectral signal. The correction assumed a high water vapour content since wetlands typically feature abundant atmospheric water content ($+ 3 \text{ g/cm}^2$) and high variability ($1\text{-}6 \text{ g/cm}^2$) (Guzzi & Rizzi, 1984).

A field survey was conducted between September 4th and 7th, 2010 to collect prototypical ground truth for use as training data. Training data consisted of $1\text{ x }1\text{ m}$ quadrats samples obtained by following the point intercept method for macrophyte monitoring guidelines (Alberta Environment, 2006). Sample sites were pre-selected at random in a $50\text{ x }50\text{ m}$ grid pattern prior to the field survey. Quadrats lacking a predominant class with over 80% of the total canopy cover were excluded. Class labels were assigned to each sample based on the predominant class within the quadrat. The labels assigned matched the colonization patterns documented by local experts (South Nation Conservation Authority) who indicated that the study area was stable and the invasive species European Frog-bit had been dominant each year for the past ten years. Since the species present were likely in equilibrium with their environment, the current distribution of species was likely due to environmental determinants (water depth, current speed) that were not expected to shift significantly over the temporal lag. Furthermore, the data set was previously used by Proctor et al., (2012) in a land cover classification achieving an overall classification accuracy of 84.3%. The samples collected were split approximately 70:30 into a training and reference data set (Table 2). Complete details on the collection and processing of training data

can be found in (Proctor, et al., 2010).

2.2 *Spectral variables under investigation*

To comprehensively investigate whether image texture could improve classification accuracy, textural attributes derived from pansharpened, select vegetation indices and spectral transformation are investigated. Pansharpening of the multispectral bands is assessed as image textures are plausibly more apparent in higher spatial resolution imagery, especially when texture depends upon small canopy gaps. In addition, a number of commonly derived vegetation indices are arbitrarily examined under the notion that the indices would better express the image texture through enhancing the greenness of the vegetation or reduce the influence of the background on the spectral signal. This reasoning is similar for the two spectral transformations. Tasseled cap transformation is examined in order to enhance brightness, greenness or wetness, while principal components examine textures related to variance. These transformations are commonly utilized to improve classification accuracy and could theoretically be utilized to improve the derivation of texture.

ERDAS IMAGINE 9.2 (Leica Geosystems Geospatial Imaging, 2008) was utilized to conduct the tasseled cap transformation. The tasseled cap coefficients were modified from the defaults to those suggested by the comparison paper by Yarbrough, et al., (2005). Pansharpening was performed on all four multispectral bands using the PCI Pansharp tool. PCI was also utilized to conduct the principal components analysis. The vegetation indices, Normalized Difference Vegetation Index (NDVI) (Rouse et al., 1973), Modified Soil Adjusted Vegetation Index (MSAVI) (Qi et al., 1994), Difference between Vegetation and Water (DVW) (Gond et al., 2004) and Normalized Difference Water Index of Mc Feeters (NDWIF) (Mc Feeters, 1996) were

calculated in PCI modeller. In total 214 vectors were scrutinized (Table 3).

2.3 Identification of appropriate window size using semivariograms

An important factor that has substantial impact on the derivation of texture is the spatial autocorrelation of pixel values (Franklin, Wulder, & Lavigne, 1996). Since the degree of spatial autocorrelation is not readily apparent, a simple means to quantify the spatial relationship is to calculate the semivariance. The semivariogram range and sill indicate the distance at which pixels are no longer correlated, beyond which there is no spatial dependence among the reflectance values. Research has shown that the window size used for texture analysis should not exceed the distance represented by the semivariogram range (Franklin et al., 1996). However, each class may be spatially independent and exhibit a unique range of spatial autocorrelation (Treitz & Howarth, 2000). As a sole window size is utilized to derive texture attributes, the decision on the appropriate window size should consider class variations.

Seven image subsets were derived from the imagery in order to determine the semivariance for each class. Each image subset contained a dominant stand of the species within an area of minimal ecosystem complexity. Semivariograms were calculated for the Quickbird multispectral and panchromatic bands where the lag separation distance coincided with the data spacing and the number of lags was set to one-third the diagonal distance of the data matrix. Using the gstat package of R (R Development Core Team 2008), all semivariograms were fitted with a variogram model to provide a more robust representation of the decay in spatial autocorrelation that is less sensitive to noise. A spherical variogram model was chosen because of its commonality in the literature and it resulted in a generally lower sum of squared error when tested against the Gaussian, exponential and circular models. All semivarograms were

fitted with a standard spherical model with the optimal model parameters attuned to minimize the sum of squared error between the fitted model and the measured semivariance. The resulting coefficients of the variogram model were used to inform the window size decision.

2.4 *Deriving texture attributes using the grey level co-occurrence matrix*

In the literature, a common approach to determine the image texture is based on the Grey Level Co-occurrence Matrix (GLCM) method developed by (Haralick et al., 1973). Calculating the Haralick texture attributes consists of two parts. The first step is the construction of the co-occurrence matrix. A co-occurrence matrix is a probability matrix whose elements are indexed by gray-level values for all pixel-pairs at a defined distance and angle in a pixel neighborhood. For isotropic texture attributes, co-occurrence matrixes are generated for the four directions of adjacency (0° , 45° , 90° and 135°) and the average occurrence is retained for texture derivation (Anys & He, 1995). The second step utilizes the statistical properties of the co-occurrence matrices to derive the actual texture attributes. Homogeneity, contrast, dissimilarity and entropy are commonly cited as having the best performance (Johansen & Phinn, 2006). As the image texture of floating macrophytes has not been examined, this study opted to examine 13 texture attributes (Table 4).

Since computing the co-occurrence matrix is a computationally intensive task, the values of each vector were rescaled by a linear function. Hence, the co-occurrence matrix was calculated as a square matrix of dimension N_g , where N_g was the total number of gray levels (32 levels) in the image. The matrix was populated by counting the total occasions a pixel with value i was adjacent to a pixel with value j , storing the count in the (i, j) th element of the matrix and then subsequently dividing the matrix by the total number of such comparisons that were made.

Hence, the (i, j) th entry in a normalized GLCM probability density matrix was considered as a probability $p(i, j)$ that a pixel with value i was adjacent to a pixel of value j , in which adjacency was defined as directionally invariant. For texture attributes based on the Grey Level Difference Vector (GLDM), the matrix stores the count of the absolute difference between the reference pixel and its neighbour expressed as the probability density $p\delta(i, j)$. Each of the 13 texture attributes were calculated for the Quickbird multispectral and panchromatic bands, pansharpened bands and multispectral derived image transformations and vegetation indices (Table 3).

2.5 Feature selection of spectral and texture vectors

Feature selection is a technique for selecting a subset of vectors that consistently provide good performance in class discrimination. All vectors are rank ordered in terms of performance and sequentially trimmed until the relevant vectors providing the greatest class separability remain. The performance of each combination of vectors is assessed via a distance measure. However, a number of distance measures are available and no single index can reliably indicate which vectors are optimal. We therefore employ a feature selection process based on two tests of separability performance utilizing a standard training data set of prototypical ground truth.

In the first test, the Mann-Whitney U-test (Sawilowsky, 2007) is a nonparametric approach that does not assume a normal distribution when assessing whether the differences in the medians between class pairs are statistically significant. For each vector, the distributions of two classes are examined. If they are sufficiently intermingled, such that their medians are similar and there is a high degree of overlap, then the class pair is deemed to come from the same population. Hence, the Mann-Whitney U-test indicates the number of class pairs out of the 21 possible that are separable on the basis of a single vector

In essence, the Mann-Whitney U-test examined whether the variance within the two classes are smaller than between them. To tests this hypothesis (H_1) that there is no significant difference between the medians η of a class pair, Mann–Whitney U-test examined for $c, c+1$ classes and vector i if:

$$H_1: \eta_c(i) = \eta_{c+1}(i) \quad 1$$

At significance level of a $\alpha=0.01$ the null hypothesis was rejected and the alternative hypothesis that the medians are not equal was accepted. For each vector, the number of statistically significant class pairs with different medians was tabulated, with vectors approaching 21 class pairs considered useful for class separability.

The Mann-Whitney U-test also provides a numerical measure (the U-Statistic) that scales positively with the degree of separability between the medians of a class pair. The U-Statistic is given as the minimum U value calculated independently for each class. The U value for a class is based on the number of pairs for which the value of the first class is less than the second class after being placed in ascending order. When two classes are completely separate, one class always out ranks the other, hence its rank sum is the maximum possible while the other has a zero U value. Consequently the U-Statistic in the minimum, zero indicating high class separability. Conversely, when both groups are interpenetrated the rank sums are similar as the class that out ranks the other fluctuates. Hence, the U-Statistic is the maximum which is half of the number of training data samples, n_c times n_{c+1} .

For each class pair, the Mann–Whitney U-Statistic was calculated as:

$$U = \min(U_c, U_{c+1}) \quad 2$$

$$U_c = n_c n_{c+1} + \frac{n_c(n_c + 1)}{2} - R_c \quad 3$$

$$U_{c+1} = n_c n_{c+1} + \frac{n_{c+1}(n_{c+1} + 1)}{2} - R_{c+1} \quad 4$$

284 where U_c, U_{c+1} are the U values calculated for classes $c, c + 1$, n_c, n_{c+1} are the number of
 285 training data samples for each class and R_c, R_{c+1} are the sum of the ranks for classes $c, c + 1$.
 286 As the U-Statistic was scaled from 0 to $n_c * n_{c+1}$ it was subsequently normalized between 0 and
 287 1 by:

$$U_{norm} = \frac{n_c n_{c+1}}{2} - \frac{U}{\frac{n_c n_{c+1}}{2}} \quad 5$$

288 The second test evaluates class separability based on the Jefferies-Matusita distance
 289 (Richards, 1993) for a combination of vectors. The Jefferies-Matusita distance is widely used to
 290 identify the band combination that yields the best spectral separability between two classes
 291 (Adam & Mutanga, 2009). There are multiple strategies to extend the Jefferies-Matusita distance
 292 to the multi-class case (Bruzzone et al., 1995) with the simplest accomplished by calculating the
 293 distance between all 21 class pairs and calculating the average distance.

294 The similarity of two class density functions was measured by the Bhattacharya distance
 295 defined as follows:

$$b = \frac{1}{8} (\mu_2 - \mu_1)^T \left[\frac{\Sigma_1 - \Sigma_2}{2} \right]^{-1} (\mu_2 - \mu_1) + \frac{1}{2} \ln \frac{|(\Sigma_1 - \Sigma_2)/2|}{|\Sigma_1|^{\frac{1}{2}} |\Sigma_2|^{\frac{1}{2}}} \quad 6$$

296 where μ_i and Σ_i are the mean vector and covariance matrix of class i , respectively.

297 Since Bhattacharya distance increases exponentially it was converted to the Jefferies-
 298 Matusita distance which has a saturating behavior with increasing class separation and is
 299 asymptotic to the value 2. The Jefferies-Matusita distance was calculated as:

$$JM = 2 * (1 - e^{-b}) \quad 7$$

A Jefferies-Matusita distance greater than 1.0 indicates the two classes are very similar and thus hard to separate. Values between 1.00 and 1.9 indicate that the two classes could be separated at least to some extent while values greater than 1.9 are considered to yield good to excellent separation.

Calculating the Jefferies-Matusita distance for all possible band combinations was not feasible given the number of potential permutations. In order to save computation time, sequential forward selection was used as opposed to an exhaustive search of each vector combination (Gruninger et al., 2001). Forward selection utilizes an interactive process to identify the best performing vector and sequentially adds additional vectors until the improvement in performance declines. Hence, the first iteration selected the best single vector based upon Jefferies-Matusita distance. This vector was then paired with every remaining vector to find the best two vector combination based upon the Jefferies-Matusita distance. Repeating the process, the vector combination was subsequently augmented until additional vectors contributed less than 0.01 to class separability.

2.6 Decision Trees using selected features.

A classification and regression tree classifier implemented in the rpart package of R (R Development Core Team 2008) was utilized to classify each vector combination identified through feature selection. All relevant vectors were appended to a training data set of ~ 500 samples of labelled class based on the sample location. In the supervised decision tree approach, vectors were predictor variables mapped to the target classes subject to a minimized cost function (Xu et al., 2005). The algorithm was conditioned to select the split that partitions the data into parts such that the sum of the squared deviations from the mean in the separate parts

was minimized. To minimize over fitting, a pruning process was adopted to remove surplus terminal nodes that provide little power to classify instances and may have been based on noisy or erroneous data. Selection of the surplus terminal nodes was guided by the cost-complexity parameter, which is a measure of average error reduced per terminal nodes. The pruned tree was used to predict the class of all unknown pixels in the imagery.

2.7 *Classification accuracy*

For the final classification, the accuracy was assessed utilizing a standard error matrix (Congalton, 1991; Congalton, & Green, 1999). The global classification accuracy metrics were the overall classification accuracy and kappa coefficient. The overall accuracy was the number of correctly classified pixels over the number of pixels utilized in the accuracy assessment. As a number of pixels were likely allocated to the correct class by chance, the kappa coefficient was used to determine the classification accuracy after chance has been accounted for. The measures of class accuracy were the user's accuracy (UA) and producer's accuracy (PA) derived from the error matrix. UA was calculated as the percentage of pixels correctly assigned to a class out of the total pixels classified as said class. PA was calculated as the percentage of pixels correctly assigned to a class out of the total pixels of said class utilized in the accuracy assessment.

3. Results

3.1 *Semivariogram Analysis*

Semivariance for the multispectral bands generally began to saturate at a lag of six pixels. However, per class semivariograms indicate that certain classes had unique spatial autocorrelation. The Mixed Forest (MF) class has a considerable shorter range of spatial

autocorrelation (3.25 pixels, 7.8m) than the Grasses, Sedges, Rushes (GSR) class (8.5 pixels, 20.4m). The lower range of spatial autocorrelation for the MF class is likely the result of canopy gaps between individual trees. Comparing the floating macrophytes, Fragrant Water-lily (FWL) spatial autocorrelation (Figure 2a) is shorter than European Frog-bit (EFB) (Figure 2b) which forms denser tessellated canopies. Examination of FWL patches revealed they rarely exceeded 10 pixels in size and were always surrounded by open water. In contrast, EFB patches are linear, stretching 100 of meters along the shoreline and extending >10 m from shore, if not completely covering the water surface. Considering the considerable contrast between FWL and the surrounding open water, FWL stands may have a greater range in grey levels provided the window is sufficiently large to capture the surrounding water column. Hence the panchromatic band may be more appropriate to derive image texture than the multispectral bands. The level of spatial detail captured is greater and the difference in spatial autocorrelation range between EFB and FWL is greater. Considering the mean and mode in the semivariance range of all classes (Table 5), these results indicate that a window size of 5x5 is more appropriate for the multispectral bands and 13x13 for the panchromatic band.

3.2 *Selected Features*

Out of 214 vectors examined, 154 have statistically significant Mann-Whitney U-test results which considered useful for class separability (defined as >19 out of 21 statistically significant class pairs) (Figure 3). The multispectral Quickbird bands perform well, eliciting both a high number of class pairs and U-Statistic. The pansharpened multispectral bands have a slightly reduced performance, possibly due to color distortion from the pansharpening process. The top performing vectors are generally the transformed vectors and vegetation indices. Indices

such as NDVI slightly outperformed the sole spectral bands, as to be expected from the higher information content and close relationship of NDVI to vegetation biochemistry. In particular, the Normalized Difference Water Index had the highest U-Statistic (0.908), slightly higher than all spectral bands (blue: 0.815, green: 0.883, red: 0.895, NIR: 0.831).

Texture attributes have generally lower performance than the baseline provided by the spectral bands. Fewer class pairs are statistically significant and the U-Statistic is noticeably reduced (Figure 3). The texture attribute Mean is the exception, with comparable performance if derived from the multispectral NIR band or Tasseled Cap brightness (0.871 and 0.892 respectfully). It is important to note that Mean texture is a descriptive statistic based on the frequency of occurrence of a value in combination with a certain neighbour pixel value. Mean texture thus differs from the mean pixel value within a window, but shares some similarities. Other high performing texture attributes are contrast, dissimilarity and entropy. There is little difference between entropy and its related cousin, GLDV entropy.

The performance of a texture attribute is strongly related to its derivative source. Texture derived from multispectral band 1 and the 2nd or 3rd principal components consistently performed poorly, regardless of the texture attribute derived. In contrast, texture derived from the panchromatic band often outperformed all other sources. For instance, dissimilarity derived from the panchromatic band has 20 out of 21 statistically significant class pairs and a high U-Statistic (0.84). The next highest performing dissimilarity texture vector is derived from the Tasseled Cap brightness band (21 significant class pairs, U-Statistic 0.77). The performance of panchromatic derived texture for certain texture attributes is comparable to the poorer performing spectral bands. These results indicate some potential utility for image texture in combination with the spectral bands.

The second test based on Jefferies-Matusita distance employing a forward selection search indicates increasing class separability as additional vectors are utilized up until four vectors (Figure 4). Beyond four vectors the increase in Jefferies-Matusita distance is negligible. Based on the average Jefferies-Matusita distance between all class pairs, the first iteration of the forward selection search identifies multispectral red as vector providing greatest class separability. As expected for a sole band, class separability between class pairs ranges considerably and the overall Jefferies-Matusita distance is a poor 1.43. The second iteration recalculated the Jefferies-Matusita distance for all combinations of the multispectral red vector and an additional vector. The second vector, multispectral NIR, improves class separability considerably (Table 6). The average Jefferies-Matusita distance of 1.87 approaches the good-excellent separation threshold. Hence, the spectral bands alone are likely sufficient to achieve satisfactory classification accuracy. Additional iterations identified the texture attributes, panchromatic dissimilarity and Tasseled Cap band 1 contrast as vectors improving class separability. Incorporation of panchromatic dissimilarity increased the Jefferies-Matusita distance to 1.97. An additional fourth vector (Tasseled Cap band 1 contrast) negligibly improves separability.

Both test results indicate that augmenting the spectral vectors with an image texture yield a slight improvement in class separability that may translate into improved classifier performance. To examine this premise, the band combination results from iteration 2-3 are classified. Thus, a spectral only classification involving two bands is compared to two classifications augmenting the spectral vectors with image texture, one involving two texture bands.

3.3 *Decision Tress Classification*

Visually the three classifications are similar and colonization patterns of each floating macrophyte species generally match the patterns noted in the field (Figure 5). The Submerged (Sub) class has a slightly greater extent in the third iteration while patches of Duckweed (DW) are smaller and more fragmented. The salt and pepper pattern of misclassified pixels within the forested areas is also reduced. The fourth iteration has noticeably increased the prevalence of misclassified terrestrial pixels. There is also greater confusion between the MF and FWL classes.

The pruned decisions trees for the suite of vectors from the second and third iterations had similar nodes for the majority of the tree (Figure 6). The land cover classes MF, GSR and Open Water (OW) were similarly classified on the basis of the NIR and red bands. The decision trees diverge in the classification of SUB, FWL and GSR. The Red/NIR only decision tree utilizes the NIR band to separate the SUB land cover class. In contrast, the texture augmented decision tree utilizes panchromatic dissimilarity for the same task. In both cases FWL and GSR are separated by the red band. The four vector decision tree is markedly different with only the first node in common. Texture is utilized further up the tree at the second and third node level.

3.4 *Classification Accuracy*

The overall classification accuracy of the three decision tree classifiers is high. Each classifier performed comparably well in terms of accuracy for the land cover classes. Accuracies for these classes are >90% and stable between classifiers. However, performance in classifying the three species level varied slightly. Incorporation of image texture slightly improved the accuracy for FWL for iteration 3, but not iteration 4 (Table 7).

While iteration 4 saw a slight improvement in accuracy for other classes, the accuracy for

the FWL class is reduced compared to the second and third iteration. The incorporation of a second texture band appears to have a negative effect on classifying the species level classes and the overall accuracy. While Kappa increased with the third iteration (second iteration 90.4 versus third iteration 93.0) the fourth iteration saw a decrease (fourth iteration 89.8). Hence the classification accuracy peaked for the decision tree classification involving panchromatic dissimilarity. Incorporation of additional textures may increase the classification complexity, resulting in decreased accuracy.

4. Discussion and Conclusions

The results suggest that the practical value of texture augmented classification for floating macrophyte species discrimination is low. The slight increase in accuracy comes at a large cost in terms of computational complexity and time requirements. Furthermore, suitable image textures are sensitive to their parameterization. Considerable variations in the efficacy of the texture attributes contrast and dissimilarity were noted between a GLCM of 32 and 256 levels, with the lower number of grey levels yielding better performance. Hence, there is considerable trial and error in the process of identifying a suitable texture attribute and the results may be case specific. Considering the slight benefits versus the increased resource cost, the payback of a texture augmented classifier is unclear.

However, the hypothesis that canopy gaps in certain species of floating macrophytes would manifest as detectable differences in texture may have some merit. The study results indicate a greater tendency in texture attributes such as contrast and dissimilarity, which respond to heterogeneity in land cover and complex spatial structures, to have some utility in improving class separation and in land cover classification. In the case of FWL, the surrounding open water

461 produced a noticeable texture that could be utilized to reduce its confusion with submerged
462 macrophytes. This result suggests that image texture in floating macrophyte stands has a stronger
463 association with spatial heterogeneity and canopy gaps than an internal systemic texture. Hence,
464 the number of open water cells is the surrounding area maybe a simpler means to express texture
465 in this instance.

466 These findings can also be interpreted in the context of other studies on image texture of
467 wetland vegetation. Laba et al., (2010) reported that texture augmented classification utilizing 4
468 texture bands in addition to the IKONOS multispectral bands reduced accuracy approximately
469 30% versus the baseline multispectral only classification. Ultimately the overall classification
470 accuracy was slightly improved by incorporating texture (77.7% with texture versus 76.2%
471 without) using an edge-preserving spectral-smoothing-segmentation procedure. However, the
472 improvements were not across the board. In many cases accuracies decreased for certain classes
473 in lockstep with accuracy increase in other classes. Overall no class had major improvements
474 relative to the accuracies found for baseline method. Our findings are in line with those of Laba
475 et al., (2010).

476 As demonstrated by Laba et al., (2010) the contribution of image texture may depends upon
477 the methodology. It is plausible that more robust methodologies to derive image texture may
478 yield greater improvements in performance, especially methodologies that account for the
479 tendency of macrophytes to occur in complex and narrow patches such those that occur along
480 shorelines. In addition, the spectral similarity between the classes of interest may influence the
481 relative contribution of image texture. As the classification accuracy of this study utilizing
482 spectral only variables was high, the need for additional vectors was low. Image texture is more
483 likely to yield a greater contribution when discriminating between macrophytes with highly

similar spectral signatures, but contrasting biophysical attributes.

Factors such as spectral and spatial resolution may be more related to the classification accuracy than image texture. Using a ground and airborne hyperspectral sensor, Malthus & George, (1997) noted clear spectral differences between 11 species in the Cefni Reservoir, UK. Utilizing only 3 bands a 79% classification accuracy was achieved. In terms of spatial resolution, often higher resolution yields more inner class complexity, decreasing the final accuracy. Pasqualini et al., (2005) documented lower accuracy (73%) when utilizing pansharpened 2.5m Spot 5 imagery for seagrass detection versus the non-pansharpened 10m imagery (96%). Classification methodology can also subtly influence the final accuracy. Slightly lower classification accuracies for this study site in a similar land cover classification were reported by Proctor, et al., (2010). The fuzzy support vector machines classification methodology yielded 87.4% while a fuzzy c-means classifier yielded a 72.8% classification accuracy. The difference between the three classification methodologies is much larger than the additional accuracy provided by image texture, suggesting that a suitable processing technique for extracting spectral information of wetland vegetation maybe more linked to the overall classification accuracy than the incorporation of image texture.

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Table 1. Classification schema

Class Name	Abbreviation	Class Type	Class (# of species)
European Frog-bit	EFB	Species Level	Floating macrophyte (1)
Fragrant Water-Lily	FWL	Species Level	Floating macrophyte (1)
Submerged	Sub	Land Cover	Submerged macrophytes (2)
Duckweed	DW	Species Level	Floating macrophyte (1)
Grasses, Sedges, Rushes	GSR	Land Cover	Terrestrial grasses (multiple)
Mixed Forest	MF	Land Cover	Terrestrial trees (multiple)
Open Water	OW	Land Cover	No vegetation

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Table 2. Samples per Training and Reference Data Sets

Class Name	Training	Reference
European Frog-bit	92	47
Fragrant Water-Lily	64	28
Submerged	50	26
Duckweed	28	14
Grasses, Sedges, Rushes	90	45
Mixed Forest	90	45
Open Water	90	45

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Table 3. List of textural and spectral vectors under investigation

	Data Source	Derivative	# of Bands	Total Vectors
Textural vectors				
	Multispectral bands	N/A	4	52
	Panchromatic band	N/A	1	13
	Multispectral bands	Tasseled Cap	3	39
		Principal Components	3	39
		NDVI	1	13
		MSAVI	1	13
		DVW	1	13
		NDWIF	1	13
Spectral Vectors				
	Multispectral bands	N/A	4	4
	Panchromatic band	N/A	1	1
	Pansharpened bands	N/A	4	4
	Multispectral bands	Tasseled Cap	3	3
		Principal Components	3	3
		NDVI	1	1
		MSAVI	1	1
		DVW	1	1
		NDWIF	1	1

Table 4. List of Haralick texture attributes derived in this study (Haralick et al., 1973).

Texture Attribute	Equation	Description
Homogeneity	$t_{hom} = \sum_{i,j=0}^{N_g-1} \frac{1}{1 + (i-j)^2} p(i,j)$	The deviation from the main diagonal.
Contrast	$t_{con} = \sum_{i,j=0}^{N_g-1} p(i,j)(i-j)^2$	Local variation, increases exponentially from diagonal.
Dissimilarity	$t_{diss} = \sum_{i,j=0}^{N_g-1} p(i,j) i-j $	Local variation, increases linearly from diagonal.
Mean	$t_{mean} = \sum_{i,j=0}^{N_g-1} i * p(i,j)$	Average grey level in the local window
Variance	$t_{var} = \sqrt{\sum_{i,j=0}^{N_g-1} p(i,j) * (1 - \mu_i)^2}$	Measure of dispersion around the central pixel.
Entropy	$t_{ent} = \sum_{i,j=0}^{N_g-1} -p(i,j) \log(p(i,j))$	The randomness of the intensity distribution.
Angular 2nd Moment	$t_{ang} = \sum_{i,j=0}^{N_g-1} p(i,j)^2$	Local homogeneity that is low when entries are almost equal.
Correlation	$t_{corr} = \sum_{i,j=0}^{N_g-1} \frac{p(i,j) * (1 - \mu_i) * (1 - \mu_j)}{\sqrt{(\sigma_i - \sigma_j)}}$	Measures the linear dependency of grey levels.
GLDV Angular 2nd Moment	$t_{G_ang} = \sum_{i,j=0}^{N_g-1} p\delta(i)^2$	Measures local homogeneity.
GLDV Entropy	$t_{G_ent} = \sum_{i,j=0}^{N_g-1} -p\delta(i)\log(p\delta(i))$	The opposite of GLDV Angular Second Moment
GLDV Mean	$t_{G_mean} = \sum_{i,j=0}^{N_g-1} i * p\delta(i)$	Mathematically similar to Dissimilarity
GLDV Contrast	$t_{G_cont} = \sum_{i,j=0}^{N_g-1} i^2 * p\delta(i)$	Mathematically similar to Contrast
Inverse Distance	$t_{invd} = \sum_{i,j=0}^{N_g-1} \frac{p(i,j)}{ i-j ^2} \text{ for } i \neq j$	Measures image homogeneity.

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Table 5. Semivariogram range at sill (# of pixels)

Class Name	Multispectral Band (band average)	Panchromatic Band
European Frog-bit	6.44	18.91
Fragrant Water-Lily	4.09	8.96
Submerged	6.66	15.25
Duckweed	6.54	10.80
Grasses, Sedges, Rushes	8.51	16.80
Mixed Forest	3.25	10.39
Open Water	6.29	25.30

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Table 6. Jefferies-Matusita distance through forward selection

Iteration	Vector(s)	Distance
1	Red	1.47
2	Red + NIR	1.87
3	Red + NIR + panchromatic dissimilarity	1.97
4	Red + NIR + panchromatic dissimilarity + tasseled cap band 1 contrast	1.98

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Table 7. Accuracy statistics of the three decision tree classifications.

	Iteration 2		Iteration 3		Iteration 4	
	UA	PA	UA	PA	UA	PA
EFB	95.0	89.3	100.0	87.2	100.0	87.2
FWL	82.5	81.2	85.0	90.4	77.9	82.8
DW	86.2	89.3	96.5	100.0	100	100.0
Species Only	87.3		93.1		91.3	
Overall Acc.	91.9		94.1		91.5	
Kappa	90.4		93.0		89.8	

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Figure 1. False color Quickbird imagery of study area and the spatial location of the training and reference data sets, shown on two insets at 30:000 scale.

Figure 2. Semivariograms for panchromatic band with fitted models for the Fragrant Water-lily class (a) and the European Frog-bit class (b)

Figure 3. Plot of the one-dimensional distance measures. The grey columns are the results of the Mann-Whitney U-test expressed as the number of significant class pairs (left axis). The line indicates the average U-Statistic distance measure for all class pairs (right axis).

Figure 4. Jefferies-Matusita distance versus forward selection iteration.

Figure 5. Decision trees classifications using Red/NIR bands (top right), Red/NIR/panchromatic dissimilarity (bottom right) and Red/NIR/panchromatic dissimilarity/Tasseled Cap brightness contrast (bottom left). False color Quickbird imagery (top left).

Figure 6. Decision tree indicating the similarity and divergence of the second and third iteration.