Effect of Feature Dimensionality on Object-based Land Cover Classification: A Comparison of Three Classifiers

Gerhard Myburgh[1], Adriaan Van Niekerk[2]

[1]Department of Geography and Environmental Studies, Stellenbosch University, Stellenbosch, South Africa, g0myburgh@gmail.com

[2]Centre for Geographical Analysis, Stellenbosch University, Stellenbosch, South Africa

Abstract

The efficient mapping of land cover from remotely sensed data is highly desirable as land cover information is essential for a range of environmental and socio-economic applications. Supervised classifiers are often applied in remote sensing to extract land cover information. While spectral information is typically used as the main discriminating features for such classifiers, additional features such as vegetation indices, transformed spectral data, textural information, contextual information and ancillary data may also considerably influence the accuracy of classification. Geographic object-based image analysis (GEOBIA) allows the easy integration of such additional features into the classification process. This paper compares the performance of three supervised classifiers in a GEOBIA environment as an increasing number of object features are included as classification input. Classification tree analysis (CTA) was employed for feature selection and importance ranking. Object features were considered in the order of their obtained rank. The support vector machine (SVM) produced superior classification accuracies when compared to those of nearest neighbour (NN) and maximum likelihood (ML) classifiers. Both SVM and NN produced stable results as the feature-set size was increased towards the maximum (22 features). ML's performance, however, decreased considerably when few training samples are used and when the feature-set size (dimensionality) is increased.

1. Introduction

Detailed, accurate and up-to-date land cover information is essential for environmental and socio-economic research (Lu & Weng, 2007; Heinl et al., 2009). Many satellite platforms are currently operational; producing remotely sensed data at various spatial and temporal scales (Foody, 2002). Consequently, an abundance of remotely sensed data is available. This provides great potential for generating up-to-date thematic maps as remotely sensed images covering large areas are acquired at regular intervals and are less costly than traditional ground-survey methods (Pal & Mather, 2004; Foody, 2009; Szuster et al., 2011). Current image processing techniques are limited in their ability to automatically extract accurate land cover features (Baraldi et al., 2010). Many factors, such as the nature of remotely sensed data, the availability of appropriate training data, the choice of classification method and the definition of target classes may affect the accuracy of image classification (Lu & Weng, 2007) and the quality of land cover maps is often perceived as being insufficient for operational use (Foody, 2002).

Supervised classification, an approach commonly used for remotely-sensed data classification, requires samples of known identity (training samples) to construct a model capable of classifying unknown samples. Apart from selecting a suitable classifier, the number and quality of training samples are key to successful classification (Hubert-Moy et al., 2001; Lu & Weng, 2007). A sufficient number of training samples is generally required to perform a successful classification and the samples need to be well distributed and sufficiently representative of the land cover classes being evaluated (Mather, 2004; Campbell, 2006; Lu & Weng, 2007). In remote sensing applications, the availability of labelled training samples is often limited (Gehler & Shölkopf, 2009; Mountrakis et al., 2011) as their collection is time-consuming, expensive and tedious, often requiring the visual interpretation of existing topographical maps and aerial photographs, as well as carrying out extensive field visits (Campbell, 2006).

While the selection of an appropriate classifier and the delineation of the training set are crucial, the addition of variables other than the original spectral bands can significantly influence the performance of image classification (Lu & Weng, 2007; Heinl et al., 2009;). In particular transformed images, textural information, contextual information and ancillary data are often incorporated into image classification (Lu & Weng, 2007). Heinl et al. (2009) have compared the performance of maximum likelihood (ML), artificial neural network (ANN) and discriminant analysis (DA) classifiers when topographic measures, normalized difference vegetation index (NDVI), and texture measures are incrementally added to Landsat 7 ETM+ spectral data as input variables. The addition of such variables generally leads to an increase in classification accuracy implying that the addition of such variables could potentially be as important as classifier selection. However, for some classifiers an increase in input dimensionality decreases the reliability of statistical parameter estimations and may consequently result in a decrease in classification accuracy (Pal & Mather, 2005; Oommen, et al. 2008). This is known as the Hughes effect (Hughes 1968) – the so-called curse of dimensionality – which postulates that the classification accuracy will decrease after a certain feature-set size is reached unless the number of training samples is proportionally increased (Chen & Ho, 2008). The Hughes effect is therefore more likely to be encountered when small training sets are used and the input dimensionality is increased.

Geographic object-based image analysis (GEOBIA) has emerged as an alternative to pixel-based image processing (Blaschke & Lang, 2006; Hay & Castilla, 2008; Blaschke, 2010). GEOBIA involves a segmentation step during which image pixels are grouped into homogeneous interlocking regions as determined by a specific segmentation algorithm (Campbell, 2006). These image segments contain additional spectral and spatial information when compared to single pixels (Blaschke, 2010). Its ability to incorporate contextual information and ancillary data makes GEOBIA suitable for the integration of various additional features for image classification. Usually, the mean values of the pixels within an object are used to train an object-based supervised classifier. Because this effectively reduces the number of training samples available to the classifier (Tzotsos

& Argialas, 2008), GEOBIA is generally more sensitive to the Hughes effect when statistical classifiers are used.

Support vector machines (SVMs) have been shown to improve the reliability and accuracy of supervised classifications (Oommen et al., 2008). SVMs are known for their good generalizing ability even when few training samples are available (Foody & Mathur, 2004b; Pal & Mather, 2005; Lizarazo, 2008; Li et al., 2010; Mountrakis et al., 2011) and they are less sensitive to increases in input dimensionality compared to other statistical classifiers (Mercier & Lennon, 2003; Camps-Valls et al., 2004; Melgani & Bruzzone, 2004; Pal & Mather, 2004; 2005; Camps-Valls & Bruzzone 2005; Oommen et al., 2008). Comparative studies have shown that SVMs produce superior, or at least comparable, results for multispectral and hyperspectral image classification opposed to more commonly used methods such as ML, NN, ANN and decision trees (Gualtieri & Cromp, 1998; Huang et al., 2002; Keuchel et al., 2003; Mercier & Lennon, 2003; Camps-Valls et al., 2004; Foody & Mathur, 2004a; Melgani & Bruzzone, 2004; Pal & Mather, 2004; 2005; Camps-Valls & Bruzzone, 2005; Tzotsos & Argialas, 2008; Oommen et al., 2008; Dixon & Candade, 2008; Watanachaturaporn et al., 2008; Kavzoglu & Colkesen, 2009; Szuster et al., 2011).

Very few studies have compared the performance of different supervised classifiers in an object-based environment. A notable exception is Tzotsos & Argialas (2008), who reported that SVM outperformed NN classifiers for mapping land cover when using Landsat TM spectral bands as input variables. Other recent studies have also implemented object-based SVM classification (Lizarazo, 2008; Wu et al., 2009; Li et al., 2010; Liu & Xia, 2010; Tzotsos et al., 2011; Duro et al., 2012) and found that object-based SVM classification compared favourably to pixel based SVM classification. To the best of our knowledge no studies have been published that investigate the comparative performance of SVM as feature space is increased through the use of additional object features for GEOBIA land cover classification. Although it is expected, due to its non-parametric nature, that SVM would be more effective than statistical classifiers for incorporating additional features, it has not been demonstrated with land cover mapping in an object-based environment.

This paper aims to investigate the performance of object-based SVM for land cover classification compared to NN and ML classifiers. The research focusses on the effect of feature dimensionality on classifier performance when a limited number of training samples are available. The NN and ML classifiers were chosen for benchmarking as the latter is the most commonly used supervised classification method in remote sensing (Albert, 2002; Waske et al., 2009) and NN is the supervised classifier most commonly employed for object-based supervised classification (Campbell 2006).

2. Methodology

2.1 Study Area

The study area is located near Paarl in the Western Cape province of South Africa (Figure 1). The boundaries of the study area were chosen to match those of a Chief Directorate National GeoSpatial Information (CDNGI), 1:10 000 orthophoto map (3318DD5) and they extend from 33°44′55″ to 33°48′05″S and from 18°56′54″ to 19°00″06″E. The area, measuring 4.9 km × 5.9 km, was chosen because it was considered a good representation of the Western Cape rural landscape, particularly of the south-western Cape region. It would consequently be possible to, without much modification, apply the methodology to a larger area should the results be favourable. In addition, the study area was easily accessible by road and was consequently suitably located for field visits.

2.2 Pre-processing

SPOT 5 multispectral and panchromatic scenes (dated 29 March 2010) were acquired for the area. The scenes were orthorectified using PCI Geomatica's OrthoEngine module. Suitable ground control points were collected from 0.5m resolution colour orthophotographs obtained from CDNGI. The resulting orthorectified SPOT 5 images had root means square errors less than half a pixel. Atmospheric and topographic correction was applied using the ATCOR 3 module of PCI Geomatica and by using the 5m Stellenbosch University Digital Elevation Model (Van Niekerk 2012). The corrected multispectral and panchromatic scenes were then fused using a statistical fusion algorithm (PCI Geomatica's *PanSharp* algorithm) to create a single 2.5-m-resolution multispectral image consisting of four spectral bands (green, red, near infrared and shortwave infrared). Fusion was required as the higher spatial resolution would improve discrimination of land cover features (Pohl & Van Genderen, 1998; Amarsaikhan et al., 2010). In a comparison of commonly used pan-sharpening techniques, Zhang & Mishra (2012) found that the *PanSharp* algorithm produced superior fusion results for all types of sensors, images and spectral bands. A subset image was created to match the extents of the study area.

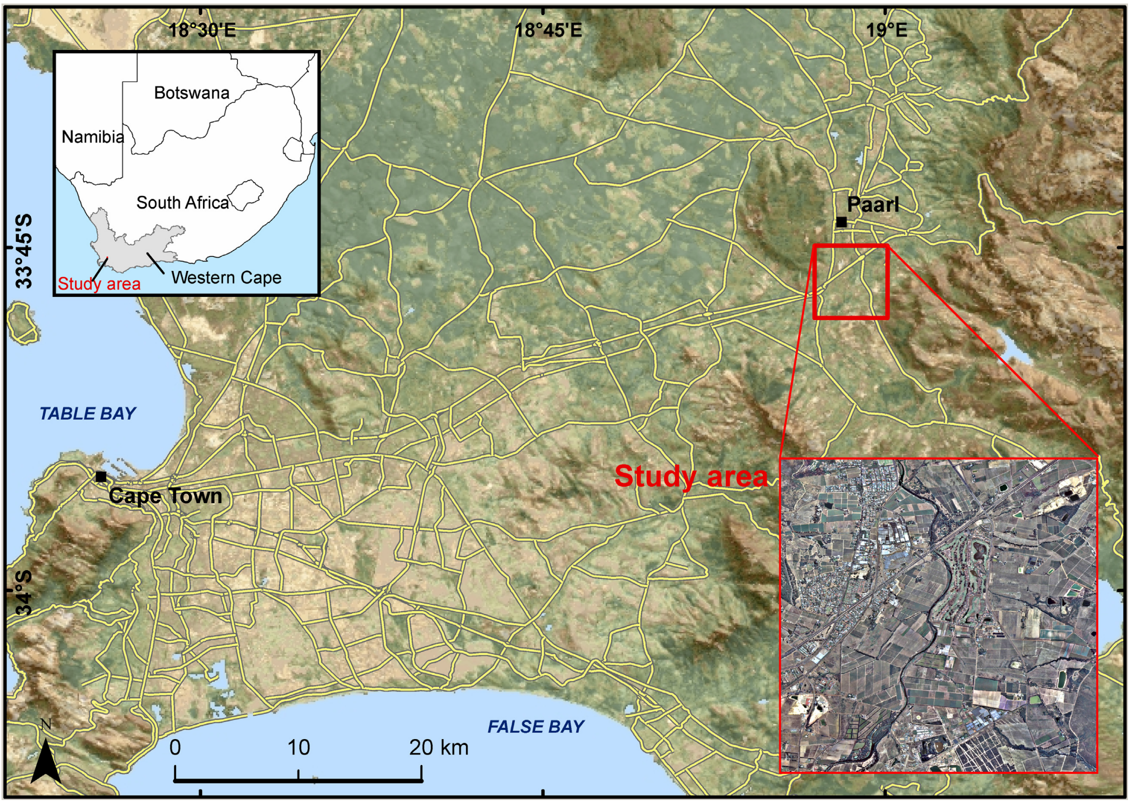


Figure 1. Location of the study area near Paarl in the Western Cape province of South Africa.

2.3 Image Segmentation, Training Data Selection and Feature Ranking

It is well known that poor image segmentation can negatively affect the results of an object-based classification (Baatz et al., 2008; Tzotsos et al., 2011). The multiresolution segmentation (MRS) algorithm as implemented in eCognition 8.0 was used to produce suitable image objects. Various segmentation parameters were sequentially tested until a segmentation was obtained that, based on visual inspection, adequately represented all land cover features. To limit the impact of under segmentation on the classification results, a scale parameter that produced a slight over segmentation was considered preferable. A scale parameter of 30, a shape parameter of 0.2 and a compactness value of 0.3 produced the best results and provided a total of 6439 image objects with a high level of homogeneity.

A broad four-class (*Trees & shrubs; Forbs, herbland & graminoids; Bare ground & built up; Water & shadow*) classification scheme was adopted to limit subjectivity during the generation of training sets. Some field visits were made and class samples were selected by visual interpretation of a high-resolution (0.5m) colour aerial photograph. Forty object samples per class were selected for use as training and reference data.

A total of 47 object features, based on the features used by Yu et al. (2006) and Laliberte et al. (2012), were considered in this study (Table 1). Many of these features, particularly those relating to the geometry of the objects, are unique to GEOBIA. Classification tree analysis (CTA) was used for selecting the most significant features for the particular application. CTA has been shown to be an effective feature selection method and has been successfully applied in GEOBIA (Chubey et al., 2006; Yu et al., 2006; Laliberte et al., 2007; 2012; Addink et al., 2010). CART® software (by Salford Systems) was employed to perform a CTA on the 160 samples and to statistically rank the importance of the features. CART® calculates a variable importance score for each feature based on the frequency and significance of its use as either a primary or surrogate splitter in the decision tree (Yu et al., 2006). Twenty-two of the initial 47 features were identified as primary or surrogate splitters and were subsequently considered for classification. The resulting feature ranking is also shown in Table 1.

Table 1. Considered object features (feature ranks for selected features are given in brackets).

Type		Features
Spectral Features	Mean	Green, red, NIR (5), SWIR (11), brightness (9)
	Standard deviation	Green, red, NIR, SWIR
	Ratio	Green (8), red (1), NIR (14), SWIR (21)
		Maximum difference (7)
Vegetation Indices		NDVI (3), OSAVI (2)
Texture Features	GLCM	Homogeneity (15), contrast, dissimilarity (17), entropy (16), ang. 2nd movement, correlation, mean (10), std. deviation
	GLDV	Ang. 2nd movement (19), mean (18), contrast, entropy (20)
Geometric		Area, asymmetry, border length, compactness, density, length, length/width (22), main direction, rectangular fit, roundness, shape index, width,
Contextual Features	Mean diff. to neighbour	Green, red, NIR (12), SWIR
Image Transforms	HSI	Hue (13), saturation (4), intensity (6)

The class samples and segmentation were stored as ESRI shapefiles with the values of the 22 selected variables as attributes (ordered according to their importance ranking). These shapefiles were inputted to the classification and accuracy assessment software.

2.4 Software Development

A software system was developed using C++ and the Microsoft® Visual Studio® 2010 (Express edition) development environment to automate the processes of classification and accuracy assessment. Additional open-source libraries were acquired to complete the implementation of the system. Libsvm 3.0 (Chang & Lin, 2011) was used to implement one-against-one multiclass SVM. The ML and NN classifiers were implemented using the OpenCV 2.2 library (Bradski, 2000) and the geospatial data abstraction library (GDAL) (GDAL Development Team, 2010) was used for the manipulation of shapefiles and raster datasets.

The radial basis function kernel, as recommended by Hsu et al., (2010), was selected for the SVM implementation. Appropriate values for the error parameter (C) and the kernel parameter (γ) were determined using a simple grid search and cross-validation approach. A coarse grid search was carried out on $C = 2^{-5}, 2^{-3}, \dots, 2^{-15}$ and $\gamma = 2^{-15}, 2^{-13}, \dots, 2^{3}$, after which a finer grid search was performed based on the results of the first search (as recommended by Hsu et al., (2010)). All data were scaled linearly from -1 to 1 to prevent data with higher numerical ranges having greater effect than those with lower ranges (Hsu et al., 2010).

2.5 Experiment Workflow

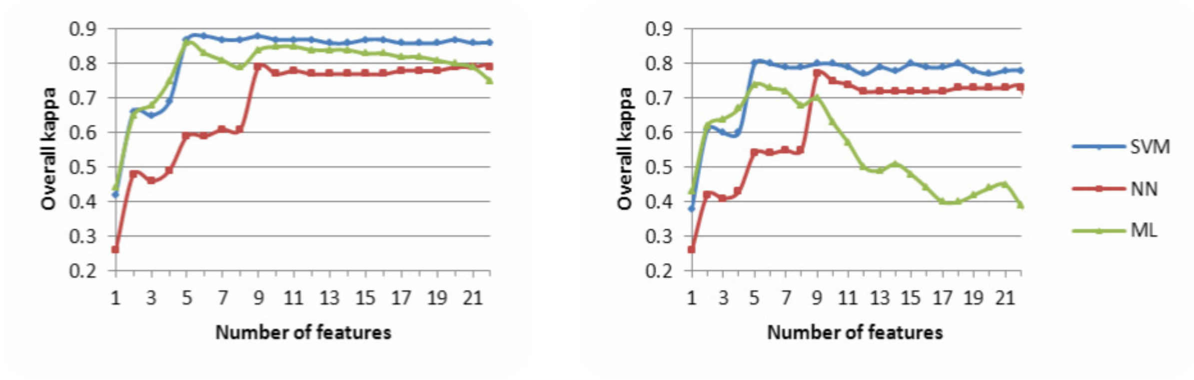
The developed system was designed to test the performance of SVM, NN, ML classifiers as the number of object features were increased. At the start of each experiment (program run), the object samples are randomly split into a training and a reference data set of equal size. The following steps were then repeated:

1. Select only the first feature in the shapefiles as input for classification.
2. Train the SVM, NN and ML classifiers using the training data set and the currently selected input feature space.
3. Use each of these classifiers to classify the unclassified shapefile, and perform automated accuracy assessments using the reference data set.
4. Add the next object feature to the current input feature space and repeat Steps 2 to 4 until all the object features (22) have been incorporated.

As mentioned in section 3.2, the features in the shapefiles were ordered according to the importance scores obtained by the CTA as performed on the 160 class samples. Features were therefore incorporated into the experiment in the order of their importance (Table 1). Results from 50 individual program runs were averaged, thus adopting a 50-fold repeated random sub-sampling validation with a 20/20 samples per class training/validation split. A second set of 50 program runs were also performed using a 10/30 samples per class training/validation split to investigate classifier specific relationships between feature dimensionality and training-set size. The accuracy assessment was performed at pixel level, resulting in 82881 individual samples. Confusion matrices were investigated at each feature-set size iteration and used to compare the performance of the different classifiers concerning the specific land cover classes. The matrices were also used to calculate the producer's, user's and overall accuracies, as well as the kappa statistic, for each classifier and feature-set size combination.

3. Results and Discussion

The results of the investigation into the effect of feature dimensionality on object-based supervised classification performance using 20 training samples per class are summarized in the overall kappa graph (Figure 2a). Overall, SVM produced more accurate results compared to those of NN and ML. This finding supports those of other comparative studies that have found SVM to produce superior classification results (Huang et al., 2002; Keuchel et al., 2003; Foody & Mathur, 2004a; Pal & Mather, 2005; Tzotsos & Argialas, 2008; Dixon & Candade, 2008; Oommen et al., 2008; Kavzoglu & Colkesen, 2009; Szuster et al., 2011).



(a) (b)

Figure 2. Average kappa values for SVM, NN and ML with an increasing number of features for 20 training samples per class (a) and 10 training samples per class (b).

All three classifiers performed poorly (< 0.75 overall kappa) until the addition of the fifth feature (mean NIR). At this point the performance of SVM and ML increased dramatically – achieving overall kappa values of 0.87 and 0.86 respectively. The performance of NN, while also receiving a boost from the addition of the fifth feature (mean NIR), remained comparatively weak (0.59 overall kappa). NN's overall kappa improved significantly (to 0.79) after the addition of ninth feature (mean brightness). The graph also indicates an improvement in performance for ML at this point (after ML's accuracies had dropped after the addition of features six through eight). The sudden increases in accuracy after the fifth and ninth features were added suggests that, in combination with the previous features, mean NIR and mean brightness considerably improves the discrimination of land covers.

After the inclusion of the mean NIR band, the overall performance of SVM is not significantly influenced by an increase in feature dimensionality. As the number of features was increased from five to 22, SVM's overall kappa remained between 0.86 and 0.88. NN's overall performance remained largely unaffected by the increase in feature dimensionality (from nine features) with overall kappa values ranging from 0.77 to 0.79. Conversely, ML's performance was significantly affected by the increase in dimensionality. While it performed consistently between nine and sixteen features (overall kappa ranging from 0.83 to 0.85), a gradual decrease in accuracy is observed when more features were used. ML's overall kappa dropped to 0.75 at 22 features –lower than NN's (0.79) at the same feature-set size. The drop in accuracy is most likely due to the susceptibility of ML to the Hughes effect which has been well documented (Pal & Mather, 2005; Oommen et al., 2008).

Confusion matrices were investigated to compare the performance of the different classifiers concerning specific land cover classes. Only one set of confusion matrices are provided due to space limitations. Confusion matrices for the classifiers at a feature set size of five are shown (Tables 2 to 4) as the addition of the fifth feature (mean NIR) proved significant for all classifiers. From Tables 2 to 4, it is clear that the *Water & shadow* class was the most accurately mapped by all the classifiers as it is the most distinct class and it is relatively easy to discern (Kavzoglu & Colkesen, 2009). The more complex *Bare ground & built-up* class was mapped more accurately by SVM than the other classifiers. The very weak overall performance of NN at five features is mostly due its inability to correctly classify this class. This indicates that, for NN, the first 5 features as ranked by the CTA are not sufficient for identifying *Bare ground & built-up* areas. Only after the inclusion of the mean brightness feature (nine features) could NN classify this class more accurately. Compared to SVM, ML produced more commission errors for this class, indicating slight over classification. This is consistent with the findings of Dixon & Candade (2008) that ML considerably over classified their *Urban* class (which would be similar to the *Bare ground & built-up* class used in this study) compared to SVM and ANN.

Table 2. SVM confusion matrix for five features.

	Trees& shrubs	Forbs,herbland & gramminoid	Bare ground & built-up	Water & shadow	TOTALS	PA%†	EO%†
Trees & shrubs	24676	2341	149	337	27502	89.7	10.3
Forbs,herbland & gramminoid	2668	24185	160	0	27014	89.5	10.5
Bare ground & built-up	285	211	8091	960	9548	84.7	15.3
Water & shadow	179	113	507	18019	18818	95.8	4.2
TOTALS	27808	26850	8907	19317	82881		
CA%	88.7	90.1	90.8	93.3			
EC%	11.3	9.9	9.2	6.7			
Overall accuracy:	90.5						
Overall kappa:	0.87						

†PA = Producer's accuracy; EO = Errors of omission; CA = Consumer's accuracy; EC = Errors of commission

Table 3. NN confusion matrix for five features.

	Trees& shrubs	Forbs,herbland & gramminoid	Bare ground & built-up	Water & shadow	TOTALS	PA%†	EO%†
Trees & shrubs	15485	3297	8719	0	27502	56.3	43.7
Forbs,herbland & gramminoid	4417	19685	1716	1195	27014	72.9	27.1
Bare ground & built-up	2239	1026	5340	943	9548	55.9	44.1
Water & shadow	0	341	1282	17195	18818	91.4	8.6
TOTALS	22141	24349	17057	19334	82881		
CA%	69.9	80.8	31.3	88.9			
EC%	30.1	19.2	68.7	11.1			
Overall accuracy:	69.6						
Overall kappa:	0.59						

†PA = Producer's accuracy; EO = Errors of omission; CA = Consumer's accuracy; EC = Errors of commission

Table 4. ML confusion matrix for five features.

	Trees& shrubs	Forbs,herbland & gramminoid	Bare ground & built-up	Water & shadow	TOTALS	PA%†	EO%†
Trees & shrubs	24581	2921	0	0	27502	89.4	10.6
Forbs,herbland & gramminoid	1649	24584	780	0	27014	91.0	9.0
Bare ground & built-up	293	38	8050	1167	9548	84.3	15.7
Water & shadow	1191	0	537	17090	18818	90.8	9.2
TOTALS	27715	27542	9367	18257	82881		
CA%	88.7	89.3	85.9	93.6			
EC%	11.3	10.7	14.1	6.4			
Overall accuracy:	89.7						
Overall kappa:	0.86						

†PA = Producer's accuracy; EO = Errors of omission; CA = Consumer's accuracy; EC = Errors of commission

The *Trees & shrubs* and the *Forbs, herbland & graminoid* classes are spectrally similar and resulted in much classification confusion throughout the experiment. When the first five features were used, ML performed slightly better (9.3% confusion) than SVM (10.3% confusion) at distinguishing between these classes while NN (21.9% confusion) was far less successful (Tables 2 to 4). The percentage confusion between any two classes was calculated by adding the number of misclassifications between them and dividing by the sum of the reference pixels for the two classes, e.g. the percentage confusion for SVM at five features (Table 4) was calculated as follows: (2341+2668)/(24676+24185)*100 = 10.3%. These findings are in contrast with those of Dixon & Candade (2008), Szuster et al. (2011) and Kavzoglu & Colkesen (2009) who have shown SVM to be superior at discerning spectrally similar classes. It should be noted, however, that these pixel-based studies used only spectral band values as classification input. The object-based nature of this study, as well as the object features selected through CTA, might have contributed to ML achieving slightly better discrimination between the spectrally similar *Trees & shrubs* and *Forbs, herbland & graminoid* classes than SVM.

The general findings regarding specific class accuracies held true for most feature set sizes after five features, however, some variations were notable. The kappa and accuracy graphs revealed a decline in ML's performance when features six to eight (HSI intensity, maximum difference and ration green) were included. Inspection of the corresponding confusion matrices showed this decline to be caused by increased over classification of the *Trees & shrubs* and *Bare ground & built up* classes. Since ML's best results (0.86 overall kappa) were obtained before the inclusion of these features (despite the increase in accuracy that occurs after mean brightness is included at nine features used), it is likely that the HSI intensity, maximum difference and ratio green features negatively affected parameter estimation and were not suitable for ML classification despite being ranked as relatively important by the CTA. These features did, however, not negatively affect the SVM and NN classifiers. This indicates that the influence of certain features on supervised classification may be classifier specific. Furthermore, SVM showed a considerable improvement in identifying *Bare ground & built up* and *Water & shadow areas* after the inclusion of GLCM

Homogeneity at 15 features. This was, however, at the expense of SVM's ability to discern *Trees & shrubs* and *Forbs, herbland & graminoids.* ML's and NN's results remained largely unchanged by the addition of the 15th feature (GLCM Homogeneity).

The experiment was repeated with a smaller training-set size (10 samples per class) to gain insights into classifier specific relationships between feature dimensionality and training set size. The overall kappa results are summarised in Figure 2b. As expected, all three classifiers produced less accurate results when fewer training samples were used. The shape of the SVM and NN graphs in Figure 2b is not much different when compared to the 20 samples per class graph (Figure 2a). Again the SVM stabilized after the addition of the fifth feature (mean NIR), while NN stabilized after the ninth feature (mean brightness) was added. This indicates that, although the smaller training-set size influenced the overall performance of the classifiers, the classifier specific influence of certain features was consistent regardless of the number of training samples used. The shape of the ML graph in Figure 2b is initially similar to the one generated from the 20 sample per class experiment, but became unstable when more than five features were used, resulting in a general decline in performance. This is likely due to poor parameter estimation often associated with small training-set size and increased dimensionality – exposing ML's reliance on sufficient training data and its susceptibility to the Hughes effect (Pal & Mather 2005, Oommen *et al.* 2008).

The overall results indicate, for the data and the classification scheme used in this study, that SVM generally produces superior classification results when compared to ML and NN. For both the 20 and 10 training samples per class experiment, neither SVM's nor NN's performance was considerably affected by an increase in feature dimensionality. ML's ability to perform under conditions of small training-set sizes and large feature dimensionalities was shown to be limited. Given sufficient training data and using few selected features, ML outperformed NN. This finding suggests that NN as the weakest of the three classifiers for GEOBIA under such conditions. This should be of particular interest to eCognition users, as the latest version of the software (8.7) allows users to choose between SVM, CART and Bayes classifiers as alternatives to the commonly applied NN classifier.

4. Conclusions

It is well known that the incorporation of additional variables (e.g. vegetation indices, image transforms, textural information, contextual information and ancillary data) in the land cover classification workflow can improve the accuracy of object-based supervised classifiers. Although GEOBIA provides an ideal platform for the inclusion of such features, the number of available training samples is generally less for object-based problems than for traditional pixel-based approaches. This study compared the performance of SVM, NN and ML for object-based land cover classification, with particular attention to increasing the number of input features. SVM generally produced superior classification results. This is likely due to SVM's capability to produce maximum separation between classes through the calculation of the optimal separating hyperplane.

SVM and NN were not considerably (negatively) affected by an increase in feature dimensionality. In contrast ML's well-known susceptibility to the Hughes effect and its reliance on a sufficient number of training data was confirmed in a GEOBIA context. The results also revealed that some features are more important than others for specific classifiers and that CTA-based feature selection is not necessarily optimal for all classifiers. The nature of the data, the desired classification output and the specific classifier should therefore be considered carefully when additional features are incorporated.

This study adopted a very simple four-class land cover classification scheme as a more complex classification scheme would have increased subjectivity during training set development. More research is needed to investigate the effect of feature dimensionality on the performance of SVM, NN and ML when more complex classification schemes are used. However, the findings of this study indicate that object-based supervised classification using SVM may be a cost-effective solution for mapping land cover over large areas as it reduces the need for a large number of training samples.

The findings of this study are of particular value in South Africa where SPOT5 imagery is freely available to government agencies and research institutions. Although the study focused on a relatively small test site, similar levels of accuracy can be expected elsewhere in South Africa if similarly pre-processed SPOT5 imagery is used. More research is, however, needed to test the robustness (i.e. repeatability in other areas) of object-based supervised classifiers and to compare the cost-effectiveness of such an approach to a rule-based (i.e. expert system) approach.

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