SUB-PIXEL LAND COVER CLASSIFICATION IN A RESOURCE CONSTRAINED ENVIRONMENT: ONE STUDY AREA, THREE ALGORITHMS AND SEVEN IMAGES - WHAT CAN WE LEARN?

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Statistical approaches can help coastal managers in resource constrained environments to better manage the coastal zone by enabling improved decision making through the use of sub-pixel classification algorithms of easier, cheaper and more frequently available Sentinel-2 data. For such managers, it is important to know if the same method would yield the best classifications for all seasons and years for their study area. It is known from literature that for different studies, the best algorithm varies, however, this study considers if the same holds true for the same study area across different seasons and years. Seven Sentinel-2 images across two seasons and four years are classified using three algorithms which area both seasonally and own date trained. Results show that the wet season imagery classifications are more accurate than those from the dry season for both seasonal and own date classifications. It is also shown that seasonal classifications are more acceptable for the wet season classifications while for the dry season there are larger differences between the accuracies for seasonally and own date trained algorithms. Finally, it is determined that even for the same study area and season, the best algorithm varies for different images.

Key words: Land Cover Classification, Maximum Likelihood Classification, Mixture Discriminant Analysis, Sub-pixel Classification

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1. Introduction

Remotely sensed imagery is increasingly being used by ecologists (Wegmann, 2017). For African ecologists its application is especially relevant as some areas remain inaccessible due to terrain, financial constraints or political situations. African ecologists, however, face a number of challenges in their use of remotely sensed imagery. These have been found to include data costs, specialised software costs, costs of training and weak IT infrastructure (de Klerk and Buchanan, 2017).

While free low to medium spatial resolution imagery is available, some applications require high resolution imagery and this imagery frequently remains unaffordable for many African institutions (de Klerk and Buchanan, 2017). For such applications, sub-pixel classification is required to make use of the freely available imagery. Even with increasing access to data, it has been noted that limited analytical expertise continues to limit widespread use of remote sensing data within conservation studies (Wegmann, 2017). Thus, it is determined that the use of simple, easy to interpret sub-pixel classification methods need to be considered for such ecologists to make the methods fully accessible. Based on this both Maximum Likelihood Classification (MLC) and Mixture Discriminant Analysis (MDA) are considered as they are easy to implement and interpret.

MLC is an older algorithm, however, it remains one of the most popular (Hogland, Billor and Anderson, 2013). MLC relies on the statistical likelihood of a pixel belonging to a class. MLC is dependent on the training data selected to fit a single distribution (routinely Gaussian for remote sensing (Campbell and Wynne, 2011)) to each of the classes and then making use of Bayes' rule the posterior probabilities of class membership are generated (Tso and Mather, 2009). While, MLC was found to perform better than other parametric classifiers (Otukei and Blaschke, 2010), the resulting classification may be not satisfactory if the data are not Gaussian distributed and unimodal (Otukei and Blaschke, 2010).

MDA can be seen as an extension of MLC (Ju, Kolaczyk and Gopal, 2003), where the observed classes are treated as mixtures of unobserved sub-classes. These sub-classes can be fitted with various distributions including the Gaussian. MDA is simple to implement and interpret (Ju et al., 2003) without the restrictive MLC assumptions of unimodality and normally distributed data. These restrictions are addressed by means of the finite mixture models (FMM) used within MDA to model the class distributions as FMM are able to model arbitrarily complex distributions (Figueiredo and Jain, 2002). Thus, MDA is a semi-parametric method, i.e. the individual distributions to be used in the FMM need to be specified. However, they do not have to match the true distribution of the data as the mixture of these individual distributions can generate more complex distributions (MacLachlan and Peel, 2000). For this study, both the Gaussian MDA (GMDA) and t-distribution MDA (TMDA) are considered. In order to use all of these methods at a sub-pixel level, the probabilities of class membership are normalised to sum to one and these probabilities are then taken as the class membership proportions.

Such statistical methods employed at the sub-pixel level for land cover classification could be of great use to the managers of coastal areas who operate within resource constrained environments such as those described above. However, even when considering fully accessible methods, it has been shown in literature that no single algorithm is the best for all studies (Giacinto and Roli, 1997). This study investigates whether or not this also holds true for the same study area but for different years and seasons using the same satellite sensor. Specifically, we investigate the affect of seasonality on classification accuracy, whether or not a method trained on a single year's data can be used to classify imagery from multiple years and whether or not the best method is consistent for a single study area across all images classified.

2. Study Area

The study area lies between the towns of Khayelitsha and Gordons Bay in False Bay, City of Cape Town Municipality, South Africa. The area has a Mediterranean climate with cool and wet winters followed by hot and dry summers with high risk of fires (Yates, Elith, Latimer, Maitre, Midgley, Schurr and West, 2010). The total annual rainfall varied between a high 968 mm in 2014 to a low of 505 mm in 2017 at the closest station (Streenbrasdam Lower) (Department of Water and Sanitation, Republic of South Africa, 2018). This is indicative of the multiyear drought in the area during the later years. A Sentinel-2 image of study area can be seen in Figure 1. Based on knowledge of the study area, classes of interest were identified and can be seen in Table 1

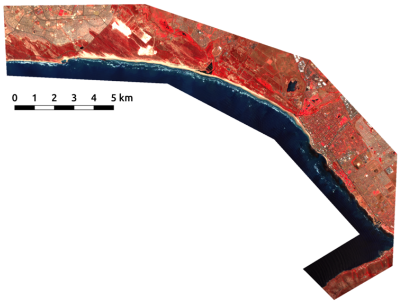

Figure 1. Sentinel-2 image of the study area from December 2015 in band combination 8-4-3

Table 1. Land cover classes and their descriptions

Class	Description
Bare Ground	Any kind of uncovered soil
Built Up/Urban	Any man-made structure including but not limited to buildings, roads and bridges
Herbaceous Vegetation	Grass and other herbaceous i.e. non-woody vegetation
Shadow	Shadow caused by tall buildings and steep relief
Water	Any kind of open water bodies
Woody Vegetation	Trees and shrubs

3. Data

Seven Sentinel-2 images chosen for their low cloud cover percentage were available for this study. There were three images available for the wet season and four available for the dry season. These were generated between December 2015 and February 2018. The dates for the images be seen in Table 2. The images were atmospherically corrected making use of ATCOR-2 software embedded in Interactive Data Language (IDL) by the Council for Scientific and Industrial Research (Richter and Schläpfer, 2017). The images were then trimmed to the study area. Sentinel-2's four 10 m resolution

Table 2. Date label and associated date of Sentinel-2 imagery

Date Label	Date
Wet Season 2015	28 December 2015
Dry Season 2016_1	17 January 2016
Dry Season 2016_2	06 February 2016
Wet Season 2016	13 October 2016
Dry Season 2017	02 March 2017
Wet Season 2017	18 October 2017
Dry Season 2018	25 February 2018

bands were used in this study, these are the band 2/Blue band (457.5—522.5 μm), band 3/Green band (542.5—577.5 μm), band 4/Red band (650—680 μm) and band 8/Near Infrared band (784.5—899.5 μm). For validation of the classifications, sub-meter spatial resolution aerial photography is available from the City of Cape Town for January 2016, January 2017 and February 2018.

4. Methodology

4.1 Selection of training and validation data

To determine if a classification scheme developed on a single imagery date can be used to accurately classify multiple images from the same season, a date must be chosen for each season. The wet season 2015 image is from December 2015 (which is not strictly the wet season) as Sentinel-2 imagery was not available from before December 2015. As such the first true wet season image (Wet Season 2016) is chosen for the training of the wet season algorithms. For the dry season, due to the cloud cover in both 2016 images, the next dry season image (Dry Season 2017) was selected for training of the dry season algorithms. These seasonal classifications are to be compared to those obtained by classification of each image based on training data taken from the image itself (own date classification).

The number of training points per class for each date can be seen in Table 3, these training points were selected using QGIS (QGIS Development Team, 2018) from across the entire image in a desktop approach assisted by Google Earth (Google Earth, 2018) and knowledge of the area. This approach is consistent with that followed by Otukei and Blaschke (Otukei and Blaschke, 2010). For seasonal classification (Dry Season 2017 and Wet Season 2016), Herbaceous Vegetation was more difficult to identify for dry season image than for the wet season one. As such, there are less points available for the Herbaceous Vegetation class for the Dry Season 2017. Otherwise, the number of training points is fairly consistent between the Dry Season 2017 and Wet Season 2016 images. When selecting training data for the remaining images, the number of training points per class was fixed to be close to those from the Wet Season 2016 image. The exception to this is the Built Up/Urban class where an additional 200 points are selected. Shadow is the class for which the number of points was not fixed as very few points were available in the images for this class and as such as many points as possible were selected.

In order to validate the algorithms, 671 validation points were used from across the image. 500 of these were collected randomly from ten areas of interest spread across the image while the remainder were randomly chosen from across the whole image. The images were aligned with the closest date

Table 3. Number of training points per class for each image

		Wet Season			Dry Season			
		2015	2016	2017	2016_1	2016_2	2017	2018
Class	Bare Ground	600	619	600	600	600	625	600
	Built Up/Urban	950	750	950	950	950	750	950
	Herbaceous Vegetation	400	430	400	400	400	250	400
	Shadow	33	43	37	37	32	41	48
	Water	700	651	700	700	700	635	700
	Woody Vegetation	400	450	400	400	400	505	400

of aerial photography for validation. The aerial photographs were overlaid with a 10×10 m grid which was aligned to the pixels of the Sentinel-2 imagery. An additional grid composed of 1×1 m blocks aligned to the larger 10×10 m blocks was also used. This allowed for validation proportions to be produced for the 671 validation points.

4.2 Classification

Classification was performed by first training the various FMMs. MLC was treated as a finite Gaussian mixture model with a single sub-component. The FMMs were trained using the EMMIXSkew module (Wang, Ng and McLachlan., 2013) within R (R Core Team, 2014). A minimum of 20 points per sub-component are required by this module. The number of sub-classes fitted per FMM ranged from one to ten or the maximum allowed by the 20 point minimum per sub-class. The spectral values for the samples are inputted for each class. The models were run 100 times using varying starting values to increase the probability that the EM algorithm had converged to the global maximum and not a local maximum or saddle point. The algorithms were run using the default settings of the module, namely “nrandom=10” initialisation and a maximum of 1 000 iterations per EM algorithm run (Wang et al., 2013). Once trained for multiple numbers of sub-classes per class, the appropriate number of sub-classes needs to be selected for the MDA algorithms. Both the Integrated Complete Likelihood (ICL) and Bayesian Information Criterion (BIC) were considered and both are generated by the EMMIXskew package.

The images are then classified using the posterior class probabilities, generated with non-informative priors, as class proportions. Once the classifications have been performed and the proportions have been normalised such that they sum to 100%, a filter is applied to remove any class proportion less than 1% before the proportions are re-normalised such that they once again sum to 100%. The 1% minimum is used to remove any noise created by insignificant probabilities.

5. Results and Discussion

The accuracy of the classifications is assessed by means of Overall Accuracy (OA), Kappa (κ) and Root Mean Square Error (RMSE). The accuracies per image can be seen for the wet and dry seasons in Figures 3 and 2 respectively.

For the wet season imagery trained using a single wet season date (left panel of Figure 2), MLC is shown to produce the best classification across all three accuracy measures for 2015, with TMDA-ICL being the second best performing algorithm. However, 2015 also has the lowest accuracies of the

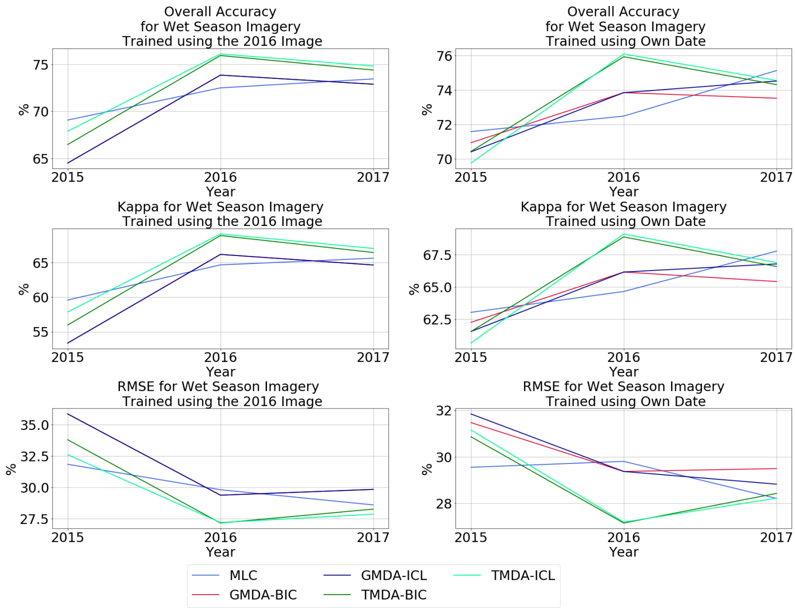

Figure 2. Accuracies for all algorithms for wet season imagery

three wet season dates considered. For the wet season images for 2016 and 2017 TMDA performs best based on all three accuracy measures. When considering the results from each image being classified using data from itself (the right panel of Figure 2), 2016 naturally remains unchanged as it was the date used to train for the seasonal classification. For 2015, there is an improvement in accuracy. However, the image still has the lowest accuracies of the three years and MLC is still the best algorithm. The second best algorithm, when OA and κ are considered, is now GMDA-BIC followed by GMDA-ICL tied with TMDA-BIC and TMDA-ICL coming last. However, when considering RMSE, the TMDA and GMDA algorithms are switched with TMDA being more accurate. MLC is the best algorithm for 2017 based on OA and κ, however, based on RMSE TMDA yields the same accuracy as MLC.

Considering the results of the dry season classifications trained using the 2017 dry season image (left panel of Figure 3), it can be seen for the 2016_1 and 2016_2 images that the accuracies are significantly lower than for the remaining two dry season classifications. Across all the dates, OA and κ show GMDA to be the best of the algorithms followed by TMDA and finally MLC, however, if one considers the RMSE values, TMDA is shown to be best followed by GMDA and then MLC.

For both 2016_1 and 2016_2 trained using own date data, TMDA produces the best results. For 2017, GMDA produces the best OA and κ results with TMDA only slightly less accurate, however, if one considers the RMSE, TMDA is shown as the most accurate algorithm for 2017. For 2018, MLC shows great improvement in accuracy from 2017 but is still the worst of the algorithms when judged by OA and κ. OA has the GMDA algorithms as best algorithms followed by TMDA. For κ, GMDA-BIC is the best of the algorithms followed by TMDA and GMDA-ICL which have practically the same accuracy. RMSE brings MLC to just marginally ahead of TMDA and GMDA-BIC algorithms for 2018.

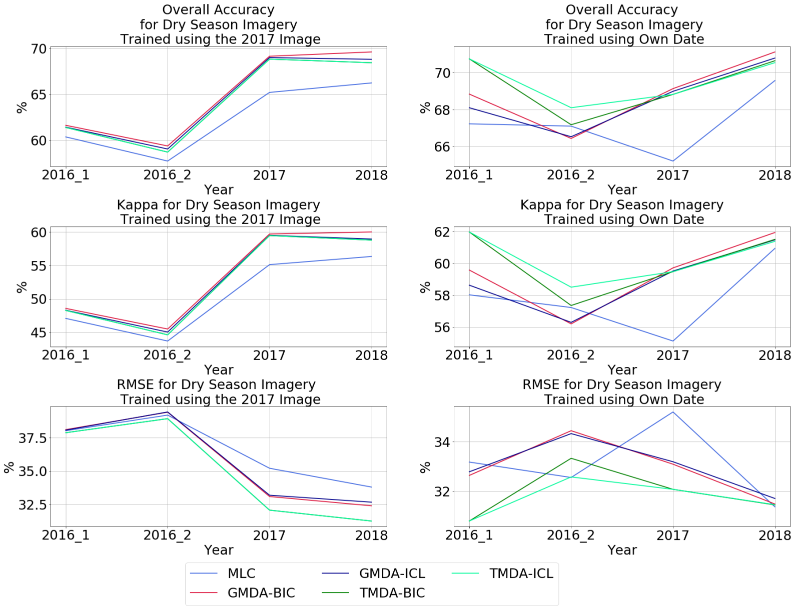

Figure 3. Accuracies for all algorithms for dry season imagery

6. Conclusions

A previous simulation study found that with more than 200 validation points, the rankings of algorithms were consistent between OA, κ and RMSE (Chen, Zhu, Imura and Chen, 2010), however, this has not been found to hold in this study with 671 validation points. However, based on the various accuracy measures, it is found that seasonality does affect the classification accuracy and it is recommended that should land cover classification be undertaken only once a year that it should be performed in the wet season as higher accuracies where achieved in this season.

For the wet season imagery considered in this study, the difference between own date and seasonal classification is fairly small, thus the analyst may decide to classify multiple dates (which have been radiometrically corrected to a single date) using a single date's training data and only update this classification if the results are unsatisfactory. However, should land cover classification be undertaken in the dry season, it is recommended that each image be classified using its own training data as the results may be unacceptable if a single date is used to train a classifier for the classification of all dates (seasonal classification). In this study, the unacceptable classifications may have been influenced by the worsening drought which may have influenced the signatures between years i.e. making the sparse vegetation signatures more similar to Bare Ground as the drought continued and the vegetation became drier.

It was also found that even for the same study area, the best method may vary across the various images even if they are from within the same season.

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