1 Effect of pan-sharpening multi-temporal Landsat 8 imagery for crop type
2 differentiation using different classification techniques

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Effect of pan-sharpening multi-temporal Landsat 8 imagery for crop type differentiation using different classification techniques

This study evaluates the potential of pan-sharpening multi-temporal Landsat 8 imagery for the differentiation of crops in a Mediterranean climate. Five Landsat 8 images covering the phenological stages of seven major crops types in the study area (Cape Winelands, South Africa) were acquired. A statistical pan-sharpening algorithm was used to increase the spatial resolution of the 30m multispectral bands to 15m. The pan-sharpened images and original multispectral bands were used to generate two sets of input features at 30 and 15 metre resolutions respectively. The two sets of spatial variables were separately used as input to decision trees (DTs), *k*-nearest neighbour (k-NN), support vector machine (SVM), and random forests (RT) machine learning classifiers. The analyses were carried out in both the object-based image analysis (OBIA) and pixel-based image analysis (PBIA) paradigms. For the OBIA experiments, three image segmentation scenarios were tested (good, over and under segmentation). The PBIA experiments were carried out at 30m and 15m resolutions. The results show that pan-sharpening led to dramatic (~15%) improvements in classification accuracies in both the PBIA and OBIA approaches. Compared to the other classifiers, SVM consistently produced superior results. When applied to the pan-sharpened imagery SVM produced an overall accuracy of nearly 96% using OBIA, while PBIA's overall accuracy was 1.63% lower. We conclude that pan-sharpening Landsat 8 imagery is highly beneficial for classifying agricultural fields whether an object- or pixel-based approach is used.

Keywords: Pan-sharpening; machine learning; object-based image analysis; supervised classification; crop type mapping

Introduction

Agricultural productivity is the foundation of developing economies and critical for food security (Awokuse & Xie 2014). Accurate and timely crop maps are needed to update agricultural databases used in planning and for carrying out yield forecasting (Monfreda et al. 2008). Traditional approaches to crop mapping and yield forecasting involve routine field visits which are costly and often biased (Castillejo-Gonzalez &

Lopez-Granados 2009). Remote sensing offers an unbiased, cost effective, and reliable procedure of mapping crops at a local, regional, and national scale (Xin et al. 2015). The use of remotely sensed optical imagery for the identification and monitoring of crop types has gained popularity in recent years, mainly due to an increase in its availability (Vieira et al. 2012; Simms et al. 2014; Muller et al. 2015; Ozelkan et al. 2015; Wardlow et al. 2015; Zheng et al. 2015). Several authors have shown that, for land cover and crop type mapping, object-based image analysis (OBIA) often outperforms the traditional pixel-based image analysis (PBIA) approach, especially when high resolution imagery is used as input. For instance, Castillejo-Gonzalez et al. (2009) compared PBIA vs OBIA for the identification of crops using 2.6m resolution Quickbird imagery and concluded that OBIA clearly outperformed PBIA. Also using Quickbird imagery, Myint et al. (2011) assessed OBIA and PBIA for urban land cover mapping and found that the former outperformed the latter by up to 27.6%. Similar conclusions were made by Bhaskaran et al (2010) and Yan et al. (2015) who saw OBIA outperform PBIA by overall accuracies of 20% and 36% respectively. Weih et al. (2010) used 1m resolution aerial photography and 10m SPOT 5 imagery for supervised land use and land cover classification and showed that merging high and medium spatial resolution imagery significantly improved classifications. In their experiments OBIA outperformed both supervised and unsupervised PBIA by 10%. From the literature it is clear that OBIA is generally preferred when the objects of interest are significantly larger than the pixels of the imagery (Blaschke 2010) and that the advantages of OBIA are reduced when lower resolution imagery is used. For instance, Duro et al. (2012) found that OBIA and PBIA did not produce significantly different results when using 10m resolution SPOT 5 data for classifying agricultural landscapes.

Generally, high spatial resolution imagery is preferred for crop type mapping owing to the reduction of mixed pixels (Grzegozewski et al. 2016). However, low to medium resolution multi-temporal data have also been shown to be effective for crop identification as it can better represent crop phenology, with optical (as opposed to microwave radio detection and ranging) multi-temporal data being the preferred data source (McNairn et al. 2009). For instance, Grzegozewski et al. (2016) used very high temporal resolution, low spatial resolution MODIS EVI (250m) imagery to map corn and soya bean. Their results showed that this approach works well provided that the pixels used for training the models were pure (i.e. representing homogenous fields of crops). Simms et al. (2014) also made use of multi-temporal MODIS normalized difference vegetation index (NDVI) 250m images to monitor opium and cereal crops. The NDVI profiles generated from the images provided valuable insight into the temporal variations between crop types. Using higher resolution (30m) multitemporal Landsat TM and ETM+ images, Vieira et al. (2012) demonstrated that accurate crop maps can be generated using expert knowledge of the phenological stages of crops. Similar observations were made by Zheng et al. (2015) and Muller et al. (2015) who also used multitemporal Landsat data for crop type differentiation.

From the above overview of using single-date high resolution imagery (e.g. Quickbird) and multitemporal medium resolution (e.g. MODIS and Landsat) imagery for mapping crop types, it would seem that high resolution, multitemporal imagery would be ideal for crop type mapping. However, acquiring and processing such data over large areas is often prohibitively expensive. Pan-sharpening, the process of fusing lower resolution multispectral data with higher resolution panchromatic imagery, may offer a solution to increase the spatial detail of medium resolution multitemporal imagery such as Landsat. The technique, also known as pan-fusion, has been shown to

be effective not only for visual enhancements of imagery (Ghodekar et al. 2016) but also for quantitative analyses such as land cover mapping (Ai et al. 2016). Pan-sharpening essentially combines the superior spatial resolution of a panchromatic band (required for accurate description of texture and shapes), with the spectral information of the lower resolution multispectral bands (required for accurate discrimination of informational classes) (Ghassemian 2016). Although many different pan-sharpening methods exist, not all are suitable for quantitative analyses. It is inevitable that some of the spectral fidelity of the original multispectral information is lost during the fusion process, but some algorithms are designed to maximize spectral preservation. Zhang & Mishra (2012) reviewed a range of commercially available pansharpening techniques and concluded that the PANSHARP algorithm, available in the software package PCI Geomatica, retained most of the spectral information of the original imagery and consistently produced superior results for all the types of sensors, images and spectral bands considered (Zhang 2002A; Zhang 2002B). MS-split, a new pan-sharpening technique introduced by Guo-dong et al. (2015) also shows promise, but the technique is not yet available in commercial software. Johnson (2014) analysed the effects of pan-sharpening on two Landsat 8 vegetation indices (NDVI and simple ratio) using fast intensity-hue-saturation, Bovey transform, additive wavelet transform, and smoothing filter-based intensity modulation. The results showed that these pan-sharpening algorithms were able to downscale both single-date and multi-temporal Landsat-8 imagery without introducing significant distortions of index values.

Non-parametric machine learning algorithms has recently gained much popularity in remote sensing as they have the ability to use known data (training samples) to classify large sets of imagery, whilst incorporating ancillary spatial data. Their capacity to handle input variables that are not normally distributed is one of their

main strengths (Jwan et al. 2013), but they are also very effective for classifying different types of input data (e.g. nominal, ordinal, ratio, and interval) and have been shown to be relatively robust under conditions of high dimensionality (Zheng et al. 2015). Popular algorithms include decision trees (DTs), k-nearest neighbour (k-NN), random forests (RF), and support vector machine (SVM). Decision trees perform well for land cover classification as demonstrated by Waheed et al. (2006) and Yang et al. (2003), while random forests have been used successfully for crop identification, vegetation classification and change analysis (Pal 2005; Gislason 2005). Alganci et al. (2013) and Zheng et al. (2014) showed that SVM is effective for agricultural classification and Myburgh and Van Niekerk (2013) found that SVM is a cost-effective solution for mapping land cover over large areas. K-NN has been used in many studies, partly because it was for long the only classifier available in the popular OBIA software eCognition. Examples include Myint et al (2011), Mountrakis et al (2011), and Myburgh & Van Niekerk (2013).

This study investigates the value of pansharpened, multitemporal Landsat 8 imagery and machine learning for crop differentiation. The aim is to determine whether pan-sharpening Landsat 8 imagery (from 30m to 15m resolution) has any effect on crop classification accuracies. The multitemporal imagery was used to generate an extensive set of spatial features (including vegetation indices and texture measures), which were then used as input to DTs, k-NN, RF, and SVM. The four classifiers were trained and assessed using in situ data collected during field surveys. A series of experiments were carried out in both the PBIA and OBIA paradigms to assess whether the increase in spatial resolution that pan-sharpening provides outweighs the loss of spectral fidelity; and whether OBIA is more effective in classifying the fused imagery into crop types.

The results are interpreted in the context of finding an operational solution for monitoring crop types over extensive areas.

Material and Methods

Study Area

The study was carried out in the Cape Winelands region of South Africa (Figure 1). The 1040km² study site, which extends from 33°34'39" to 33°52'17" S and 18°32'24" to 18°54'43" E, was chosen owing to the availability of multitemporal cloud free Landsat 8 imagery and the variety of winter and summer crops that are produced in the region. The study site has a Mediterranean climate with cool wet winters and warm dry summers, an average annual rainfall of 550mm, and the mean annual temperature minima and maxima are 11°C and 22°C respectively (Tererai et al. 2015).

Figure 1. Location of the study area in the Western Cape, South Africa.

The area produces a wide range of crops, the most common of which are canola, grapes (mainly for wine production), lucerne (alfalfa), lupine, olives, managed pasture, and wheat. The phenological and agricultural production stages phases of these crops are shown in Figure 2. The annuals canola, lupine, pasture grasses and wheat are grown during Southern hemisphere winter (April to August), while grapes are harvested during summer months (December to February). Lucerne is cut throughout the year, while olives are harvested during the early winter months.

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Canola				Sowing					Harvest			
Grape	Harvest					Pruning		Sowing				
Lucerne			Multiple cutting options (Colour and vigour varies)									
Lupine				Sowing				Harvest				
Olive				Harvest								
Pasture				Establishment			Possible Summer senescence					
Wheat				Sowing						Harvest		

Figure 2. Phenological and agricultural production phases of targeted crops. Dark grey represents important agricultural phases, light grey the growth of the crop, and white represents bare field. The selected imagery dates are indicated with dotted lines.

Satellite imagery acquisition and pre-processing

Five Landsat 8 level 1T images captured on 7 February, 11 May, 12 June, 31 August, and 5 December 2015 were acquired from the USGS (United States Geological Survey). The image dates were chosen based on phenological data and agricultural production phases (Figure 2) (covering all major growing stages for all crop classes), as well as the literature (McNairn et al 2009; Pena-Barragan et al. 2011). Five images were chosen based on Hao et al. (2015) who found that a set of five images is optimal. The images were atmospherically corrected and pan-sharpened in PCI Geomatica. The atmospheric and topographic correction (ATCOR) model was applied to all the images

owing to its positive impact on land cover classification as demonstrated by Lin (2015). The PANSHARP algorithm, as recommended by Zhang (2012) and Lin (2015), was used to resample and fuse the corrected images from 30m to 15m spatial resolution.

Image segmentation

Image segmentation was carried out on the original multispectral and pan-sharpened imagery. Multiresolution segmentation (MRS), as implemented in Trimble eCognition software, was used for generating the image objects. MRS is a region-merging pair-wise algorithm in which each data point is associated with another data point, where the delineation algorithm will predict which of the two is "more" relevant according to the input parameters. It segments on pixel or object level based on user-defined scale, shape, and compactness parameters. All the image bands were used as input to MRS, with a heavier weighting allocated to the green (15%), red (20%), near-infrared (40%), and short wave infrared (25%) spectral bands. No thematic layers were used in the segmentation process. Based on a structured, iterative process of segmentation generation and visual assessments, a "good" delineation of target objects was achieved using settings of 0.45, 0.55, and 14 for shape, compactness and scale parameters respectively (for the pan-sharpened dataset). The aim of the "good" delineation was to generate the minimum number of objects that will best represent a field (see Figure 3d). The ESP (Estimation Scale Parameter) tool developed by Dragut et al. (2010) was initially used to quantitatively estimate an optimal scale parameter, but did not produce a satisfactory scale recommendation. Two additional segmentation scenarios, namely "oversegmented" (Figure 3d) and "undersegmented" (Figure 3c), were also generated using visual assessments. In addition, two PBIA scenarios were emulated by employing the chessboard segmentation (CS) algorithm in Trimble eCognition. CS generates square objects with equal size. When the scale factor is set to one, the objects equate to

the pixels of the input imagery. The first CS (Figure 3a) was carried out on the original 30m resolution multispectral imagery, while the second (Figure 3e) was carried out on the pan-sharpened 15m resolution data. A scale factor of one was used in both cases.

Figure 3: Example of a canola field to illustrate the five different segmentation scenarios, namely: a) standard 30m resolution CS objects (pixels); b) under-segmented, c) over-segmented, d) and “good” segmentation as derived from the standard 30m images; e) pan-sharpened 15m resolution CS objects (pixels); f) under-segmented, g) over-segmented, and h) “good” segmentation as derived from the 15m pan-sharpened dataset.

The input parameters used for the eight different segmentation scenarios are summarized in Table 1. Each scenario was labelled with a unique four-character identifier.

Table 1. Summary of input parameters used for the segmentation scenarios. The first column shows the unique four-character identifier that was allocated to each scenario. The first character in the ID signifies the type of segmentation, with P indicating pixel-based (i.e. as emulated using CS segmentation) and O object-based (using MRS). The second character represents the input imagery used, with S signifying “standard” and P representing “pan-sharpened”. The last two characters represent a number that defines the size of the objects. For the pixel-based scenarios the value denotes the width of the object (pixel) in metres, while for the object-based scenarios the number represents the scale parameter used.

ID	Approach	Algorithm	Scale	Shape	Compactness
PP15	Pan-sharpened 15m pixels	CS	1	-	-
PS30	Standard 30m pixels	CS	1	-	-
OS07	Over segmented objects	MRS	7	0.45	0.55
OS12	Good segmented objects	MRS	12	0.45	0.55

OS34	Under segmented objects	MRS	34	0.45	0.55
OP06	Over segmented objects	MRS	6	0.45	0.55
OP14	Good segmented objects	MRS	14	0.45	0.55
OP35	Under segmented objects	MRS	35	0.45	0.55

Image feature set generation

In addition to the Landsat 8 spectral bands, several other features were used as input to the classifications. Table 2 outlines the 195 features considered (41 per image capture date). For the spectral features, mean and standard deviation values were calculated for each of the objects. Coastal aerosol (band 1), cirrus (band 8), thermal infrared 1 (band 10), and thermal infrared 2 (band 11) were excluded as they were deemed unsuitable for crop type differentiation. Nine indices commonly used in vegetation studies were generated from the remaining bands. The textural features considered included contrast, correlation, and entropy as recommended by Clausi (2002). Several image transforms relating to principal component analysis (PCA), colour transformations and tasselled cap were carried out. PCA was performed on all mean spectral features and components were chosen based on a scree test. This was done by creating a scree plot using the “percent of Eigenvalues” and removing all components that formed part of the flat line trend, resulting in 83% of the total variance. Coefficients for the tasselled cap transformation were obtained from Baig et al. (2014).

Table 2. Features used as input to the classifiers.

Type	Subtype	Features
<i>Spectral Features</i>	Mean	Blue, Green, Red, NIR, SWIR 1, SWIR 2, Panchromatic
	Standard deviation	Blue, Green, Red, NIR, SWIR 1, SWIR 2
<i>Indices</i>		ARVI, EVI, GCI, GNDVI, Greenness, NDVI, RGRI, SAVI, SRI
<i>Textural features</i>	GLCM	Contrast, Correlation, Entropy, Homogeneity
	GLDV	Contrast, Entropy, Mean
<i>Image transforms</i>	PCA	PC1, PC2, PC3, PC4
	Tasselled cap	Brightness, Greenness, Wetness, Transformation 4, Transformation 5, Transformation 6

237 *In situ data collection*

238 A crop type database in vector format was obtained from the Western Cape Department
239 of Agriculture. The database contains polygons representing agricultural fields and crop
240 types as determined during extensive field surveys in 2013. Because the data set was
241 produced in 2013, it could only be used to produce samples for perennial crops. In order
242 to find samples for non-perennial crops and to further validate the accuracy of the data
243 set, field visits were carried out in 2015. Stratified random sampling was used to select a
244 total of 159 crop fields from the database. A minimum of 20 samples per class was set.

245 *Classification and accuracy assessment*

246 The Supervised Learning and Image Classification Environment (SLICE) software
247 developed by the Centre for Geographical Analysis was used for classification and
248 accuracy assessment. SLICE was developed using the C++ programming language and
249 libraries from OpenCV 2.2 (Bradski & Pisarevsky 2000) and Libsvm (Chang and Lin
250 2011). SLICE includes a range of classification algorithms, including decision trees
251 (DTs), *k*-nearest neighbour (k-NN), random forests (RF) (called random trees in
252 OpenCV), and support vector machine (SVM). In the interest of brevity, the reader is
253 referred to Pal (2005) and Al-Doski et al. (2013) for an overview of these classifiers.

254 Parameters for DT and RF were chosen based on recommendations in the
255 OpenCV library documentation. For DT the maximum depth was set to 50, K-fold
256 cross-validation was disabled, the minimum number of samples was set to one, and
257 pruning harshness was set to the minimum. For RF the maximum depth was set to 50,
258 the minimum sample count to one, and pruning harshness to minimum. For the k-NN
259 classification *k* was set to one as suggested by Qian et al. (2015). For SVM the radial

basis function kernel was chosen for this study, as recommended by Hsu et al. (2010)..

The geospatial data abstraction library (GDAL) is used to manipulate shapefiles and raster files.

A 3:2 sample split ratio was employed for classification and accuracy assessment (i.e. 40% of the 150 samples were randomly excluded from classifier training and used exclusively for assessing the accuracy of the resulting models). The same set of training and testing samples were used for all experiments.

SLICE automatically generates confusion matrixes, overall accuracies (OA) and the kappa coefficients (K) for each experiment. OA is easily interpreted as it represents the percentage of classified pixels or objects that corresponds to errors of commission and omission (Campbell J & Wynne 2011), while K can be used to assess statistical differences between classifications (Foody 2004). McNemar's test, as implemented in IBM SPSS software, was used for assessing the statistical significance of the accuracies obtained from the experiments, as recommended by Foody et al. (2004) and applied by and Duro et al. (2012).

Results

Prior to analysis of classification accuracy and algorithm performance, a rudimental statistical analysis was performed on one of the more commonly used product derivatives. The analysis involved comparing the extracted NDVI values from pixels of the pan-sharpened (15m) and standard resolution (30m) data sets. Approximately 50 objects and pixels for each crop type were chosen at random to compare. The image date with the most vegetation vigour was selected (Table 4).

Table 4. Mean and standard deviation values for the randomly selected fields from each crop class). The image dates were based on when each crop would have the most foliage (estimated using Figure 2).

Crop type	Mean of difference	Standard deviation of difference
Lucerne	-0.0360	0.0047

Grape	-0.0326	0.0199
Canola	0.0219	0.0057
Lupine	0.0239	0.0029
Wheat	0.0252	0.0062
Olive	0.0340	0.0303
Pasture	0.0385	0.0125
Average	0.0107	0.0117

284

285 The differences between the extracted NDVI values were minor, with the largest
286 mean difference recorded for pasture (0.0385). A two-tailed t-test revealed that the
287 change in NDVI values after pan-sharpening were not statistically significant
288 ($P=0.893271$; 0.05). This is in accordance with conclusions reached by Johnson (2014).

289 The results of the crop classification experiments are provided in Table 5. The
290 highest classification accuracy was achieved for segmentation scenario OP14 (object-
291 based “good” segmentation) using the SVM classifier, with an OA and K of 95.9% and
292 0.95 respectively. This is marginally higher than the SVM classification of
293 segmentation scenario PP15 (pixel-based segmentation at 15m resolution), which
294 achieved an OA of 94.3% and K of 0.93. According to McNemar’s test the difference
295 between the SVM results for OP14 and PP15 is statistically insignificant (two-tailed $P =$
296 1).

297 Table 5. OA and K values for each experiment, as well as the average (AVG) and standard deviation (SD)
298 per segmentation scenario and classifier. Refer to Table 2 for explanation of the scenario IDs.

<i>Scenario</i>	<i>DT</i>		<i>k-NN</i>		<i>RF</i>		<i>SVM</i>		<i>OA</i>		<i>K</i>	
<i>ID</i>	OA	K	OA	K	OA	K	OA	K	AVG	SD	AVG	SD
<i>PP15</i>	85.1	0.82	77.4	0.73	88.7	0.86	94.3	0.93	86.4	6.1	0.84	0.07
<i>PS30</i>	74.0	0.69	55.5	0.47	75.3	0.71	79.3	0.75	70.0	10.3	0.73	0.02
<i>OS07</i>	74.0	0.69	52.3	0.43	74.9	0.70	77.7	0.73	69.7	10.1	0.64	0.12
<i>OS12</i>	74.5	0.70	52.2	0.43	72.7	0.76	80.6	0.77	70.0	10.7	0.67	0.14
<i>OS34</i>	55.5	0.47	51.9	0.43	66.0	0.59	69.3	0.68	60.7	7.1	0.54	0.10
<i>OP06</i>	77.7	0.73	73.5	0.68	86.5	0.83	90.7	0.89	82.1	6.8	0.78	0.08
<i>OP14</i>	81.7	0.78	78.9	0.75	87.5	0.85	95.9	0.95	86.0	6.5	0.83	0.08
<i>OP35</i>	59.0	0.50	52.8	0.44	68.8	0.63	75.6	0.71	64.1	8.7	0.57	0.11
<i>AVG</i>	72.5	0.67	61.8	0.56	77.5	0.74	82.9	0.80				
<i>SD</i>	10.3	0.12	11.5	0.14	8.2	0.09	8.9	0.10				

When the OA for each experiment result is plotted per experiment (Table 5) it is clear that there is considerable variation between the different approaches. It is also apparent that pan-sharpening had a positive overall effect on both the PBIA and OBIA scenarios, with PP15 outperforming PS30 by 14.9%, and OP14 producing a classification that is 15.8% more accurate than OS12. McNemar's test confirmed the statistical significance of these increases.

Very similar results were obtained for the scenarios that used the original 30m resolution imagery as input, with the exception of OS34 (under-segmented scenario) for which the OA was nearly 10% lower compared to the other three 30m resolution scenarios (PS30, OS07, OS12). A similar – but more emphasized – pattern is observed when the pan-sharpened scenarios are compared. PP15, OP06 and OP14 achieved similar OAs (82.1-86.4%), while the OA of OP35 (under-segmented scenario) was more than 18% lower at 64.1%.

When all the classifiers are considered, PP15 produced a mean OA of 86.4% compared to the slightly lower mean OA (86.0%) of OP14. According to McNemar's test there is no significant difference between the results of these two scenarios. Similarly, there is no significant difference between the results of PS30 and OS12. These results suggest that OBIA does not improve crop discrimination when Landsat 8 imagery (standard or pan-sharpened) is used.

SVM outperformed the other classifiers in all the segmentation scenarios (Figure 4), with a mean OA of 82.9% and K of 0.8. The second-best performing classifier was RF, which scored 77.5% and 0.74 for OA and K respectively. The poorest accuracy results were delivered by k-NN, with an OA of 61.8% (K=0.56).

324

325 Figure 4. OAs for all classifiers grouped by segmentation

326 To assess the effect of pan-sharpening individual types of crops, producer's
 327 accuracies (PA) were analysed (Table 6). Both the PBIA and OBIA scenarios showed
 328 increases of around 13% in mean PA difference when the imagery was pan-sharpened.
 329 The crops responded differently to the change in spatial resolution. Some crops, such as
 330 olive trees, benefited substantially from the higher spatial resolution (up to 31.7%).
 331 while others (e.g. grape, lupine, and wheat) were negatively influenced. These
 332 reductions are, however, minor and not significant.

333 Table 6. Producers accuracy for all crop classes. Accuracies are taken from the best performing PBIA and
 334 OBIA scenarios using the SVM classifier.

Crop	PS30	PP15	Difference	OS12	OP14	Difference
<i>Canola</i>	63.1	94.8	31.7	63.1	90.7	27.6
<i>Grape</i>	100.0	95.1	-4.9	100.0	97.7	-2.3
<i>Lucerne</i>	62.4	96.2	33.8	66.9	87.1	20.2
<i>Lupine</i>	98.9	89.4	-9.4	100.0	97.2	-2.8
<i>Olive</i>	58.2	100.0	41.8	56.8	100.0	43.2
<i>Pasture</i>	88.9	92.5	3.6	90.5	95.7	5.2
<i>Wheat</i>	95.8	91.7	-4.0	98.2	100.0	1.8
<i>Mean</i>	81.0	94.3	13.2	82.2	95.5	13.3

335

Discussion

Although a comprehensive comparison of classification algorithms was not within the scope of this study, the results show that classifier selection can have a significant impact on crop classification accuracies (Table 5 and Figure 4). SVM's dominance is attributed to its ability to generalize well even when relatively few training samples are available (Myburgh and Van Niekerk 2013). SVM is also very effective for separating classes that are spectrally similar (e.g. lucerne and wheat) and has been shown to be robust under conditions of high dimensionality (Zheng et al. 2015). The use of the radial basis function kernel recommended by Hsu et al. (2010) has also been proven to improve performance with higher feature dimensionality.

Figure 34. Visual comparison of two classification results. The map is based on the selection of a few fields that show clear difference between classifiers using the OP14 scenario. SVM classification is shown on the left and k-NN on the right.

The high (>90%) accuracies achieved when using SVM on the pan-sharpened imagery (in both the PBIA and OBIA paradigms) is impressive considering the relatively low (15m) spatial resolution of the imagery, the complexity of the classification scheme (seven winter and summer crops), and intra-crop variations. Intra-crop variations are caused by farming practices such as different crop planting and harvesting schedules, which results in different phenological stages per crop. The selection of cover crops can also cause variations. For instance, vineyards and grapes (summer crops) may have triticale, weeds, wheat, or fynbos as its ground cover crop during winter, all of which have different spectral properties that can lead to classifier confusion. In spite of these variations, SVM did well to successfully separate the crops in the study area. The good performance of SVM agrees with Kumar et al. (2015) and Zheng et al. (2015) who also employed SVM for crop differentiation and achieved overall accuracies of 90% and 88% respectively.

Many of the agricultural fields considered in this study were small and contained only one complete (i.e. not intersecting the boundaries) 30m Landsat 8 pixel (Table 4). The number of pixels per field increases substantially at 15m resolution, which explains why pan-sharpening improved the classification accuracies of the SVM PBIA and OBIA scenarios by 14.9% and 15.2% respectively. Similar improvements were observed for the other three classifiers considered. From these results it seems that the loss in spectral fidelity associated with pan-sharpening (in this case using the PANSHARP algorithm) is outweighed by the increase in spatial resolution and the additional information that is provided by the panchromatic band. One would expect that spatial (textural) features played an important role in the classification improvements when the pan-sharpened imagery was used as input, but further experimentation involving feature selection is required to verify this.

375 Table 5. Average field area per crop type and the number of pixels fully contained per field.

<i>Crop Type</i>	<i>Mean field area (m²)</i>	<i>Mean pixel count (15m)</i>	<i>Mean pixel count (30m)</i>
<i>Canola</i>	5623	25	6
<i>Grape</i>	5862	26	6
<i>Lucerne</i>	2180	9	2
<i>Lupine</i>	1718	7	1
<i>Olive</i>	1324	5	1
<i>Pasture</i>	5529	24	6
<i>Wheat</i>	6100	27	6

376

377 Of the six OBIA segmentation scenarios considered, the under-segmented
378 scenarios (OS34 and OP35) produced substantially (~15%) lower accuracies compared
379 to the good (OS12 and OP14) and over-segmented (OS07 and OP06) scenarios. These
380 results highlight the potential impact of selecting an inappropriate scale factor when
381 using MRS and the negative effect that under-segmentation (i.e. an inappropriately high
382 scale factor) has on OBIA results. Over-segmentation also reduced accuracy, but not as
383 dramatically as under-segmentation. This is attributed to the under-segmented objects
384 generally being larger than the agricultural fields being targeted, which results in
385 spectral mixing by other crop types on neighbouring fields, and other land covers (e.g.
386 roads, hedgerows, natural vegetation, waterbodies) occurring adjacent to fields. The
387 negative effect of under-sampling was less dramatic when the standard 30m spatial
388 resolution imagery was used as input (compare OS12 and OS34), likely because the
389 level of spectral mixing (mixed pixels) at 30m is inherently higher than at 15m. Because
390 the edges of land cover features such as roads, trees and waterbodies are better defined
391 by the 15m panchromatic band, the MRS and classification algorithms are consequently
392 more successful in delineating and excluding such features from consideration when the
393 pan-sharpened imagery is used as input. Again, these results demonstrate that
394 appropriate MRS scale factor selection is critical when Landsat 8 imagery (pan-
395 sharpened or not) is used for crop classification. Given the relatively small (1.63%)

difference between the best OBIA result (OP14 with SVM) and the best PBIA result (PP15 with SVM), it is questionable whether the modest improvement that OBIA provided is worth the effort of selecting an appropriate scale factor (and the risk of choosing one that is inappropriate). This finding is contrary to those of Castillejo-Gonzalez et al. (2009), but in agreement with Duro et al. (2012). This is most likely because Castillejo-Gonzalez et al. (2009) used 2.6m resolution Quickbird imagery, while Duro et al. (2012) used 10m resolution SPOT 5 data. High spatial resolution imagery is generally preferred for crop type mapping owing to the reduction of mixed pixels (Grzegozewski et al. 2016). Based on the work by Castillejo-Gonzalez et al. (2009) and Duro et al. (2012), as well as the findings of the present study, it would seem that an OBIA approach would improve classification performance with imagery of between 2.6m and 10m spatial resolution. More work is, however, needed to verify this observation. Notwithstanding, when using Landsat imagery for operational crop type mapping purposes, a pixel-based approach will be easier to implement (and automate) and will also be more efficient in terms of processing.

The results per individual crop (Table 6) clearly show that olives benefitted the most from the increase in spatial resolution. This is likely because of the small size of olive plantations, as well as their fragmented nature. Canola and lucerne also benefitted from the increased resolution, particularly in the PBIA scenario. Wheat hardly benefitted from pan-sharpening, likely because it is grown in very large, often rectangular fields.

Many studies have demonstrated the value of feature selection/reduction on classifier accuracies (Hao et al. 2015; Löw et al. 2015), especially when large numbers of feature sets are being considered. This study assumed that the effect of high dimensionality and redundancy among features would be the same for the pan-

sharpened and standard resolution feature sets. However, more work is needed to investigate to what extent feature selection/reduction will improve the crop classification results obtained in this study.

Conclusion

Accurate and up-to-date crop type maps are essential for yield forecasting and agricultural planning. Remote sensing offers an unbiased, cost effective, and reliable method for mapping crops over extensive areas. This study provides insight into the value of using pan-sharpened, (five-date) multi-temporal Landsat 8 imagery and machine learning algorithms for crop type classification. We demonstrated that machine learning algorithms can be employed to accurately differentiate between seven crops grown in a 1040km² area in the Cape Winelands of South Africa. The principal finding of this study is that pan-sharpening led to dramatic (~15%) improvements in accuracies in both the PBIA and OBIA paradigms. When the SVM classifier was applied to the pan-sharpened imagery it produced an overall accuracy of nearly 96% using OBIA, while PBIA's overall accuracy was 1.63% lower. For operational mapping of crop types using pan-sharpened Landsat 8 imagery, the potential negative effect of over- and under-segmentation may outweigh the possible improvements in accuracy that OBIA provides. Notwithstanding, whether an object- or pixel-based approach is used, it is clear that pan-sharpening of Landsat 8 imagery is highly beneficial for classifying agricultural fields.

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References

- Ai J, Gao W, Gao Z, Shi R, Zhang C & Liu C 2016. Integrating pan-sharpening and classifier ensemble techniques to map an invasive plant (*Spartina alterniflora*) in an estuarine wetland using Landsat 8 imagery. *Journal of Applied Remote Sensing*. 10(2): 026001-026001.
- Al-Doski J, Mansori SB & Shafri HZM 2013. Image Classification in Remote Sensing. Department of Civil Engineering, Faculty of Engineering, University Putra, Malaysia.
- Alganci U, Sertel E, Ozdogan M & Ormeci C 2013. Parcel-level identification of crop types using different classification algorithms and multi-resolution imagery in south-eastern turkey. *Photogrammetric Engineering & Remote Sensing*. 79(11): 1053-1065.
- Altman M, Hart TG, & Jacobs PT 2009. Household food security status in South Africa. *Agrekon* 48(4): 345-361.
- Avci ZDU & Sunar F 2015. Process-based image analysis for agricultural mapping: A case study in Turkgedli region, Turkey. *Advances in Space Research* 56: 1635-1644.
- Awokuse TO & Xie R 2014. Does agriculture really matter for economic growth in developing countries? *Canadian Journal of Agricultural Economics* 63(1): 78-98.
- Baig MHA, Zhang L, Shuai T, & Tong Q 2014. Derivation of a tasselled cap transformation based on Landsat 8 at satellite reflectance. *Remote Sensing Letters* 5(5): 37-41.

474 Bhaskaran S, Paramananda S, & Ramnarayan M 2010. Per-pixel and object-oriented
 475 classification methods for mapping urban features using Ikonos satellite data.
 476 *Applied Geography* 30: 650-665.

477 Blaschke T 2010. Object based image analysis for remote sensing. *ISPRS Journal of*
 478 *Photogrammetry and Remote Sensing* 65: 2-16.

479 Bradski GR & Pisarevsky V 2000. Intel's computer vision library: applications in
 480 calibration, stereo, segmentation, tracking, gesture, face and object recognition.
 481 1: 2796.

482 Breiman L 2001. Random forests. *Machine learning* 45(1): 5-32.

483 Burger C & Jansen A 2014. Increasing block tariff structures as a water subsidy
 484 mechanism in South Africa: An exploratory analysis. *Development Southern*
 485 *Africa* 31(4): 553-562.

486 Campbell J 2008. *Introduction to Remote Sensing*. 4th Edition. New York: The Guilford
 487 Press. 1-550.

488 Campbell J & Wynne R 2011. *Introduction to Remote Sensing*. 5th Edition New York:
 489 The Guilford Press. 399-404.

490 Castillejo-Gonzalez I & Lopez-Granados F 2009. Object and pixel-based analysis for
 491 mapping crops and their agro-environmental associated measures using
 492 QuickBird imagery. *Computers and Electronics in Agriculture* 68(2): 207–215.

493 Chang CC & CJ Lin 2011. LIBSVM: A library for support vector machines. *ACM*
 494 *Transactions on Intelligent Systems and Technology* 2(3): 27.

495 Trimble 2015. Trimble user guide. [Online]. Available at:
 496 <http://ecognition.cc/download/userguide.pdf>

497 Gislason PO, Benediktsson JA, & Sveinsson JR 2006. Random forests for land cover
 498 classification. *Pattern Recognition Letters* 27(4): 294-300.

499 Congalton R & Green K 2008. Assessing the accuracy of remotely sensed data:
 500 principles and practices. CRC press.

501 Dragut L, Tiede D, & Levick S 2010. ESP: a tool to estimate scale parameter for
 502 multiresolution image segmentation of remotely sensed data. *International*
 503 *Journal of Geographic Information Science* 24(6): 859-871.

504 Dube T & Mutanga O 2015. Evaluating the utility of the medium-spatial resolution
 505 Landsat 8 multispectral sensor in quantifying aboveground biomass in uMgeni
 506 catchment, South Africa. *ISPRS Journal of Photogrammetry and Remote*
 507 *Sensing* 101: 36-46.

508 Duro DC, Franklin SE, & Dube MG 2015. A comparison of pixel-based and object-
509 based image analysis with selected machine learning algorithms for the
510 classification of agricultural landscapes using SPOT-5 HRG imagery. *Remote*
511 *Sensing of Environment* 118: 259-272.

512 Finney KM 2004. Utilizing Pansharpened LANDSAT 7 Imagery to Detect Urban
513 Change in the Vancouver Census Metropolitan Area: 1999-2002. *Graduate*
514 *Program in Spatial Analysis Research Paper*. Toronto, Ontario, Canada,
515 *Ryerson University (2004)*.

516 Foody G & Atkinson P 2004. Uncertainty in Remote Sensing and GIS. Uncertainty in
517 remote sensing and GIS (pp. 2002-2002). Chichester: Wiley.

518 Gardner M & Altman G 1986. Confidence intervals rather than P values: estimation
519 rather than hypothesis testing. *BMJ* 292(6522):746-750.

520 Ghassemian H 2016. A Review of Remote Sensing Image Fusion Methods. *Information*
521 *Fusion* 0(1): 1-15.

522 Ghodekar HR, Deshpande AS & Scholar PG 2016. Pan-Sharpening Based on Non-
523 Subsampled Contourlet Transform. *International Journal of Engineering*
524 *Science* 1: 2831.

525 Grzegozewski DM, Johann JA, Uribe-Opazo, MA, Mercante E & Coutinho AC 2016.
526 Mapping soya bean and corn crops in the State of Paraná, Brazil, using EVI
527 images from the MODIS sensor. *International Journal of Remote Sensing* 37(6):
528 1257-1275.

529 Guo-dong Y, Xin-yu X, Xiang Z, & Hong-wei Z 2015. MS-split and Analysis of the
530 Comparison It with another Three Image Fusion Approaches. *International*
531 *Journal of Signal Processing, Image Processing and Pattern Recognition* 8(10):
532 331-342.

533 Guyon I & Elisseeff A 2003. An introduction to variable and feature selection. *The*
534 *Journal of Machine Learning Research* 3: 1157-1182.

535 Hao P, Zhan Y, Wang L, Zheng Nm & Shakir M 2015. Feature Selection of Time
536 Series MODIS Data for Early Crop Classification Using Random Forest: A Case
537 Study in Kansas, USA. *Remote Sensing* 7: 5347-5369.

538 Heidl M, Walde J, Tappeiner G, & Tappeiner U 2009. Classifiers vs. input variables—
539 The drivers in image classification for land cover mapping. *International*
540 *Journal of Applied Earth Observation and Geoinformation* 11(6): 423-430.

541 Hess T, Andersson U, Mena C, & Williams A 2014. The impact of healthier dietary
542 scenarios on the global blue water scarcity footprint of food consumption in the
543 UK. *Food policy* 50: 1-10.

544 Hsu CW, Chang CC, & Lin CJ 2003. A practical guide to support vector classification.
545 Available at: <http://www.csie.ntu.edu.tw/~cjlin/papers/guide/guide.pdf>

546 Johnson B 2014. Effects of pansharpening on vegetation indices. *ISPRS International*
547 *Journal of Geo-Information*. 3(2): 507-522.

548 Jwan A, Shattri B & Helmi ZMS 2013. Image Classification in Remote Sensing.
549 *Journal of Environment and Earth Science*. 3(10): 141-147.

550 Lewinski S 2007. Applying fused multispectral and panchromatic data of Landsat
551 ETM+ to object oriented classification. *New Developments and Challenges in*
552 *Remote Sensing* 1: 233-240.

553 Lin C, Wu CC, Tsogt K, Ouyang YC, & Chang CL 2015. Effects of atmospheric
554 correction and pan sharpening on LULC classification accuracy using
555 WorldView-2 imagery. *Information Processing in Agriculture* 2(1): 25-36.

556 Löw F, Duveiller G, Conrad C, & Michel U. 2015. Impact of Categorical and Spatial
557 Scale on Supervised Crop Classification using Remote Sensing.
558 *Photogrammetrie-Fernerkundung-Geoinformation* 1: 7-20.

559 Lu D & Weng Q 2007. A survey of image classification methods and techniques for
560 improving classification performance. *International journal of Remote*
561 *sensing* 28(5): 823-870.

562 Mackowiak P, Wasserman S, & Levine M 1992. A Critical Appraisal of 98.6 Degrees
563 F, the Upper Limit of the Normal Body Temperature, and Other Legacies of
564 Carl Reinhold August Wunderlich. *Journal of the American Medical*
565 *Association* 268:1578-1580.

566 McNairn H, Champagne C, Shang J, Holmstorm D, & Reichert G 2009. Integration of
567 optical and synthetic aperture radar (SAR) imagery for delivering annual crop
568 inventories. *ISPRS Journal of Photogrammetry and Remote Sensing* 64:434-449.

569 Monfreda C, Ramankutty N, & Foley J. A. 2008. Farming the planet: 2. Geographic
570 distribution of crop areas, yields, physiological types, and net primary
571 production in the year 2000. *Global biogeochemical cycles* 22(1).

572 Mountrakis G, Im J, & Ogole C 2011. Support vector machines in remote sensing: A
573 review. *ISPRS Journal of Photogrammetry and Remote Sensing* 66(3): 247-259.

574 Muller H, Rufin P, Griffiths P, Siqueira JBS, & Hostert P 2015. Mining dense Landsat
575 time series for separating cropland and pasture in a heterogeneous Brazilian
576 savanna landscape. *Remote Sensing of Environment* 156: 490-499.

577 Murthy CS, Raju PV, & Badrinath KVS 2015. Classification of wheat crop with multi-
578 temporal images: performance of maximum likelihood and artificial neural
579 networks. *International Journal of Remote Sensing*. 24(23): 4871-4890.

580 Myburgh G & Van Niekerk A 2014. Effect of feature dimensionality on object-based
581 land cover classification: A comparison of three classifiers. *South African
582 Journal of Geomatics* 2(1):13-27.

583 Myint SW, Gober P, Brazel A, Grossman-Clarke S, & Weng Q 2011. Per-pixel vs.
584 object-based classification of urban land cover extraction using high spatial
585 resolution imagery. *Remote sensing of environment*, 115(5): 1145-1161.

586 Ohmann J, Gregory M, Roberts H, Cohen W, Kennedy R, & Yang Z 2012. Mapping
587 change of older forest with nearest-neighbour.

588 Ortiz A & Oliver G 2006. On the use of the overlapping area matrix for image
589 segmentation evaluation: A survey and new performance measures. *Pattern
590 Recognition Letters* 27(16): 1916–1926.

591 Ozelkan E, Chen G, & Ustundag BB 2015. Multiscale object-based drought monitoring
592 and comparison in rainfed and irrigated agriculture from Landsat 8 OLI
593 imagery. *International Journal of Applied Earth Observation and
594 Geoinformation*. 44: 159-170.

595 Pal M & Mather P 2003. An assessment on the effectiveness of decision tree methods
596 for land cover classification. *Remote Sensing of the Environment* 86(4): 554-
597 565.

598 Peña-Barragán JM, Ngugi MK, Plant RE, & Six J 2011. Object-based crop
599 identification using multiple vegetation indices, textural features and crop
600 phenology. *Remote Sensing of Environment*. 115: 1301-1316.

601 Rodriguez-Galiano VF, Chica-Olmo M, Abarca-Hernandez F, Atkinson PM, &
602 Jeganathan C. Random Forest classification of Mediterranean land cover using
603 multi-seasonal imagery and multi-seasonal texture. *Remote Sensing of
604 Environment* 121: 93-107.

605 Roy DP, Wulder MA, Loveland TR, Woodcock CE, Allen RG, Anderson MC, Helder
606 D et al. "Landsat 8: Science and product vision for terrestrial global change
607 research." *Remote Sensing of Environment* 145 (2014): 154-172.

608 Saeys Y, I Inza, & P Larrañaga 2007. A review of feature selection techniques in
609 bioinformatics. *Bioinformatics* 19: 2507-2517.

610 Schlund M, von Poncet F, Hoekman DH, Kuntz S, & Schmullius C 2014. Importance of
611 bistatic SAR features from TanDEM-X for forest mapping and
612 monitoring. *Remote Sensing of Environment*, 151: 16-26.

613 Simms D, Waite T, Taylor J, & Juniper G 2014. The application of time-series MODIS
614 NDVI profiles for the acquisition of crop information across Afghanistan.
615 *International Journal of Remote Sensing* 35(16): 6234–6254.

616 Senf C, Leitao P, Flugmacher P, van der Linden S, & Hoster P 2015. Mapping land
617 cover in complex Mediterranean landscapes using Landsat: Improved
618 classification accuracies from integrating multi-seasonal and synthetic imagery.
619 *Remote Sensing of Environment* 156: 527-536.

620 Tererai F, Gaertner M, Jacobs SM 2015. Resilience of invaded riparian landscapes: The
621 potential role of soil-stored seed banks. *Environmental Management* 55:86-99.

622 Vieira MA, Formaggio AR, Renno CD, Atzberger C, Aguiar DA, & Mello MP 2012.
623 Object Based Image Analysis and Data Mining applied to a remotely sensed
624 Landsat. *Remote Sensing of Environment* 123: 553-562.

625 Waheed T, Bonnell RB, Prasher SO, & Paulet E 2006. Measuring performance in
626 precision agriculture: CART-A decision tree approach. *Agricultural water
627 management* 84(1): 173-185.

628 Walsh CM & Van Rooyen FC 2015. Household Food Security and Hunger in Rural and
629 Urban Communities in the Free State Province, South Africa. *Ecology of food
630 and nutrition* 54(2): 118-137.

631 Wardlow B, Egbert S, & Kastens, J 2007. Analysis of time-series MODIS 250 m
632 vegetation index data for crop classification in the US Central Great Plains.
633 *Remote Sensing of Environment* 108(3): 290-310.

634 Qian Y, Zhou W, Yan J, Li W, & Han L 2015. Comparing Machine Learning
635 Classifiers for Object-Based Land Cover Classification Using Very High
636 Resolution Imagery. *Remote Sensing* 7:153-168.

637 Xin Q, Broich M, Suyker AE, Yu L, & Gong P 2015. Multi-scale evaluation of light use
638 efficiency in MODIS gross primary productivity for croplands in the
639 Midwestern United States. *Agricultural and Forest Meteorology* 201: 111-119.

640 Yan G, Mas JF, Maathuis, Xiangmin Z, & Van Dijk PM 2015. Comparison of
641 pixel-based and object-oriented image classification approaches—a case study

642 in a coal fire area, Wuda, Inner Mongolia, China. *International Journal of*
643 *Remote Sensing* 27(18): 4039-4055.

644 Yang L, Xian G, Klaver JM, & Deal B 2003. Urban land-cover change detection
645 through sub-pixel imperviousness mapping using remotely sensed
646 data. *Photogrammetric Engineering & Remote Sensing* 69(9): 1003-1010.

647 Yu QP, Gong N, Clinton G, Biging MK, & Schirokauer D 2006. Object-based Detailed
648 Vegetation Classification with Airborne High Spatial Resolution Remote
649 Sensing Imagery. *Photogrammetric Engineering and Remote Sensing* 72 (7):
650 799-811.

651 Zheng B, Myint S, Thenkabail P, & Aggarwal R 2015. A support vector machine to
652 identify irrigated crop types using time-series Landsat NDVI data. *International*
653 *Journal of Applied Earth Observation and Geoinformation* 34:103-112.

654 Zhang Y 1996. A survey on evaluation methods for image segmentation. *Pattern*
655 *Recognition* 29(8): 1335–1346.

656 Zhang Y 2002A. Problems in the fusion of commercial high-resolution satellite as well
657 as Landsat 7 Images and Initial Solutions. *International Archives of*
658 *Photogrammetry Remote Sensing and Spatial Information Sciences*. 34(4): 587-
659 592.

660 Zhang Y 2002B. A new automatic approach for effectively fusing Landsat 7 as well as
661 IKONOS images. *In IEEE/IGARSS* 2: 24-28.

662 Zhang Y & Mishra RK 2012. A review and comparison of commercially available pan-
663 sharpening techniques for high resolution satellite image fusion. *In Geoscience*
664 *and Remote Sensing Symposium (IGARSS), 2012 IEEE International* 1:182-185.