The South African land cover change detection derived from 2013_2014 and 2017_2018 land cover products

Luncedo Ngcofe[1], Rory Hickson[2], Pradeep Singh[2]

[1] Chief Directorate: National Geospatial Information. Department of Rural Development and Land Reform, luncedo.ngcofe@drdlr.gov.za
[2] Land Resource International (Pty) Ltd

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Abstract

The appetite for up-to-date information about the earth's surface is ever increasing, as such information provides a basis for a large number of applications. These include the earth's resource detection and evaluation, land cover and land use change monitoring together with other vast environmental studies such as climate change assessment. Due to the advantages of repetitive data acquisition, the synoptic view, together with the varied spatial resolution it provides, and its available historically achieved dataset, remote sensing earth observation has become the major preferred data source for various earth studies. This study assesses land cover change detection of the land cover products (2013_2014 and 2017_2018) derived from earth observation.

There are vast number of change detection methodologies and techniques with some still emerging. This study embarked on post classification change detection methodology which entailed morphological and spectral filtering techniques. The 10 land cover classes that were assessed for change detection are: natural wooded land, shrubland, grassland, waterbodies, wetlands, barren lands, cultivated, built-up, planted forest together with mines and quarries. The change detection accuracy result was 74.97%. Through the likelihood analysis, the likelihood for change to occur (e.g. cultivated to grassland) and unlikelihood of change to occur (e.g. built-up to planted forest), resulted in 72.2% areas of potential realistic change.

The change detection results, further depend on the quality, compatibility and accuracy of the input land cover datasets. The application of different ancillary data together with different modelling techniques for land cover classification also affect the true reflectance of land cover change detection. Therefore extra caution should be exercised when analysing change detection so as to provide true and reliable changes.

1. Land cover change detection

Sustainable management of natural resources require continuous monitoring of land cover, amongst other earth observation features, for analysis of their trends and changes at various spatial and temporal scales. Abrupt land cover changes have significant negative environmental impacts such as the acceleration of land degradation, soil erosion, high rate of deforestation and urban sprawl. The precise understanding of change detection factors due to natural and anthropogenic influences is vital to promote better decision making relating to environmental management. Chen *et al.*, (2012(a); Thompson *et al.*, (2001) concurs, arguing that the dramatic land cover change over the past several centuries has severely affected our biodiversity ecosystem. Land cover change detection being defined as the assessment of changes in the types or conditions of surface features of interest, at different times in order to identify the actual transformation in those features of interest (Campbell & Wyne 2011; Ross & Bhadauria, 2015; Singh, 1989).

Due to the advantages of repetitive data acquisition, the synoptic view, together with the varied spatial resolution it provides, and its available historical achieved dataset, remote sensing imagery has become the major preferred data source for different change detection applications. The basic premise in using remotely sensed data for change detection is that changes in features of interest (be it land cover or land use) must result in changes in the radiance value between the compared dates. The changes in radiance value of features of interest must be large enough with respect to radiance changes caused by other factors such as atmospheric conditions, difference in sun angle and differences in soil moisture (Singh, 1989; Jensen, 1996). Ideally change detection procedures should involve data acquired by the same sensor or similar sensor, recorded by using the same spatial, spectral and radiometric resolution, at the same calendar date (but different years) and time (Lillesand & Kiefer, 2004). However, such idealistic scenes are largely impossible to obtain. This may be due to different calendar date for satellite repetitive cycle of the same area. Even if the anniversary data and the satellite's overpass do coincide, there may be an extensive cloud cover for one of the imagery dates deeming it not usable. Lastly the satellite used to capture one image may not be still orbiting and capturing images. Obtaining idealistic images may prove very difficult. One is often forced to approach the change detection by determining what cloud free images are available for a specific area and thus deciding whether any of the available data are suitable for the investigation being undertaken (Gibson & Power, 2000).

A variety of change detection methods and techniques have been largely documented in literature (Singh, 1989; Mas, 1999; Campbell & Wyne, 2011; Bhatta, 2011; Chen *et al.*, 2012 (b); Ross & Bhadauria, 2015; Mirzaei *et al.*, 2015; Khanday, 2016). However, it is argued that there is no single best change detection method suitable for all scenarios requiring change assessment. Each method has its own pros and cons that must be taken into consideration. Change detection may be broadly divided into two methods with various techniques applicable to the two methods. The first method is map-to-map comparison, also known as post-classification comparison, and the second method being image-to-image comparison - also known as pre-classification comparison. The map-to-map change detection method analyses map products of interest (e.g. land cover) which are generated independently using different dates of imagery and then the results compared. While image-to-image change detection methods entails analysing the spectral characteristics of two or more images and identifying the actual spectral differences caused by features of interest.

1.1. Map-to-map or post-classification change detection

This is the most common change detection method and compares two or more independently produced image classified results of different years (Coppin *et al.*, 2004). The different image products are generated using the same class information for precise comparison. Shalaby and Tateishi (2007) emphasises that this procedure not only allows areas of no change to be identified, but also allows the nature of change to be determined (e.g. grassland changed to cultivation). However the recorded difference of features of interest (e.g. land cover classes) may be influenced by many factors including different classification systems and different mapping techniques. Thus these needs to be considered when analysing the actual change. The principal advantage, on the other hand, is that the different dates of imagery are separately classified, thereby minimising the problems of different radiometric calibration between the compared dates.

1.2. Image-to-image or pre-classification change detection

This method is based on data transformation procedures and analysis techniques which are used to delimit areas of significant change based on spectral signatures of two or more images of different years. These are generally based on three categories namely: enhancement techniques, transformation techniques and algebra based techniques.

- Enhancement techniques – is the process by which an image may be augmented for the human eye thereby increasing the distinction between features of interest. Examples entail image reduction, image magnification, colour composite, contrast enhancement and filtering.
- Transformation techniques – is the process that reduces information redundancy on multi-spectral and /or hyper-spectral bands. Furthermore, it focuses on the processing of the relevant bands of interest to compare features being observed. Examples entail principal component analysis, tasselled cap transformation, Fourier transformation and image fusion.
- Algebra based approach – this approach comprises of image arithmetic techniques such as image differencing, image regression, change vector analysis, image rationing and vegetation index differencing.

2. Aim

It has been vastly acknowledged that there still remain challenges in selecting an appropriate change detection method. One of the reasons is that there is no single method better than the other. This has been due to impossible conclusion of best method from various existing change detection methods since the 1970s-to-date. Furthermore the demand on the other hand for accurate and timely change detection information has amplified. This study therefore aims to investigate the combination of change detection methods as a potential approach for land cover change detection in South Africa.

3. Data source

There are different land cover change detection time interval preferences (Matsika, 2007), triggered by various user to user interest. Thus there is no precise time interval to conduct land cover change. Further more land cover changes is class feature dependent, caused by major catastrophic events, anthropogenic and natural factors. In South Africa (Figure 1), the land cover community of practice decided on a three year interval for determining land cover change and five year interval for land cover mapping of the country (Wessels, 2014). The land cover change for this study has been determined between the land cover 2013_2014 product in comparison to the land cover 2017_2018 product. Both of these land cover products were derived from the Landsat remote sensing imagery.

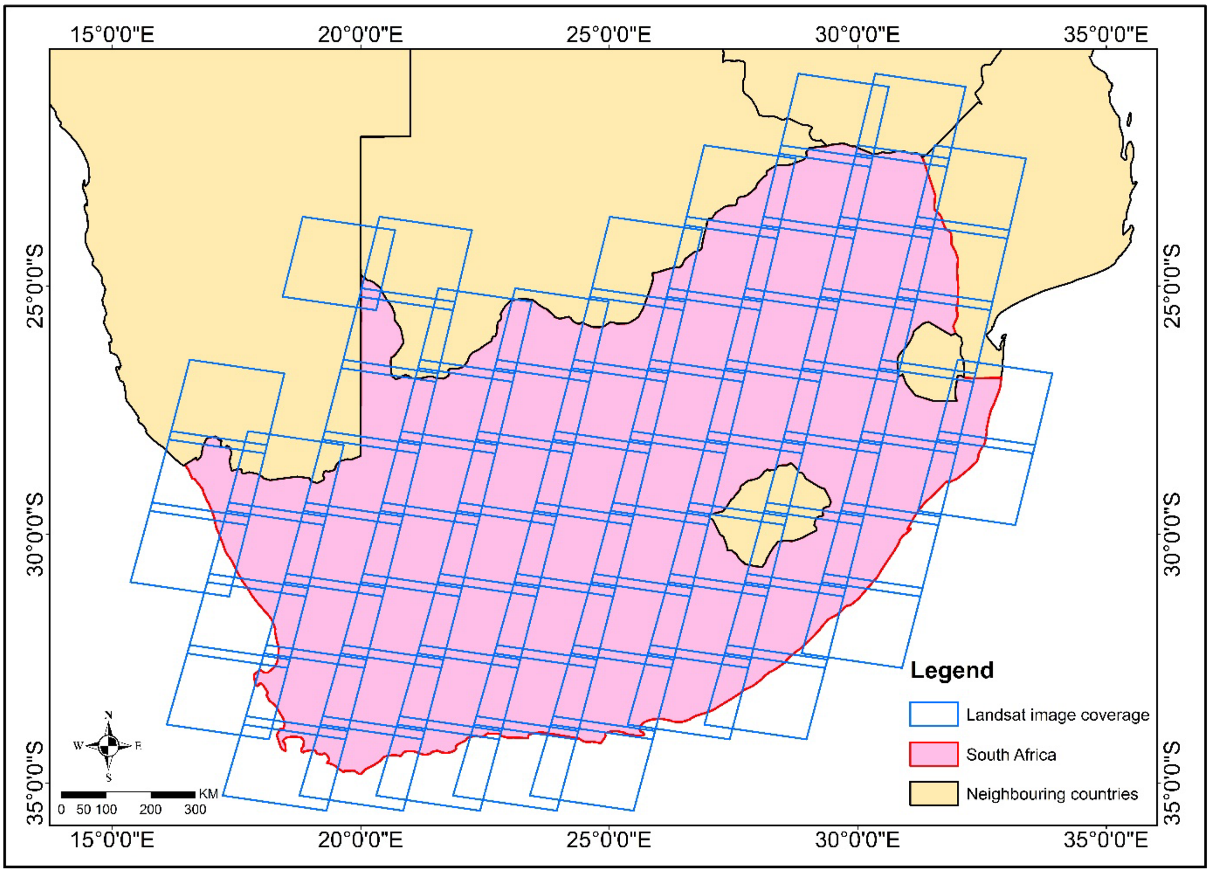

Figure 1. Study area with Landsat image footprint coverage.

3.1. Land cover 2013_2014 product

The land cover 2013_2014 dataset has been derived from a multi-seasonal Landsat 8 images using a semi-automated modelling procedure. This dataset contains 72 land cover information classes. The 2013_2014 land cover class product was based on the South African National Standard, termed SANS 1877, for class feature definitions and hierarchical format. The SANS 1877 was adopted in 2004, however, it is directly comparable to the land cover class information features derived from the South Africa Spatial Data Infrastructure (SDI) Act (no 54 of 2003) adopted in 2017. The 72 hierarchical land cover classes were resampled to 12 land cover classes which were directly comparable to the SDI derived land cover classes (Table 1).

Table 1. The relation between amalgamated land cover 2013_2014 classes (based on SANS 1877) and land cover 2017_2018 classes (based on SDI act no 54 of 2003).

Class no.	2013_2014 Land cover classes	Class no.	2017_2018 Land cover classes
1	Forest	1	Natural wooded land
2	Thicket & dense bush		
3	Woodland / open-bush		
4	Low shrubland	2	Shrubland
5	Grassland	3	Grassland
6	Water	4	Waterbodies
7	Wetland	5	Wetlands
8	Bare	6	Barren land
9	Cultivated	7	Cultivated
10	Built-up	8	Built-up
11	Mine	9	Mines and quarries
12	Forest plantation	10	Planted forest

The methodological approach to map the 72 land cover classes was based on the creation of the following foundation land cover classes namely: 1) trees 2) bush 3) grass 4) water and 5) bare-ground. The foundation land cover classes were derived from different spectral indices to enhance their discrimination amongst each other from the remotely sensed imagery. The next step was to establish land cover classes from the foundation classes, created above, through the application of ancillary datasets that served to mask the areas of interest. For example the foundation spectral land cover model for bare-ground could be a representative of a mine or a built-up area. By using appropriate ancillary datasets, the difference of a mine and a built-up area could be achieved (Figure 2). The detailed method is explained in the 2013_2014 South African National Land Cover report by Geoterra Image (2015) conducted for the Department of Environmental Affairs.

For accuracy assessment, 33 main land cover classes were verified instead of the further subclasses consisting of 72 classes. There were 150 randomly selected verification points for each of the 33 classes. Through desktop analysis of high resolution imagery of the same date as the Landsat, (which derived land cover classification), together with Google Earth imagery verification, resulted in an overall map accuracy of 81.73% with Kappa index of 0.80.

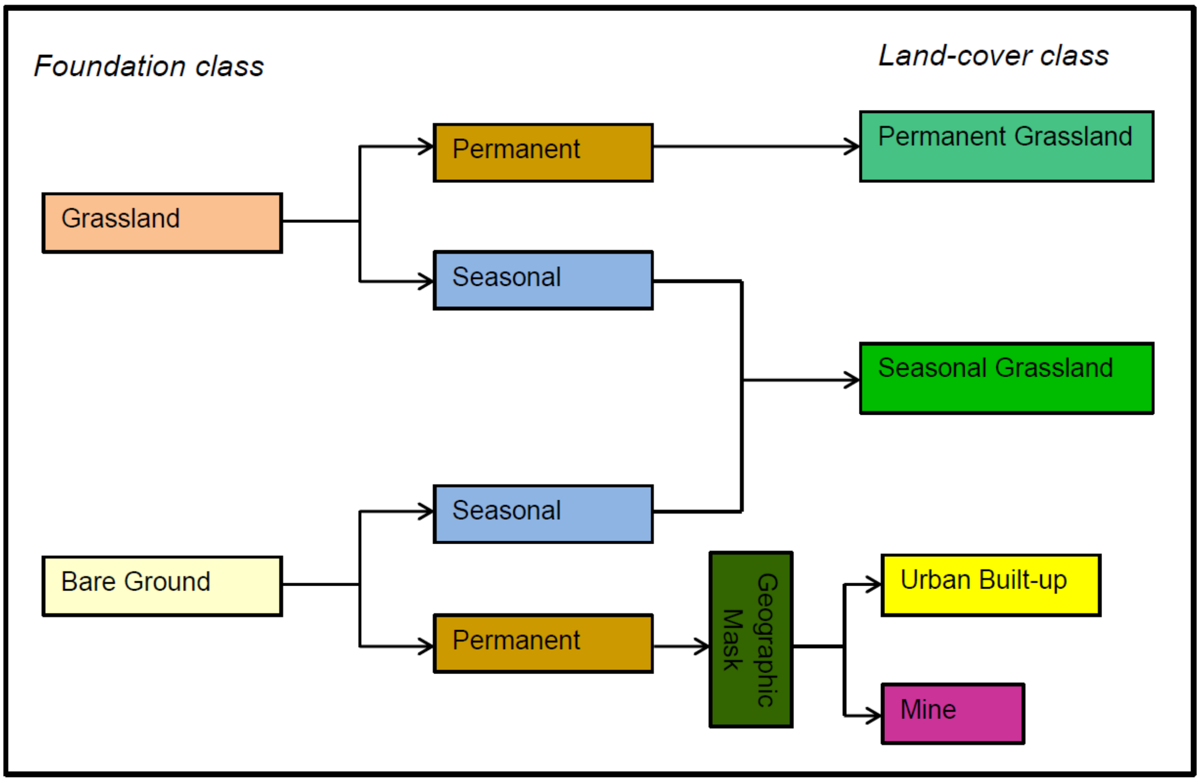

Figure 2. Processing pathways for converting spectral foundation classes to land cover information (Geoterra Image report, 2015).

3.2. Land cover 2017_2018 product

This land cover product was generated using multi-seasonal Landsat 8 imagery analysis techniques. For this study, the land cover mapping was based on 10 land cover class features (Table 1). The method followed the hierarchy decision tree (Figure 3), whereby vegetation and non-vegetated classes were separated through spectral analysis, spectral classification rules, together with spatial knowledge. The land cover classes that were not satisfactory identified due to similar spectra of other classes, were mapped through the assistance of ancillary data. Such an example of an ancillary dataset is the cultivated land cover class which was derived through mapping by the Department of Agriculture Forestry and Fisheries. The detailed methodological approach to this land cover mapping is documented in the report conducted by Land Resource International for the Chief Directorate: National Geospatial Information (SSC: WC 03 Report, 2018).

A number of stratified random sampling of 150 points per class (for each of the 10 classes) were selected to assess the accuracy assessment of the land cover product. High resolution aerial imagery, equivalent to the Landsat imagery used to derive land cover classification, together with Google Earth imagery were applied for accuracy assessment analysis. This resulted in 91.73% overall accuracy together with 0.90 kappa index.

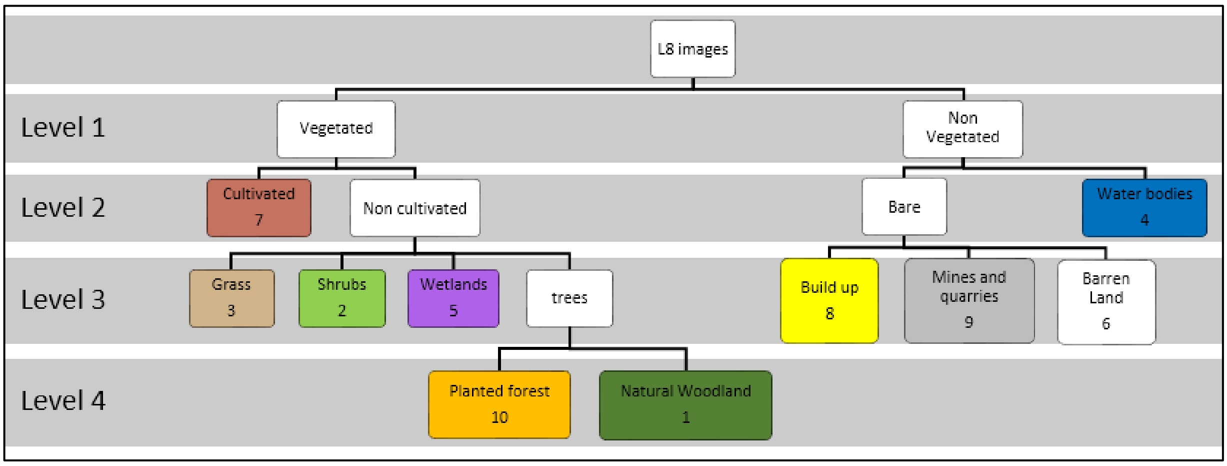

Figure 3. The hierarchical decision tree for land cover classification (Land resource International report, 2018).

4. Methodology

The change detection was based on land cover 2013_2014 and land cover 2017_2018 products which were both produced from multi-season Landsat 8 imagery. The change detection method applied was based on the combination of the available change detection techniques (both post classification and pre-classification techniques). The methodological process was based on three stages namely: 1) classification difference 2) morphological filtering and 3) spectral filtering (Figure 4).

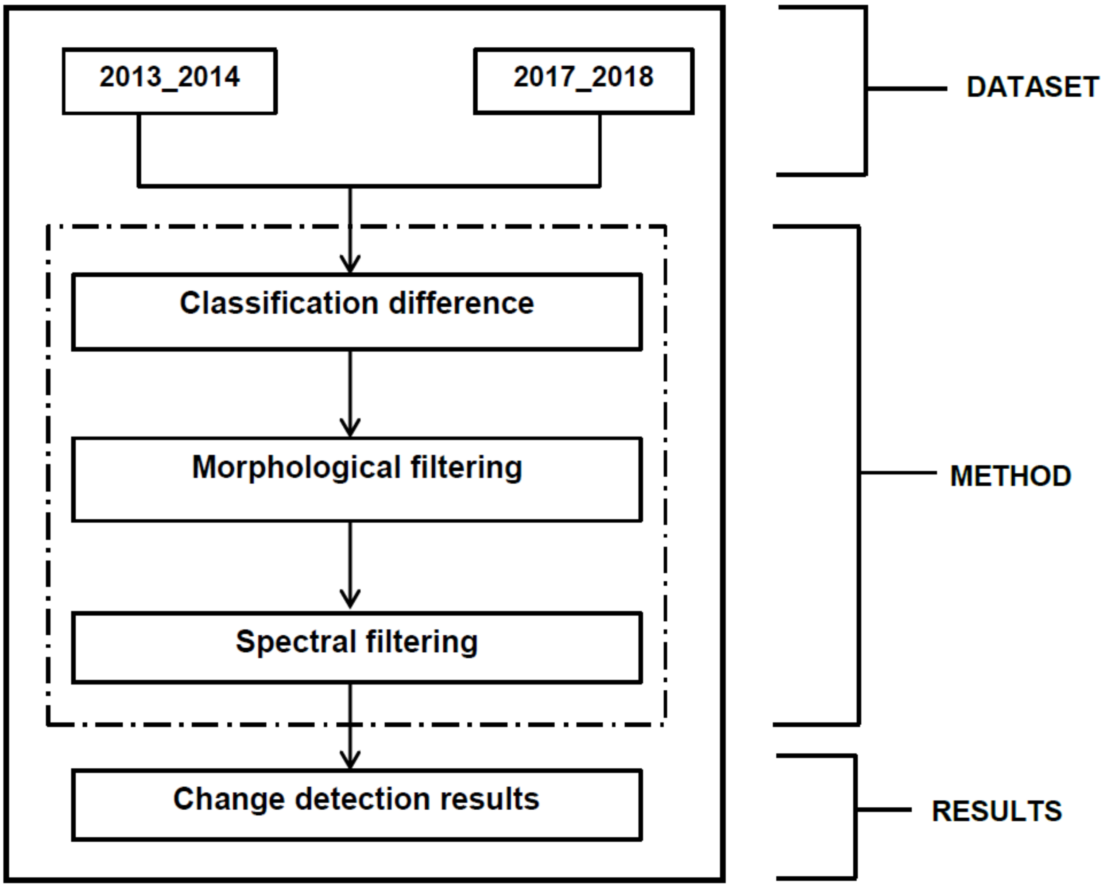

Figure 4. Land cover change detection (between 2013_2014 and 2017_2018 products) methodological flow chart.

4.1. Classification difference

The classification difference technique is represented under post classification method, whereby the difference between land cover 2013_2014 and 2017_2018 was conducted. The first step was to re-categorise the land cover classes (both 2013_2014 and 2017_2018) into class values (digital number - DN) from 1 – 10 for easier comparison (Table 2). A simple arithmetic equation below was conducted:

Classification difference = Class Values 2017_2018 – Class Values 2013_2014 [1]

The result was a thematic layer where all the areas that did not have any change were assigned a value of zero. However, this classification difference did not determine from what class the changed areas were and nor did they reveal the class they changed to (Figure 5).

Table 2. Land cover assigned class values for easy comparison.

Class values	2013_2014 Land cover classes	Class values	2017_2018 Land cover classes
1	Forest	1	Natural wooded land
1	Thicket & dense bush		
1	Woodland / open-bush		
2	Low shrubland	2	Shrubland
3	Grassland	3	Grassland
4	Water	4	Waterbodies
5	Wetland	5	Wetlands
6	Bare	6	Barren land
7	Cultivated	7	Cultivated
8	Built-up	8	Built-up
9	Mine	9	Mines and quarries
10	Forest plantation	10	Planted forest

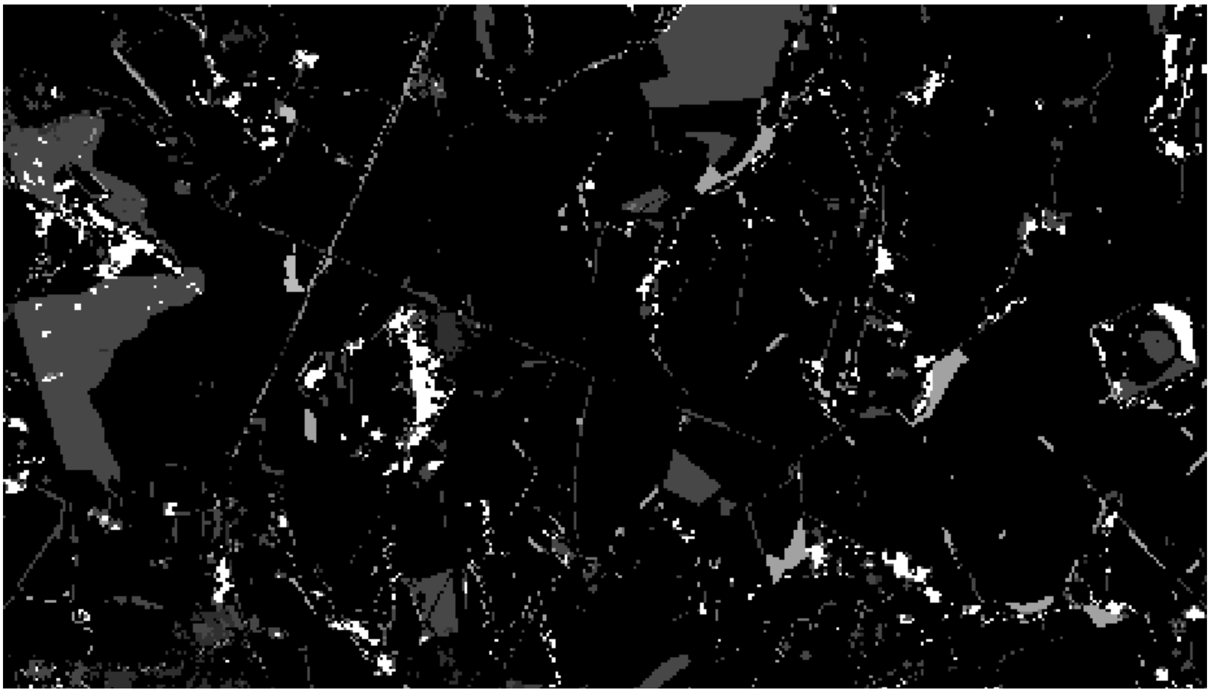

Figure 5. An example of the classification difference showing areas with no change in land cover represented by a black colour.

In order to assign individual specific values to each type of change the modification of the above technique was conducted. The class values were multiplied by 100 in order to create unique identifiers. This resulted in all the classes from the dataset having values of 100, 200, 300… etc. (instead of 1, 2, 3…etc.). Then a change detection matrix was produced which provided 90 possible combinations of change with information on direction of change and of class values (Table 3).

Table 3. Change detection matrix results

		2017 class DN values									
		1	2	3	4	5	6	7	8	9	10
2013 Class DN values	1	0	102	103	104	105	106	107	108	109	110
	2	201	0	203	204	205	206	207	208	209	210
	3	301	302	0	304	305	306	307	308	309	310
	4	401	402	403	0	405	406	407	408	409	410
	5	501	502	503	504	0	506	507	508	509	510
	6	601	602	603	604	605	0	607	608	609	610
	7	701	702	703	704	705	706	0	708	709	710
	8	801	802	803	804	805	806	807	0	809	810
	9	901	902	903	904	905	906	907	908	0	910
	10	1001	1002	1003	1004	1005	1006	1007	1008	1009	0

The smallest class (DN) value for change detection would be 102. This corresponds with areas that were class 1 (Natural Wooded land) in the 2013_2014 land cover dataset had changed to class 2 (shrubland) in 2017_2018 land cover dataset. Likewise the highest value would be 1009 corresponding to class 10 (Planted forest) in the 2013_2014 land cover dataset which had changed to class 9 (Mine and quarries) in 2017_2018 land cover dataset.

The above matrix values provide an easy way to visualise the changes within land cover classes but have the inconvenience of leaving a lot of the intermediate values with no meaning. Furthermore, the resultant largest value is greater than 255 thus forcing the output thematic layer to be a 16-bit raster, which is unnecessarily large. To avoid this, the values were recoded again numerically from [102 to 2009] to [1 to 90] to avoid having black (0 histogram) intermediate values in the thematic raster colour template (Table 4).

Table 4. Final recoded values of the thematic raster representing land cover change

102	1	natural woodland to shrubland
103	2	natural woodland to Grassland
⋮	⋮	⋮
1009	90	planted Forest to mines and quaries

4.2. Morphological filtering

The above classification difference results also entailed errors pertaining noise and silver polygons. These errors were prompted by actual class boundary differences at the edges due to distinct mapping methods of the two land cover products (2013_2014 and 2017_2018). Other factors that could possibly cause the noise include small shifts in geo-referencing and or differences in the way that an ancillary vector layers were rasterised. To reduce the effect of the noise, a morphological filter analysis was applied. One of the advantages of a morphological filter is its more flexible application of different sizes and geometric shapes (e.g. square, diamond, circle etc.) of filtering windows, rather than the pure square from traditional filters (Przemyslaw & Magdalena, 2009; Kaur & Garg, 2011; Zhi *et al.*, 2017). The morphological filter encompasses four major operator types, namely: 1) Dilation 2) Erosion 3) Opening and 4) Closing.

The dilation is defined as the maximum value in the window resulting in brighter or increased intensity in the image. It also expands the image and mainly fills the spaces. The dilation process expands the image objects by changing pixels with values of ‘0’ to ‘1’. Erosion is just the opposite of dilation. It is defined as the minimum value in the window. It shrinks images by changing pixels with a value of ‘1’ to ‘0’. Lastly the opening and closing operators both are formed by using dilation and erosion. In the opening operator, first the image will be eroded and then followed by dilation. On the other-hand for the closing operator, the image is dilated first then followed by erosion. For this study a ‘closed’ morphological filter analysis was conducted. The background value of ‘0’ of the area was made to grow eliminating any small or silver polygons using the majority analysis technique. Then the original thematic layer and the morphological closed layer were then intersected to recover the original shapes of the non-eliminated polygons that the morphological closed process may have changed and resulted in the elimination of noise. Figure 6 shows the example of the results of change detection before and after morphological closed analysis.

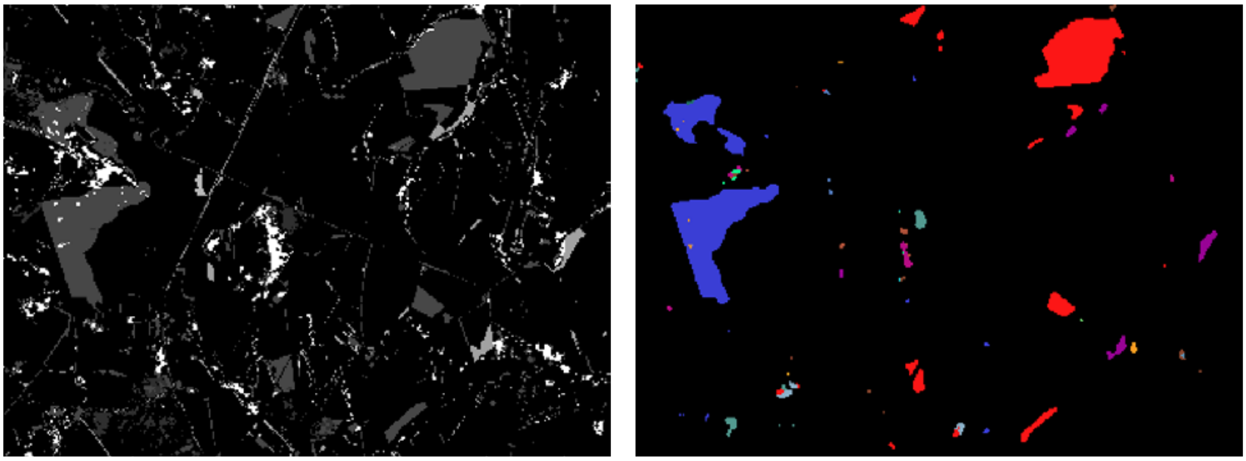

Figure 6: Example showing the results of morphological filter analysis, A) Before and B) After.

4.3. Spectral filtering

This technique entails comparison of spectral change between two different dates. For this study, spectral filtering was based on the comparison of the first three components of the tasselled cap transformation of images at similar times of the year between two dates of 2013_2014 and 2017_2018. The values within a certain defined threshold in standard deviation from the mean difference values of each component were considered non-changing areas and filtered out of the thematic change detection layer. The non-changed area results were further infused with the above mentioned filtering results to eliminate any potential areas of false change.

5. Results and discussions

The accuracy of land cover change can be affected by different classification procedures and class interpretation. Furthermore the level of detail being compared over time, together with random availability of satellite images (for example due to weather conditions) can contribute to false change. A statistically, valid assessment accuracy, for change detection products, is therefore required for managing decision making (Schoeman *et al.*, 2013). This study embarked on the modified error matrix for land cover change accuracy analysis. This method requires post classification assessment of each input classification product to have been statistically validated in terms of original classification map accuracy. This method provides an indication of reliability based on the maximum achievable change detection accuracy. Its formula is based on multiplying the accuracy derived from each individual land cover products. For land cover 2013_2014 the overall accuracy is 81.73 while for 20017_2018 overall accuracy is 91.73. Then the change detection accuracy for this study is 74.97 following the formula below:

$$\begin{aligned} \textit{Change detection accuracy} &= 81.73 \times 0.9173 \\ &= 74.97\% \end{aligned} \qquad [2]$$

The land cover class area extent for 2013_2014 and 2017_2018 has been presented in table 5. Although simple statistics show no to little change of the land cover classes (like natural wooded land had not changed with 16.84% while grassland has shown little change from 20.91% to 21.04% from 2013_2014 to 2017_2018 respectively) a more quantitative assessment of land cover change and type of change has been further conducted. The results are presented in table 6 where the direction of change and which land cover class has changed to another together with its area extent are analysed. For example table 6 indicates that 5740.52 hectares changed in 2013_2014 land cover for natural wooded land to other land cover classes. However, 5398.81 hectares of other land cover classes changed to natural wooded land in 2017_2018 resulting in -0.15147% of change of natural wooded land. It has been noted in table 6 analysis that there are degrees of change of -0.9644% of waterbodies from 2013_2014 to 2017_2018 which may be associated with drought conditions experienced over the past few years. More especially in the Western and Northern Cape Provinces the drought conditions have been severe and widely documented. The built-up areas have increased by 2.68056% which may be due to settlement development programs across the country. The mines and quarries also experienced growth of 3.83421%, however, this percentage is also influenced by false change. False change is largely due to the difference in capturing of the mines and quarries' ancillary datasets applied to the different land cover mapping products (2013_2014 and 2017_2018). The wetlands class also has an increase of 3.61617% which may be related to different models applied to derive a wetland class. A caution is required for further analysis of the wetland together with mine and quarry classes. Other land cover classes do not have drastic changes. The details of land cover inter-class change for each individual land cover class has been presented in Annexure 1. This provides a detailed interpretation of what land cover class X in 2013_2014 changed to what in 2017_2018 and the extent of change. Such analysis has further provided the ability to assess the likelihood of change transition of each individual land cover class. The time interval and the environmental context are the major attributes when assessing the likelihood character of land cover transition (Gómez et al., 2016). For this study of single period change detection analysis, only three transitions were considered according to their likelihood to occur. The first one being the '*likely*' to occur. This means that the change is normal or possible to occur during the time period. The example would be a cultivated class changing to grasslands. The second transition would be '*possible*' to occur. This merely means a change is not impossible but not normal to occur. For example a plantation class changing to mines and quarries class. It is rare for an agricultural area changing to mining due to food security programs. The third transition would be '*not likely*' to occur. This relates to changes that are ecological illogical or very rare to occur. For example built-up class changing to planted forest. The results revealed that 40% of the changes that occurred are likely to occur while 32.2% are possible with 27.8% are not likely to occur. Adding likely and possible to occur percentage equates to 72.2% areas of potential realistic change (Table 7).

Table 5: Land cover classification area extent for 2013_2014 and 2017_2018 products.

2013_2014			
Class Number	**Class Name**	**Area Km^2**	**% Area**
1	Natural wooded land	225682	16.84
2	Shrubland	462089	34.49
3	Grassland	280152	20.91
4	Waterbodies	13376	1
5	Wetlands	11105	0.83
6	Barren land	141491	10.56
7	Cultivated	151143	11.28
8	Build-up	31436	2.35
9	Mines and quarries	3361	0.25
10	Planted Forest	20131	1.5
	Total	1339966	100

2017_2018			
Class Number	**Class Name**	**Area Km^2**	**% Area**
1	Natural wooded land	225589	16.84
2	Shrubland	445629	33.26
3	Grassland	281913	21.04
4	Waterbodies	13612	1.02
5	Wetlands	13571	1.01
6	Barren land	141820	10.58
7	Cultivated	156512	11.68
8	Build-up	38887	2.9
9	Mines and quarries	3669	0.27
10	Planted Forest	18765	1.4
	Total	1339967	100

Table 6: Direction of land cover change per individual land cover class

		Sum of Area Km^2			
	Class	**2013 areas of classes that changed from**	**2017 areas of classes that changed to**	**Net Change (difference)**	**Change percent over original class area**
1	Natural wooded land	5740.52	5398.81	-341.71	-0.15147
2	Shrubland	7427.89	3639.48	-3788.42	-0.85013
3	Grassland	5700.59	6306.9	606.3	0.21507
4	Waterbodies	562.05	430.78	-131.27	-0.9644
5	Wetlands	271.68	792.43	490.74	3.61617
6	Barren land	1146.61	1797.35	650.75	0.45885
7	Cultivated	960.8	2359.46	1398.65	0.89364
8	Build-up	229.45	1271.83	1042.38	2.68056
9	Mines and quarries	52.09	192.75	140.66	3.83421
10	Planted Forest	670.98	602.88	-68.1	-0.39289
	Total	22762.66	22762.66		

Table 7: Likelihood transition of land cover classes

Number	Likelihood to change	occurrences	Percentage%
1	likely	36	40
2	Possible	29	32.2
3	Not likely	25	27.8
Total		**90**	**100**

6. Conclusion and recommendations

The vital role that remote sensing plays towards land cover mapping and land cover change detection has been widely acknowledged by several authors. Land cover changes continuously and thus change can either be dramatic and abrupt (such as changes caused by wildfires and flooding) and/or gradual such as regeneration of forests. This study investigates land cover change detection between the land cover product 2013_2014 and 2017_2018. The change detection being defined as the process of identifying differences in the state of land cover features by observing them at different times or years. The results summarily reveals the decrease in the area extent of natural wooded land, shrubland, waterbodies and planted forest while grassland, wetlands, barren land, cultivated, built-up, mines and quarries experienced an increase (Table 6). However, the change detection results depend on the quality, compatibility and accuracy of the input datasets (Gómez et al., 2016). The difference in mapping methodologies in this study resulted in 74.97% accuracy based on the modified error matrix calculation and 72.2% respectively on the likelihood to occur analysis. The application of different ancillary data together with different modelling techniques for further classification of land cover classes (such as mines and quarries together with wetlands) might affect the true reflectance of change in such land cover classes. Thus for such land cover class changes, extra caution should be taken when analysing change. This might include gathering more field data of the study area to access the true changes.

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Annexure 1: Land cover change detection classes

Row Labels	Sum of Area Km2	Sum of % change over total area	Likelihood of change
Barren land	**1146,6063**	**0,085569773**	
Build-up	35,8515	0,002675552	3
Cultivated	14,7897	0,001103737	1
Grassland	105,5358	0,007876003	1
Mines and quarries	20,6028	0,001537561	3
Natural wooded land	212,3946	0,015850739	1
Planted Forest	2,0664	0,000154213	2
Shrubland	658,6218	0,049152109	1
Waterbodies	82,4076	0,006149975	2
Wetlands	14,3361	0,001069885	1
Build-up	**229,4478**	**0,017123398**	
Barren land	2,574	0,000192094	1
Cultivated	225,0441	0,016794756	1
Grassland	0	0	1
Mines and quarries	0	0	1
Natural wooded land	0,0117	8,73156E-07	1
Planted Forest	0,3663	2,73365E-05	1
Shrubland	0	0	1
Waterbodies	1,4517	0,000108339	1
Wetlands	0	0	1
Cultivated	**960,8031**	**0,071703516**	
Barren land	14,0607	0,001049332	1
Build-up	46,4742	0,003468311	3
Grassland	507,3426	0,037862334	1
Mines and quarries	14,1156	0,001053429	3
Natural wooded land	234,5724	0,01750584	1
Planted Forest	47,6109	0,003553141	2
Shrubland	69,5304	0,005188965	2
Waterbodies	10,4121	0,000777042	2
Wetlands	16,6842	0,001245121	1
Grassland	**5700,5919**	**0,425427938**	
Barren land	237,1608	0,017699009	2
Build-up	387,612	0,028926992	3
Cultivated	702,0126	0,052390309	1
Mines and quarries	50,5197	0,003770221	3
Natural wooded land	2110,3938	0,157496011	2
Planted Forest	271,0188	0,020225789	2
Shrubland	1578,5478	0,117805019	2
Waterbodies	98,154	0,007325108	3
Wetlands	265,1724	0,01978948	2
Mines and quarries	**52,0875**	**0,003887224**	
Barren land	21,8709	0,001632198	1
Build-up	5,0724	0,000378547	3
Cultivated	0	0	2
Grassland	3,0654	0,000228767	1

Natural wooded land	2,7576	0,000205796	1
Planted Forest	0	0	2
Shrubland	10,4292	0,000778318	1
Waterbodies	8,892	0,000663599	1
Wetlands	0	0	1
Natural wooded land	**5740,5186**	**0,428407617**	
Barren land	316,7505	0,023638688	2
Build-up	464,4378	0,034660403	3
Cultivated	824,5566	0,061535612	2
Grassland	2296,1511	0,171358842	2
Mines and quarries	39,7539	0,002966783	3
Planted Forest	242,7282	0,018114497	3
Shrubland	1211,6034	0,090420424	3
Waterbodies	100,3122	0,007486172	2
Wetlands	244,2249	0,018226194	2
Planted Forest	**670,9752**	**0,050074027**	
Barren land	20,5335	0,001532389	1
Build-up	49,2336	0,003674241	3
Cultivated	20,8161	0,001553479	2
Grassland	191,3328	0,014278924	1
Mines and quarries	2,8404	0,000211975	3
Natural wooded land	342,7029	0,025575482	1
Shrubland	20,0313	0,00149491	1
Waterbodies	1,9188	0,000143198	2
Wetlands	21,5658	0,001609428	1
Shrubland	**7427,8944**	**0,554334331**	
Barren land	1035,2682	0,077260752	1
Build-up	253,4526	0,018914846	3
Cultivated	521,2287	0,038898636	1
Grassland	3090,8349	0,230665085	1
Mines and quarries	38,8125	0,002896528	3
Natural wooded land	2300,2578	0,17166532	2
Planted Forest	33,5835	0,002506294	3
Waterbodies	37,6956	0,002813175	3
Wetlands	116,7606	0,008713695	2
Waterbodies	**562,0518**	**0,041945212**	
Barren land	143,5968	0,010716447	2
Build-up	2,3814	0,000177721	3
Cultivated	8,5266	0,000636329	2
Grassland	72,6966	0,005425255	2
Mines and quarries	24,4197	0,001822411	3
Natural wooded land	146,8116	0,010956363	3
Planted Forest	1,3257	9,89353E-05	3
Shrubland	78,6114	0,005866669	2
Wetlands	83,682	0,006245081	1
Wetlands	**271,6821**	**0,02027529**	
Barren land	5,5395	0,000413406	1
Build-up	27,3123	0,002038282	3

Cultivated	42,4836	0,003170497	2
Grassland	39,9375	0,002980485	2
Mines and quarries	1,6875	0,000125936	3
Natural wooded land	48,9087	0,003649994	2
Planted Forest	4,1787	0,000311851	3
Shrubland	12,1014	0,000903112	2
Waterbodies	89,5329	0,006681727	1
Grand Total	**22762,6587**	**1,698748325**	