MONITORING LAND COVER CHANGE TO EVALUATE RESTORATION INTERVENTIONS USING SENTINEL IMAGERY

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FEBRUARY 2019
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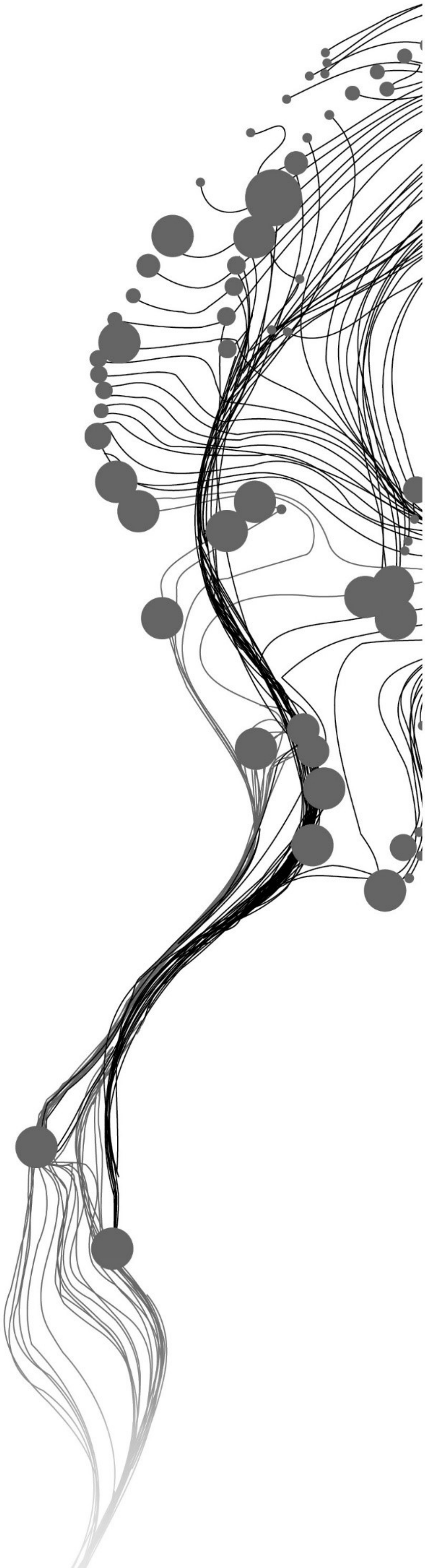

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MAY ANN RAPIO
Enschede, The Netherlands, February 2019

Thesis submitted to the Faculty of Geo-Information Science and Earth Observation of the University of Twente in partial fulfilment of the requirements for the degree of Master of Science in Geo-information Science and Earth Observation.
Specialization: Natural Resources Management

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ABSTRACT

The Baviaanskloof is a 75 km long valley between two mountain ranges in the Eastern Cape Province (South Africa). The area is a unique World Heritage Site because of its beauty and biodiversity, which has global importance. Baviaanskloof is part of the Baviaanskloof Mega Reserve (BMR) of about 500,000 ha, which comprises of clusters of state-owned protected land within a network of private and communal land. The area has been degraded due to intensive overgrazing and this is the primary reason for the implementation of four restoration interventions: Fenced/Revegetation of Spekboom/Livestock exclusion, Revegetation of Spekboom and Livestock exclusion, Livestock exclusion and Revegetation of Spekboom. This study sets out with the aim to map and analyse land cover in the Baviaanskloof based on cover classes that are relevant for evaluating restoration success. This was done through using a satellite image. The results reveal that freely accessible and relatively high-resolution Sentinel-2 imagery has adequate capability for mapping land cover with 85% accuracy, for evaluating restoration success. The result of FRAGSTAT for determining fragmentation in Spekboom vegetation and the ANOVA result indicates that among the five restoration types implemented, the 'Fenced/Revegetation/Livestock exclusion' measures is less fragmented compared to other restoration types. It also reveals that the restoration type influenced the growth of Spekboom which is the keystone for the restoration interventions in the area. However, the season for which the Sentinel image was used affects the accuracy of the land cover classification. During the dry season the obtained overall accuracy was higher compared to the wet season. One of the findings which emerged from this study is that the combination of bands from wet and dry season and the number of classes influenced the overall accuracy for image classification. The image classification with focus on Spekboom vegetation class using a combination of 10 bands from wet and dry season performed better with an accuracy of 85% compared to other band combinations. Monitoring the success of restoration interventions is crucial for stakeholders, the result of this study will guide them on which restoration type has been effective.

Keywords: Sentinel 2, Supervised Maximum Likelihood, Baviaanskloof, Restoration, Land degradation

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"In Christ alone, my hope is found, my light, my strength, my song, my cornerstone, this solid ground, firm through the fiercest drought and storm, what heights of love, what depths of peace, when fears are stilled, when striving cease, my comforter, my all in all, here in the love of Christ I stand" K. Getty

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1. INTRODUCTION

1.1. Background and justification

Land degradation is one of the most severe environmental challenges in the world today (Kertész, 2009; UNEP, 2015). It is caused and propagated by a complex mix of factors, ranging from environmental processes to human activities. Kishk (1990) argues that although land degradation can be a natural process, the misuse and mismanagement of natural resources by humans play a very important role. Land degradation has accelerated considerably in the past 10 years due to the intensification of agricultural production, urbanization, deforestation, drought, flooding and other extreme weather events (UNEP, 2015). UNEP (2015) asserted that within the last 40 years, up to 35% of the world's arable land has been lost to land degradation. Similarly, according to World Meteorological Organization (WMO, 2015), over 250 million people are affected by desertification alone, and another one billion people are at risk.

The United Nations Sustainable Development Goals specifically address the threats of land degradation in Goal 15. It emphasizes the need to "protect, restore and promote sustainable use of terrestrial ecosystems, sustainably manage forests, combat desertification, halt and reverse land degradation and biodiversity loss" (United Nations, 2015). Goal 15 also reaffirms the need to address the interdependence between sustainable management of Earth's resources and economic development through the promotion of resilient systems and disaster risk reduction (United Nations, 2015). Furthermore, Target 15.3 aims at restoring land already impacted by desertification, drought, floods and other forms of land degradation (United Nations, 2015). These, among other reasons, informed the decision to restore the Baviaanskloof catchment, which is a degraded biodiversity hotspot in a semi-arid region.

Land cover patterns are generated by human activity and natural factors, but the effects of human activities on the dynamics of land cover changes has become increasingly evident (Zhou et al., 2014). The alteration of natural land cover into a modified Land cover has become unpreventable due to growing human demands. Also, the subsequent implementation of restoration interventions to reduce the negative impacts of human activities on the environment has tremendous effect on land cover pattern (Zhao et al., 2017). The importance of the spatial and temporal dynamics of land cover transformation cannot be overemphasized. It affects the micro- and macro-climate (Cunha et al., 2015; Mahmood et al., 2010), the hydrology of surface and underground water (Lang et al., 2018; Setegn et al., 2009), land degradation and the survival and sustenance of terrestrial and aquatic ecosystems (Setegn et al., 2009). Chhabra et al., (2006), concluded that land cover change affects the proper function of the earth, the ecosystem, and human livelihood.

Restoration interventions include rehabilitation of degraded land to ensure increased food production, restore biodiversity and enhance ecological functions (TerrAfrica, 2013). According to Society for Ecological Restoration International Science & Policy Working Group (2004), restoration aims to enhance the recovery process of an ecosystem that has been damaged. As such, the purpose of restoring degraded ecosystem is to reestablish a resilient and self-sustaining ecosystem (Ruiz-Jaen & Aide, 2005; Society for Ecological Restoration International Science & Policy Working Group, 2004; Urbanska, Webb, & Edwards, 1997).

It is however necessary to periodically assess the state of a restoration intervention to provide insight into its success rate, to determine whether the set targets are being achieved. One important step in evaluating restoration success is the clear and explicit definition of criteria for this purpose. Several authors have made significant contributions by recommending some criteria that can be considered in monitoring restoration projects (Walters, 2000; Wilkins, Keith, & Adam, 2003). Nevertheless, the interpretation of the effectiveness of a restoration intervention may cover various aspects of the intervention, ranging from biophysical to ecological and socio-economic aspects (Meroni et al., 2017; Shackelford et al., 2013). Moreover, the Society for Ecological Restoration International Science & Policy Working Group(2004) specified guidelines on the comparison between restoration and controlled site based on the number of attributes measured on fieldwork species composition to ecosystem function and stability and to landscape context.

Three parameters can be used in monitoring effectiveness of restoration interventions.; (1) diversity; (2) vegetation structure and (3) ecological processes (Ruiz-Jaen & Aide, 2005). All these parameters are linked directly or indirectly to land cover. It is noteworthy that land cover (vegetation) plays a crucial role in ecological processes like carbon and hydrologic cycles, nutrients cycles, food webs, plant succession, etc. Restoration interventions are consequently implemented to rehabilitate degraded vegetation cover and recuperate land productivity(Meroni et al., 2017).

These restoration monitoring processes can be conducted using fieldwork exclusively. It is, however, time consuming and capital intensive. On the other hand, remote sensing is a relatively inexpensive, faster and efficient alternative. Remote sensing has enhanced our ability to observe ecosystem dynamics and human impact on the environment (De La Rocque, Michel, Plazanet, & Pin, 2004; Heumann, 2011; McCarthy et al., 2017). Remote sensing and GIS are important tools for studying land cover change (Singh et al., 2015). Land cover change is one aspect of change detection using remote sensing technology (Lu, Mausel, Brondízio, & Moran, 2004), which has been used to evaluate landscapes that have undergone radical change (Haque & Basak, 2017). Vegetation indices using the normalized difference vegetation index (NDVI), Iterative Self-Organizing Data Analysis (ISODATA) and Maximum likelihood supervised classification are other image classification techniques used in remote sensing to detect land cover change (Markogianni, Dimitriou, & Kalivas, 2013).

The launch of the Sentinel 2 satellite by the European Space Agency has been a major boost for effective natural resource evaluation and management. The global coverage, high spatial (10 to 60m), temporal (5-day interval) and spectral (13 bands) resolution and three red edge spectral bands, coupled with its free download and use (ESA, 2015), makes it a very important addition to the long list of currently available remotely sensed data. Moreover, Forkuor et al., (2018) pointed out that the availability of the Sentinel 2 data will greatly improve scientific investigations, effective decision making, land use planning and policy formulation. Indeed, due to the high spatial resolution and repeat time of five days Sentinel imagery may prove to be a very important and innovative tool for monitoring the inherent temporal and spatial dynamics engendered by an ecosystem restoration intervention. It may enable the detailed exploration of how the spatial extent and composition of the ecosystem has changed over time, providing insight on the success or failure of the intervention. To the best of my knowledge, this possibility has not been fully explored.

1.2. Research problem

The Baviaanskloof catchment is populated by less than 2,000 inhabitants (Boshoff, 2008). The region is located 75 km north-west of Port Elizabeth, and is the source of up to 30% of its drinking water (Jansen, 2008). Furthermore, Baviaanskloof is an area of outstanding natural beauty with remarkable landscape and diverse varieties of plants and animals (Boshoff, 2008; World Bank, 2011). Three of the world's most significant biomes can be found in the area (Conservation South Africa, 2012; Grounded, 2016). The region is also home to a wide variety of endemic plant species (Boshof, Cowling, Kerley, 2000; Boshoff, 2008; Van Wyk, 2011). Nevertheless, decades of unsustainable goat and sheep farming has led to extensive land degradation in the region (Boshoff, 2008; Waters et al., 2016).

Indeed, in semi-arid regions of the world, overgrazing of livestock is the main driver of desertification (Stringer et al., 2009; Van Luijk, Cowling, Riksen, & Glenday, 2013). If unsustainable goat farming remains the primary form of land use and income in the Baviaanskloof catchment, the land will further desertify (Living Land, 2016; Talbot & van den Broeck, 2015). In addition to desertification, soil erosion, silting of river and stream beds, and biodiversity loss are major environmental challenges in Baviaanskloof (Boshoff, 2008).

To address these issues, while safeguarding the means of livelihood of the local inhabitants, restoration interventions have been carried out in the Baviaanskloof. The interventions include planting of thicket, Lavender, Rosemary and removing of livestock. There is, however, the need to assess the impacts of restoration interventions to determine whether the landscape is being rehabilitated. This monitoring will also reassure the investor's confidence as it will show, in quantitative terms, to what extent the restoration goals are being achieved (Sewell, Bouma, & Van Der Esch, 2016). In-situ monitoring of large areas is a time-consuming and capital-intensive venture. Land use and land cover change monitoring with remotely sensed satellite imagery is a relatively cheap and sustainable alternative because it takes less time, human and financial capital to periodically assess the state and rate of change of the landscape. Indeed, several researchers have used satellite imagery to monitor the impacts of land restoration measures in semi-arid areas and other landscapes (Andres, Boateng, Borja-Vega, & Thomas, 2018; Klemas & Klemas, 2014; Meroni et al., 2017; Vanderhoof & Burt, 2018; Vanderpost, Ringrose, Matheson, & Arntzen, 2011). The role of remote sensing in the monitoring of restoration success has increased due to the possibility of mapping the full extent of vegetation at high spatial resolutions (Xie, Sha, & Yu, 2008).

The assessment of vegetation structure – i.e. trees, shrubs, herbs, woody plant density, biomass or vegetation profiles – using vegetation cover is one of the principal criteria for measuring restoration success (Kruse & Groninger, 2003, Ruiz-Jaen & Aide, 2005, Salinas & Guirado, 2002, Wilkins, Keith, & Adam, 2003). Monitoring vegetation cover has been used to study changes in spatial pattern, providing immediate and systematic evaluation on the biophysical impact in terms of vegetation cover of restored areas (Reif & Theel, 2017). Monitoring of vegetation cover and its abundance needs spatially explicit vegetation maps with sufficient spatial and thematic resolution to determine restoration success. The quality of the output should be explicit enough to allow stakeholders to evaluate ecosystem services affected during implementation of restoration interventions, identify species that need to be restored and direct their efforts to highly suitable areas where plant may thrive with relatively higher survival rate (Cordell et al., 2017).

So far, studies on the Eastern Cape of South Africa previously conducted by Nyamugama & Kakembo (2015) used satellite imagery to estimate and monitor aboveground carbon stocks using Landsat Thematic Mapper, Landsat Enhanced Thematic Mapper and Satellite Pour l'Observation de la Terre 5 (SPOT 5). Furthermore, Bailey, McCleery, Binford & Zweig (2016) assessed land cover change in Maputaland-Pondoland-Albany Biodiversity Hotspot Zone using Landsat images. It is noteworthy that since the start of Baviaanskloof restoration project in 2005, no research has attempted to monitor land cover change in the area as a proxy to assessing the success or failure of the ecosystem intervention measures implemented. Furthermore, the availability of high (spatial and temporal) resolution Sentinel 2A and 2B imageries with potential applications in agriculture, land-cover change and biophysical vegetation variable mapping (ESA, 2015), would improve our capacity for monitoring ecosystem restorations. It is, however, noteworthy that Sentinel 2A satellite was launched in June 23, 2015, while Sentinel 2B was launched in May 7, 2017. Its potential value is consequently limited by the fact that it can only be used to monitor restoration interventions, staring from 2015. Sentinel 2 is a high spatial resolution satellite, but the capability, with particular reference to its use to detect vegetation variation in this landscape is not yet known. It is for this reason that this study proposes the use of Sentinel 2 products and field validation in the detection and evaluation of land cover change for the assessment of the impact of land restoration intervention in the Baviaanskloof catchment.

1.3. Research objectives and questions

The main objective of the study was to map and analyse land cover in the Baviaanskloof based on cover classes that are relevant for evaluating restoration success. This objective will be addressed by the following specific objectives and research questions:

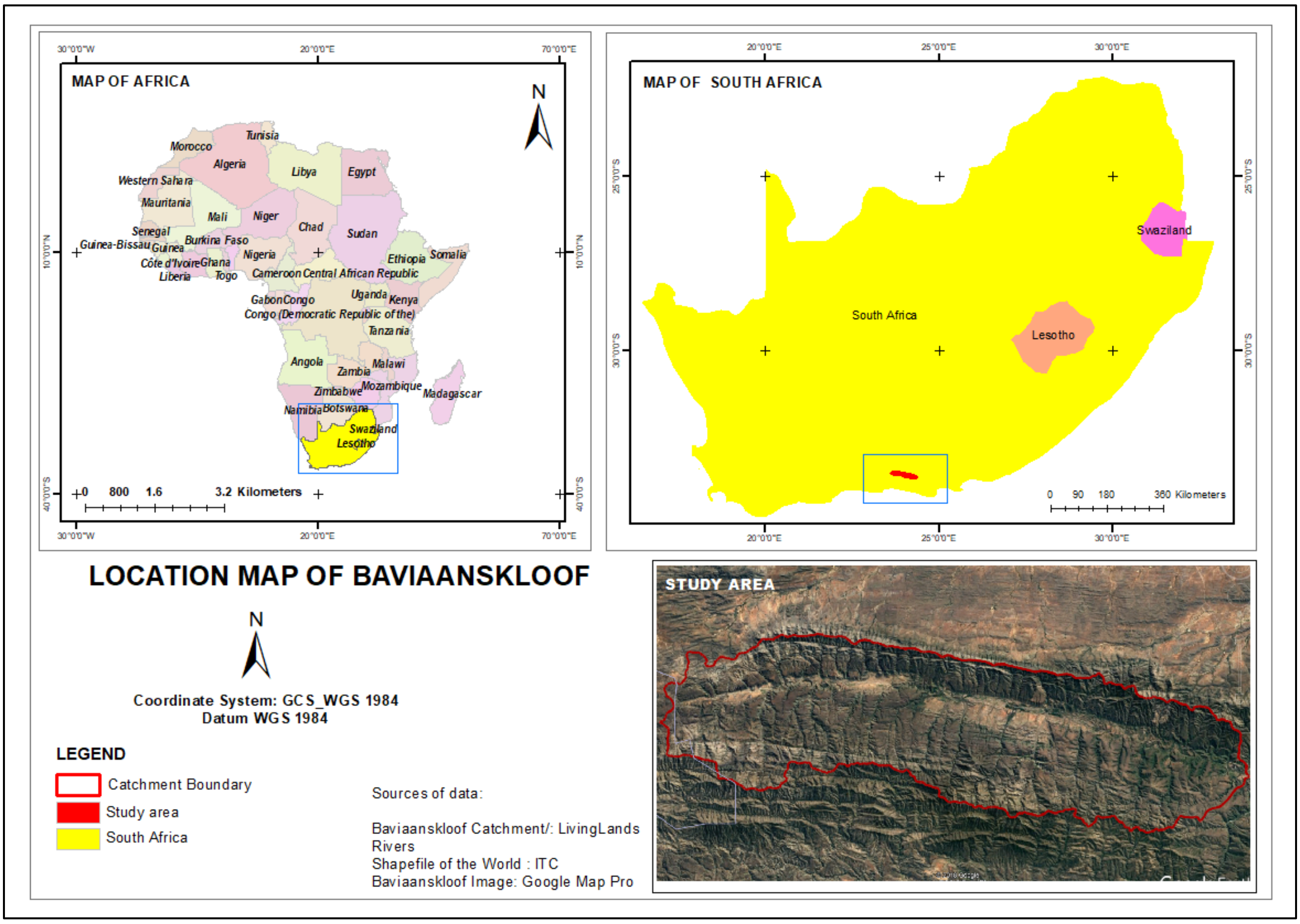
SPECIFIC OBJECTIVES	RESEARCH QUESTION
To determine which land cover classes are relevant for evaluating restoration success	1.1 How do restoration activities link to land cover? 1.2 What is the current spatial distribution of the land cover classes in the catchment area?
To determine if the wet and dry season affect how well the selected land cover classes can be distinguished	2.1. What period is the wet and dry season in Baviaanskloof? 2.2 Is accuracy of the image classification affected by dry and wet season? 2.3 Which land cover classes can best be distinguished in the wet and dry season?
To compare the land cover and land cover composition in the intervened and non-intervened area	3.1 How much do intervened and non intervened areas differ in land cover and land cover composition

2. METHODOLOGY

2.1. Study area

The Baviaanskloof "valley of Baboons" is part of the Baviaanskloof Mega Reserve (BMR)of about 500,000 ha. The area is located between -33.545869° Latitude South and 23.577686° Longitude West to -33.672957° Latitude South and 24.394790° Longitude East. The Baviaanskloof is composed of a state-owned protected area amidst 23 privately owned and communal lands (Boshoff, 2008). The study area is located between the parallel East and West running Baviaanskloof and Kouga mountain ranges in the western region of South Africa's Eastern Cape Province (Figure 1).

Figure 1. Location of the study area



The study area is located in the Mediterranean climate, has an average temperature of 17.8° C during coldest months, mild and moist during winter season, while during summer season the region are very hot and dry (George, 2018). The Eastern part of the valley is 95 km away from Port Elizabeth (Living Land, 2016). The abundance of innate biodiversity in Baviaanskloof resulted in its recognition as World Heritage Site in 2004 (Boshoff, 2008). As a result of degradation, the area has been under restoration since 2005. The restoration interventions includes Fenced/Revegetation/Livestock exclusion, Revegetation and Livestock exclusion, Revegetation and Livestock exclusion.

2.2. Restoration activities link to land cover

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Baviaanskloof mountainous areas are severely degraded as a result of overgrazing. The highlands were once a dense closed-canopy shrubland where Spekboom (Portulacaria afra) was substantial, before its degradation and transformation into an open savanna-like landscape (Waters et al., 2016). Locations where restoration activities have occurred with expected land cover changes were obtained through consultation with stakeholders, in line with the prescriptions of European Commission report on public consultation (European Commission, 2018). The consultation enabled us to locate restoration sites, and to plan field visits. Specific group of stakeholders; Living Land, Farmers and researchers were interviewed to collect data on restoration sites, boundaries of plots and testimonies of seasons. The restoration activities include planting of Spekboom, Lavender, Rosemary and excluding the livestock. It is expected that the spatial coverage of Spekboom, Lavender and Rosemary will increase, at the expense of livestock rangeland. Spekboom was selected as a reference land cover because it is related to the identified restoration activities. The preliminary identified land cover classes required consultation and validation from the stakeholder (Living Land), as they will eventually benefit from the output land cover map. Consultation with them also provided insight into the land cover classes required, kind of activities that are going on, and how it affects the transformation of land cover due to the restoration interventions. Land cover stratification was done using the percentage of vegetation or cover type estimated from field work. Estimate of cover percentages was done in circular plot with a radius of 30 x 30 m. The percentages of vegetation cover were estimated at different strata using ocular estimates or visual interpretation. Ocular estimates or visual interpretation are common approaches in collecting cover data in plots since they are more rapid than other cover methods. Vegetation covers are visually estimated as a percent in a covered area inside a plot (Godínez et al., 2009). Thresholds were adjusted from an existing land cover classification for South Africa (Department of Rural Development and Land Reform, 2017).

2.3. Land cover mapping

A Sentinel 2A image of 2018 (Level 1C), with a spatial resolution of 10m was used for the land cover identification. The satellite image was downloaded from Copernicus website, and processed in Sen2Cor plugin available on SNAP software for atmospheric correction. Sentinel 2 has 13 bands, but only bands 8, 11 and 4 were used for this study because they capture information that is relevant for discrimination of land cover types as described in the Sentinel-2 mission requirement document (ESA, 2007). Some image bands of the sentinel 2A had a resolution of 10m while others were 20m as shown in Table 1.

To harmonise the resolution of bands of interest, all bands were resampled to 10m, resolution using nearest neighbourhood algorithm. This algorithm was used because it preserves pixel information. The resampled bands were layer stacked into a raster image, and subsetted with study area shapefile to get the area of interest. Unsupervised classification was done on the subsetted raster image to aid the preliminary identification of homogenous cover types, for field investigation and validation. (Oto, 2017). A combination of stratified and purposive sampling was used during this study. According to Fan et al., (2012) stratified sampling involves the division of the population into several units and selecting a specified number of samples from each unit, which is the case in this study. Also, purposive sampling is useful when you need to reach a targeted sample quickly (Schreuder, Ernst, & Ramirez-Maldonado, 2004). Ten homogenous cover types (strata) were identified from the unsupervised classification. From each homogenous cover type, 20 sampling points were selected in ArcMap, making a total of 200 sample points envisaged for this study. The image, study area shapefile and 200 sampling points were uploaded into a tablet using Locus Software to guide field navigation and ground truthing. A total of 412 ground truth points were collected from the field, more than what was planned, because of further detailed vegetation stratification was suspected.

Table 1. The Sentinel-2 spectral bands (ESA, 2007)

Band Name	Center λ Center (nm)	Spatial Resolution (m)	Purpose
1	443	60	Atmospheric correction
2	490	10	Sensitive to vegetation senescing, carotenoid, browning and soil background; atmospheric correction (aerosol scattering).
3	560	10	Green peak, sensitive to total chlorophyll in vegetation
4	665	10	Max. chlorophyll absorption
5	705	20	Position of red edge; consolidation of atmospheric corrections/fluorescence baseline
6	740	20	Position of red edge, atmospheric correction, retrieval of aerosol load
7	783	20	Leaf Area Index (LAI), edge of NIR plateau
8	842	10	LAI
8a	865	20	NIR plateau, sensitive to total chlorophyll, biomass, LAI and protein, water vapor absorption reference, retrieval of aerosol load and type
9	945	60	Water vapor absorption, atmospheric correction
10	1375	60	Detection of cirrus for atmospheric correction
11	1610	20	Sensitive to lignin, starch and forest above ground biomass/Snow/ice/cloud separation
12	2190	20	Assessment of Mediterranean vegetation conditions. Distinction of clay soils for the monitoring of soil erosion. Distinction between live biomass, dead biomass and soil, e.g. for burn scars mapping

60 % of ground truth points collected from the field were used to train the Maximum likelihood classifier for classification, while 40% was used for accuracy assessment. This procedure is supported by Xing, (2015). Maximum Likelihood algorithm is one of the most popular supervised classification used in remote sensing image data (Haque & Basak, 2017). The method is based on the probability that a pixel belongs to a particular class and assumes that this probability are is equal for all classes and input bands have normal distribution (Rujoiu-Mare & Mihai, 2016). Six designs were used for classification based on different band combinations for wet, dry and a combination of wet and dry seasons as presented in Table 3 below. The classification accuracies were compared between Designs A.1 and A.2. Designs B, C.1, C.3, D. E.1 and E.3 were selected to determine the best band combinations with high classification accuracy in the dry season. On the other hand, Designs C.2 and E.2 were used to determine the influence of seasonality on classification accuracy. However, other band combinations were configured in an attempt to employ their characteristics for a better segregation of land cover types, the different band combinations for wet and dry seasons are summarized in Table 2 below.

Table 2. Classified image for six design types

Designs	Description
Design A .1	Layer stack image of Bands 8,11 and 4 classified with 17 classes for dry season original polygon
Design A.2	Layer stack image of Bands 8, 11 and 4 with 17 classes for dry season with improved polygons
Design B	Layer stack image of Bands 8, 11 and 4 with 11 classes for dry season with improved polygons
Design C.1	Layer stack image of Bands 2, 3, 4, 8, 11 with 11 classes for dry season with improved polygons
Design C.2	Layer stack image of Bands 2, 3, 4, 8, 11 with 11 classes for wet season with improved polygons
Design C.3	Layer stack image of Bands 2, 3, 4, 8, 11 with 11 classes for wet and dry season combined with improved polygons
Design D	Layer stack image of Bands 8, 11 and 4 with 15 classes for dry season with improved polygons
Design E.1	Layer stack image of Bands 2, 3, 4, 8, 11 with 15 classes for dry season with improved polygons
Design E.2	Layer stack image of Bands 2, 3, 4, 8, 11 with 15 classes for wet season with improved polygons
Design E.3	Layer stack image of Bands 2, 3, 4, 8, 11 with 15 classes for classes for wet and dry season combined with improved polygons
Design F	Layer stack image of Bands 2, 3, 4, 8, 11 with 5 classes for wet and dry season combined with improved polygons

2.4. Determining the seasons

According to Kottek, Grieser, Beck, Bruno, & Rubel (2006) Mediterranean climate types are classified under the Köppen climate classification system as "C" which stands for warm temperature climate. The region is located in the Mediterranean climate and has an average temperature of 17.8° C during coldest months. The winter season is, mild and moist while the summer season is very hot and dry (George, 2018). Precipitation data from a weather website of Baviaanskloof Farming community available at MeteoBlue (MeteoBlue, 2019a) was used in combination with stakeholder consultation to determine the wet and dry seasons.

2.5. Accuracy of the image classification affected by dry and wet season

Sentinel-2 images were downloaded and pre-processed as described in section 2.3. This time images were downloaded for wet (March) and dry (August) seasons and a supervised classified separately using the five-band combination with eleven classes. Bands 2,3,4,8, and 11 were used. The accuracy assessment reports were compared to determine the influence of season on classification accuracy.

2.6. Land cover classes that can best be distinguished in the wet and dry season

Following from the accuracy reports for wet and dry seasons explained in section 2.5, similar band combinations in 2.5 above, the class accuracies for the 11 classes were compared. Land cover classes with a class accuracy of greater than or equal to 50% were considered distinguishable in any of the seasons. This was done because 50% classification gives a 50:50 chance of correctness.

2.7. Difference of land cover and land cover composition in the intervened and non-intervened areas

To distinguish the difference between Land cover and Land cover composition in the intervened and non-intervened areas, the five-band classification for dry season with 11 classes was used. The classified raster image was converted to shapefile in ERDAS Imagine. The areas (ha) of each cover class was generated and compared. In addition, a second classification was done combining bands from wet and dry seasons and zooming in on Spekboom since it was the major focus of the intervention activity. The classification in this case made use of five classes; Dense shrub, high Spekboom, Dense shrub, low Spekboom, Open shrub, high Spekboom, Open shrub, low Spekboom and Others. To determine whether there is a difference in the percentage cover of Dense shrub, high Spekboom in farms across restoration types, the mean area (ha) of each class was extracted from the classified image and used to perform an Analysis of Variance (Snyman, 2003) at the 0.05 Alpha level.

Also, to determine if there is a significant difference in the extent of land cover fragmentation in farms across restoration types, FRAGSTAT was used. FRAGSTAT is a program which analyzes the spatial pattern and quantifies any particular space and spatial configuration of land cover types within the landscape (McGarigal, Cushman, & Ene, 2012). The FRAGSTAT software uses three matrices; which analyses several simple statistics representing area, extent and perimeter (or edge) at the patch, class, and landscape levels. However, for this study, the fragmentation was analyzed using the patch level matrices. Patch level matrices were computed for every land cover class in the study area using the classified map with five classes. The ratio of total area and perimeter for each cover type were used to determine the extent of fragmentation within each intervention. Furthermore, to specifically determine which among the restoration types may have influenced the percentages of land cover types and fragmentation across restoration interventions, a Tukey Post Hoc test was performed in SPSS. The Post Hoc test is conducted to further explore the data and determine which of the means are significantly different (Verma, 2013).

2.8. Flowchart showing the steps in the study

The study was done in six parts, corresponding to the six research questions as shown in figure 2 below.

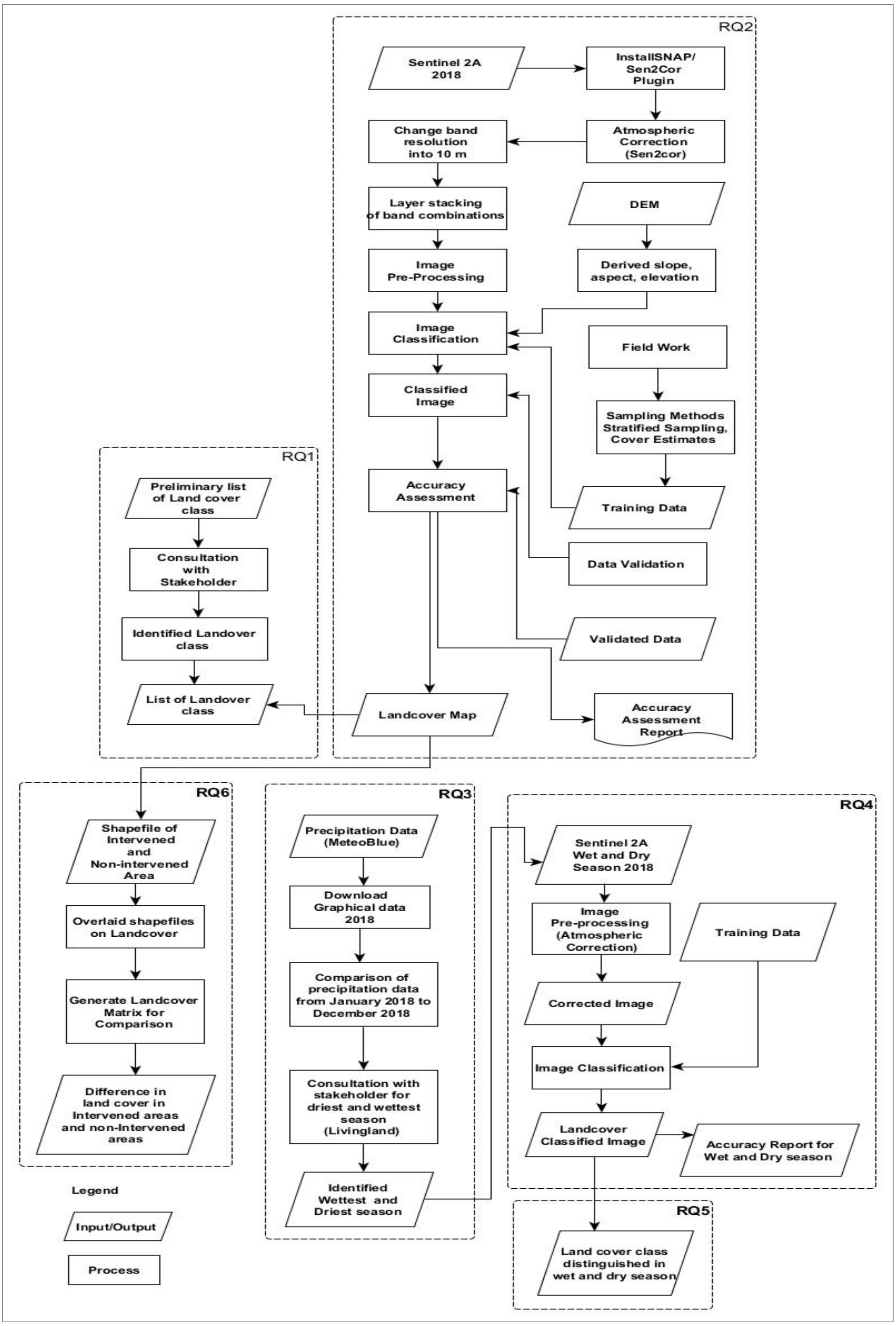


Figure 2. Methodological flowchart

3. RESULT

3.1 Restoration activities link to land cover

The identified vegetation structure related to restoration activities is presented in Table 3. The main vegetation types were Forests (7%), Thicket (52%), Fynbos (13%), Low mixed vegetation (10%), Irrigated grass (2%), Rosemary (0.29%) and Lavandin (0.23%). Forests were classified into 2 vegetation classes (Dense and Open forest). Forests with greater than or equal to 75% cover were classified as dense, while those covering 20-75% were classified as Open forest. Thicket were classified into dense and open. Dense thicket includes other shrubs with greater than or equal to 75% cover, having less than 10% of Spekboom and less than 50% of Fynbos. On the other hand, Open thicket was divided into 3 groups, namely, Open other shrub with 10-75% cover of shrubs, less than 10% of Spekboom and less than 50% of Fynbos. Nevertheless, if the Dense thicket class has between 10% and 50% Spekboom, it was classified as Dense shrub, low Spekboom; and if Spekboom was higher than 50%, it was classified as Dense shrub, high Spekboom. Dense Fynbos under the Vegetation structure of Dense shrub was identified as Shrubs with greater than or equal 75% cover of shrubs, less than 10% cover of Spekboom and greater than 50% of Fynbos. Lavandin were classified into Lavandin uniform and Lavandin mixed. If there were less than 20% of forest, less than 10% of shrub, Spekboom and fynbos having more than 50 % of Lavandin, it is considered as Lavandin uniform, and if it has less 50% cover of Lavandin it will classified as Lavandin mixed. The same classification was adopted in Rosemary however instead of using 50 % as a threshold, 60% has been applied since rosemary occupies a relatively large area of plantation. If Rosemary has greater than or equal 60% cover, it is considered as uniform and if it's less than 60% then it is mixed. If there were greater than or equal 50% of non-woody vegetation and less than 10 of low woody, it was classified as grass. In addition, if there were 10-50% low non-woody and greater than 10% of low woody it is classified as low mixed vegetation. Furthermore, if there were less 20% of forest and less than 10 % for all vegetation cover class, then it is considered as bare land.

Table 3. Vegetation structure classification

≥ 75 %								Forest	Dense Forest
20-75%									Open Forest
<20%	≥ 75%	<10%	<50%					Dense Thicket	Dense shrub
<20%	≥ 75%	>50%	<10%						Dense shrub, high Spekboom
<20%	≥ 75%	10-50%	<10%						Dense shrub, low Spekboom
<20%	≥ 75%	<10%	>50%					Dense Shrub	Dense Fynbos
<20%	10-75 %	<10%	<50%					Open Thicket	Open other shrub
<20%	10-75 %	>50%	<10%						Open shrub, high Spekboom
<20%	10-75 %	10-50%	<10%						Open shrub, low Spekboom
<20%	10-75 %	<10%	>50%					Open Shrub	Open Fynbos
<20%	<10%	<10%	<10%	>50%				Lavandin	Lavandin uniform
<20%	<10%	<10%	<10%	<50 %					Lavandin mixed
<20%	<10%	<10%	<10%		≥60%			Rosemary	Rosemary uniform
<20%	<10%	<10%	<10%		<60%				Rosemary mixed
<20%	<10%	<10%	<10%			≥50%	<10%	Grass	Grass
<20%	<10%	<10%	<10%			10-50%	>10%	Mixed low vegetation	Mixed low vegetation
<20%	<10%	<10%	<10%			<10%	< 10%	Bareland/Stone	Bare

3.2 Land cover mapping

The land cover map was based on 6 designs types, A, B, C, D, E and F. Design A.1 and A.2 utilized 17 classes as presented in Table 4, with 3 bands combinations. Some land cover classes for A.1 and A.2 designs were completely misclassified in the three band combinations, resulting in 0% accuracy. For Design B, a combination of 3 bands were used and the updated polygon with11 class where utilized merging Dense shrub, high Spekboom and Dense shrub, low Spekboom into Dense thicket, Open shrub, high Spekboom and Open shrub, low Spekboom into Open Thicket generating result higher than Design A.1 and A.2. Subsequently, adding Band 2 and Band 3 for Designs C.1 and C.3. and merging four classes of Spekboom into Dense and Open thicket achieved better accuracy than the original 17 classes, creating 11 classes in the end. For Design D, E.1, E.2, E.3, four of the classes which focused on Spekboom were included, forming 15 classes from the original 11 classes and applying 5 band combinations. This still produced lower accuracy compared to Designs which utilized 11 classes using the same 5 band combinations. Moreover, design E.2 with 15 classes and C.2 with 11 classes generated lower accuracy, with zero values for Dense thicket for wet season. Consequently, Design F with 10 band combinations of wet and dry season using 5 classes which focused on Spekboom class generated the highest overall accuracy with 85%. Figure 5 shows the classified image of Baviaanskloof and its corresponding accuracy in Table 4. Table 5 shows the vegetation types under the different land cover mapping schemes. The Spekboom were best classified in design F with class accuracies of 28.6%, 50.0%, 100% and 33.3% for Dense shrub, high Spekboom, Dense shrub, low Spekboom, Open shrub, high Spekboom and Open shrub, low Spekboom respectively. The overall classification accuracy of is 85%.

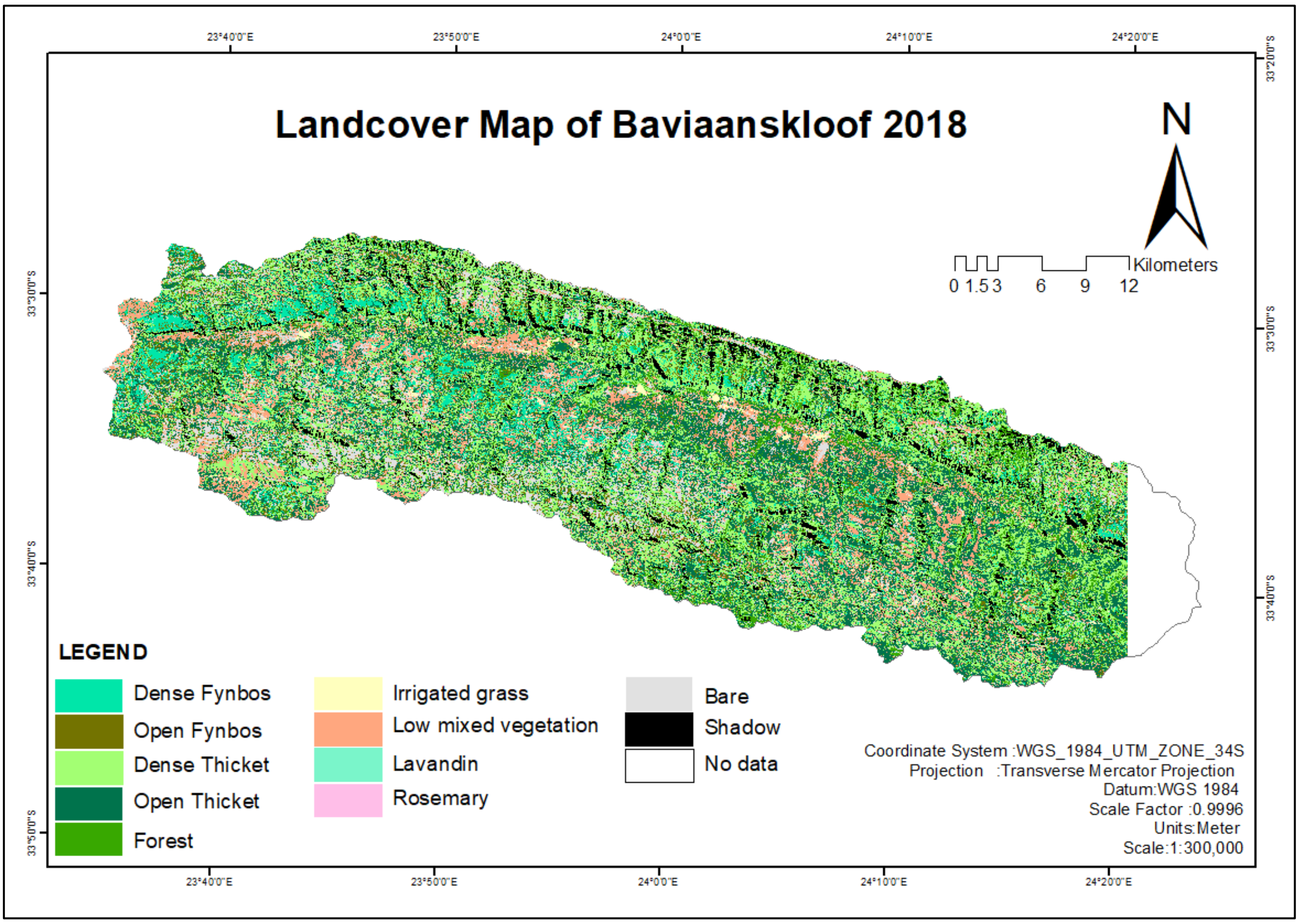


Figure 3. Land cover map of Baviaanskloof 2018 based on design F with 11 Land cover using 5 band combinations

Table 4. Accuracy of classified image for the six design types

Class	Overall accuracy (%)	Open Speekboom High	Open Speekboom Low	Dense Speekboom High	Dense Speekboom Low	Dense Thicket	Open Thicket
		User Accuracy (%)					
17 classes with original polygon (8,11,4) dry season	25	0	4	0	0	na	na
17 classes with improved polygon (8,11,4) dry season	32	50	9	33	0	na	na
12 classes with improved polygon (8,11,4) dry season	42	na	na	na	na	18	18
12 classes with improved polygon (2,3,4,8,11) dry season	43	na	na	na	na	22	34
12 classes with improved polygon (2,3,4,8,11) wet season	32	na	na	na	na	0	26
12 classes with improved polygon combination of Bands 2,3,4,8,11 wet season and Bands 2,3,4,8, 11	52	na	na	na	na	42	37
15 classes with improved polygon (8,11,4) dry season	39	50	19	40	0	33	13
15 classes with improved polygon (2,3,4,8,11) dry season	35	75	17	20	14	13	12
15 classes with improved polygon (2,3,4,8,11) wet season	26	23	15	23	13	0	23
15 classes with improved polygon combination of Bands 2,3,4,8,11 wet season and Bands 2,3,4,8, 11	43	100	25	20	67	31	17
5 classes with improved polygon combination of Bands 2,3,4,8,11 wet and Bands 2,3,4,8, 11 dry season	85	100	33	29	50	na	na

(Note: 'na' refers to not applicable)

Table 5. Vegetation types under the different land cover mapping schemes

Variation type of vegetation class	List of vegetation class
17	(1) Dense Forest (2) Open Forest (3) Dense shrub (4) Dense shrub, high Spekboom (5) Dense shrub, low Spekboom (6) Dense Fynbos (7) Open other shrub (8) Open shrub, high Spekboom (9) Open shrub, low Spekboom (10) Open Fynbos (11) Lavandin uniform (12) Lavandin mixed (13) Rosemary uniform (14) Rosemary mixed (15) Grass (16) Mixed low vegetation (17) Bare
12	(1) Dense shrub no Spekboom (2) Open shrub no Spekboom (3) Dense shrub, high Spekboom (4) Dense shrub, low Spekboom (5) Open shrub, high Spekboom (6) Open shrub, low Spekboom (7) Dense Fynbos (8) Open Fynbos (9) Bare (10) Lavandin (11) Rosemary (12) Forest
5	(1) Dense shrub, high Spekboom (2) Dense shrub, low Spekboom (3) Open shrub, high Spekboom (4) Open shrub, low Spekboom (5) Others

3.3 Determining the seasons

Figure 4 shows that September 2018 received the highest precipitation while May 2018 received the least. In 2018, the dry season ended in August with precipitation of less than 20mm., while the wet season commenced in September 2018 and is meant to last till April 2019. The trend of precipitation between February and March 2018 was consistently increasing, while the month of May registered the lowest precipitation. It could be deduced that May was the driest month in 2018.

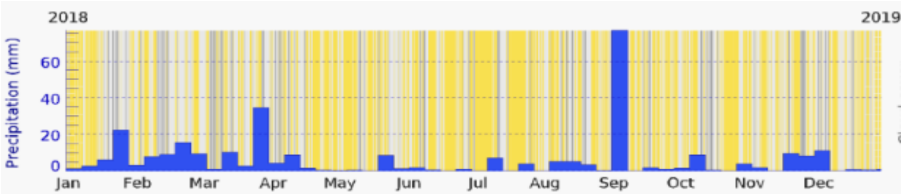


Figure 4. Precipitation trend in Baviaanskloof (MeteoBlue, 2019b)

3.4 Accuracy of the image classification affected by dry and wet season

Table 6 shows the classification accuracy report for the dry and wet seasons for the C3 and C2 designs respectively. The comparison of the dry and wet season reveals the number of correctly classified points and indicated that the image taken during dry season (August 2018) has higher overall accuracy and user's accuracy than the wet season image (March 2018) using 11 classes.

Table 6. Accuracy report for dry and wet seasons

		Dry season		**Wet season**	
Class Name	Reference Totals	Producers Accuracy (%)	Users Accuracy (%)	Producers Accuracy (%)	Users Accuracy (%)
Bare	10	30	27	50	29
Open Fynbos	10	20	29	29	67
Dense Fynbos	7	14	50	76	30
Dense Thicket	17	59	37	23	50
Forest	23	43	91	47	35
Irrigated grass	17	59	59	33	40
Lavandin	6	33	68	35	26
Low Mixed vegetation	17	68	42	20	40
Open Thicket	25	64	42	40	2
Rosemary	15	20	100	13	100
Shadow	20	100	91	60	100
Total	167				
Overall Classification Accuracy		**52 %**		**32%**	

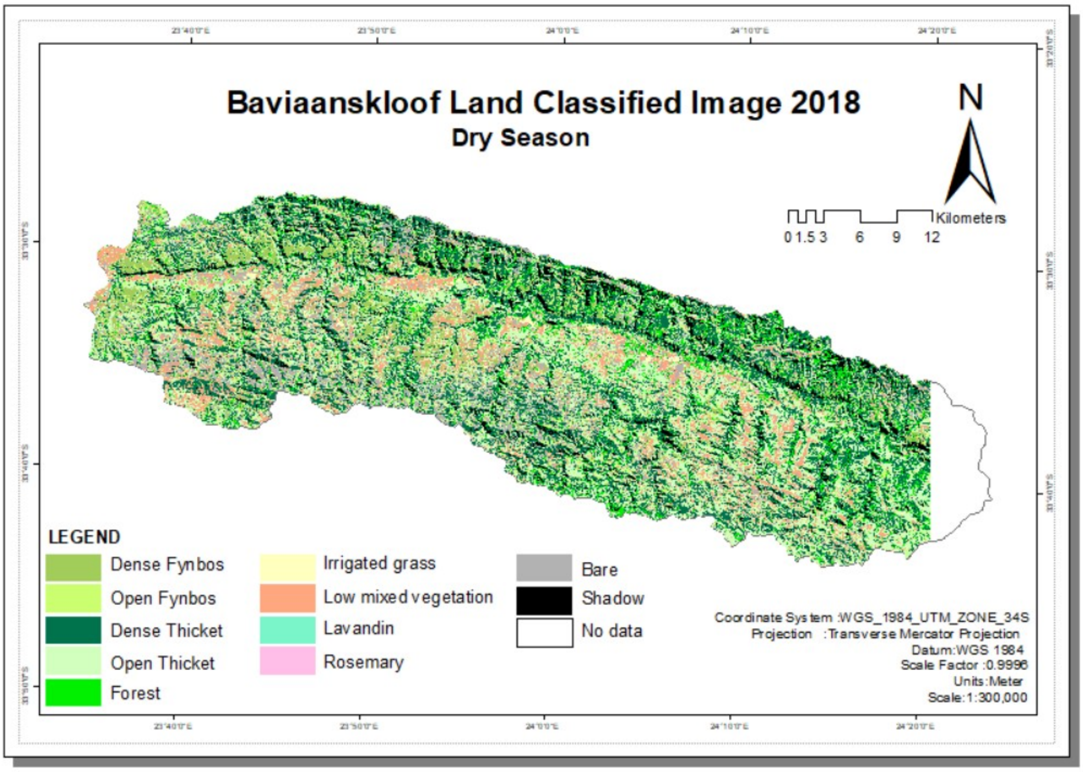
3.5 Land cover classes that can be distinguished in the wet and dry season

Table 7 shows the land cover classes that can best be distinguished in the wet and dry seasons. The minimum acceptable class accuracy considered in this study is 50% because below this accuracy, some important land cover classes like Lavandin and Rosemary would not be considered for further analysis, since the result will mean they are not detected. Based on the 50% minimum class accuracy, Forest, Lavandin, Rosemary, Irrigated Grass and Dense Fynbos were assumed classified in the dry season. In the wet season, only two land cover classes were distinguished with an accuracy greater than or equal to 50%. The classes are Dense Fynbos and Forest.

Table 7. Land cover class that can be distinguished during wet and dry season

Dry Season		Wet Season	
Class Name	Accuracy	Class Name	Accuracy
Dense Fynbos	50	Dense Fynbos	67
Forest	91	Forest	50
Irrigated grass	59		
Lavandin	68		
Rosemary	100		

Figure 5 shows the land cover maps generated from images captured in the dry and wet seasons. The area (ha) covered by the different land cover types were different for the wet and dry seasons. For example, the land covers with class accuracy greater than or equal to 50% delineated in the dry season map were Forest (91% class accuracy), Dense fynbos (50% class accuracy) with a total area of 8913 and 8503 ha respectively. In the wet season, Forest (50% class accuracy), Dense fynbos (67% class accuracy) with a total area of 21296 and 3909 ha respectively. The land cover delineated in the dry season has a visible pattern whereas the land cover classes in the wet season has a ‘salt and pepper’ effect (Figure 5).



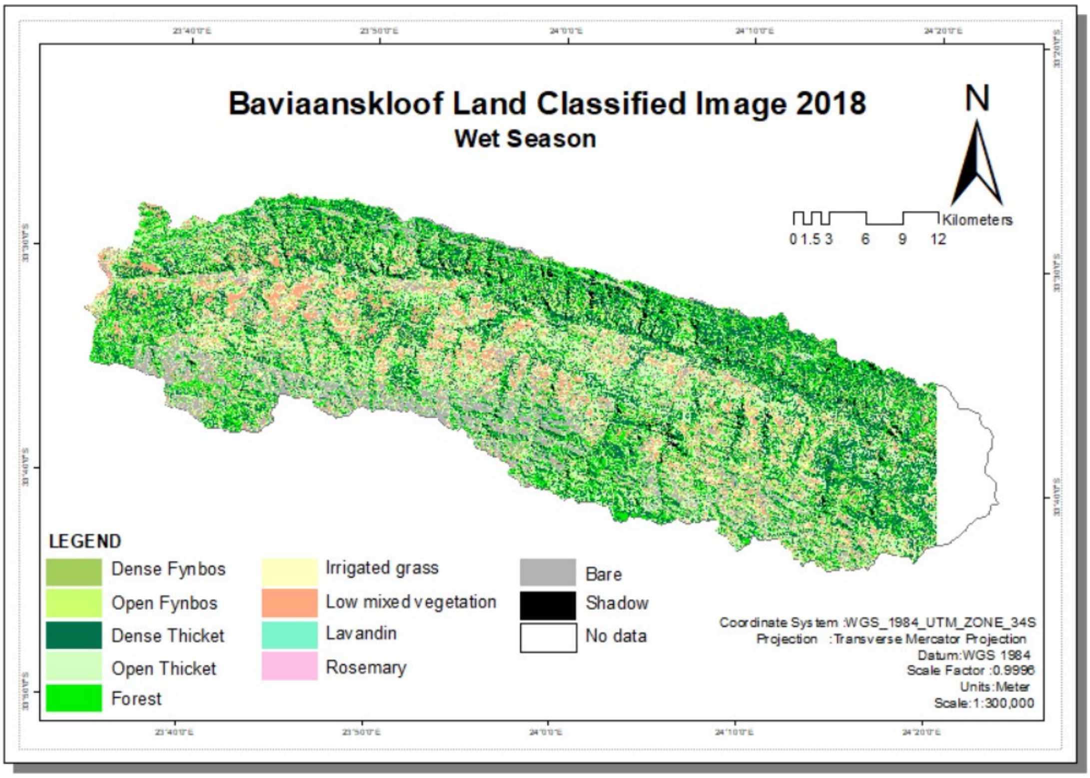


Figure 5. Classified map of dry and wet season based on C3 and C2 designs with 52 % and 32 % overall accuracy respectively

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3.6. Difference of land cover and land cover composition in the intervened and non-intervend area

The quantitative difference between land cover composition in intervened and non-intervened areas was based on the land cover map from design C3 and F. The land cover composition in the intervened and non-intervened areas estimated from the classified map from design C3 (52% overall accuracy) with 11 classes is shown in Table 8 below.

Table 8. Land cover composition in intervened and non-intervened area with 12 class

Class	Intervened Area		Non-Intervened Area	
	Area (ha)	Area (%)	Area (ha)	Area (%)
Dense shrub no Spekboom	775	5	5486	15
Open shrub no Spekboom	2406	14	4011	12
Dense shrub, high Spekboom	1134	7	952	3
Dense shrub, low Spekboom	249	1	3749	11
Open shrub, high Spekboom	329	2	1182	5
Open shrub, low Spekboom	873	5	8571	23
Dense Fynbos	325	2	1996	5
Open Fynbos	323	2	120	0
Bare	9517	57	4105	9
Lavandin	28	0	3195	9
Rosemary	20	0	56	0
Forest	657	4	2855	8

The total non-intervened area was larger than the intervened area, and the area of land cover types were different in the intervened and non-intervened area. The areas of Dense shrub with no Spekboom, Open shrub with no Spekboom, Dense shrub, low Spekboom, Open shrub, low Spekboom are lower in intervened area compared to the non-intervened area. On the other hand, only Dense shrub, high Spekboom covered much more area in the intervened area compared to the non-intervened area.

Open shrub with no Spekboom covers only 2406 ha, while the rest of land cover classes cover less than 10 % of all intervened area. The most common class in the non-intervened area was Open shrub, low Spekboom which covers 8571 ha of the Non-Intervened areas, Dense shrub, no Spekboom with 5486 ha cover, Open shrub with no Spekboom 4011 ha and Dense shrub, low Spekboom with 3749 ha. It is apparent that based on the 11 classes, there were more occurrence of land cover classes in the Non- intervened, compared to intervened area.

In the case of design F (Spekboom class with 85 % overall accuracy), the land cover composition in intervened and non-intervened areas is presented in Table 8. The result shows that in the intervened area, the dominant land cover class is Open shrub, high Spekboom which covered 841 ha, while Dense shrub, low Spekboom covered only 224 ha. Moreover, in the Non-intervened area Dense shrub, low Spekboom and Open shrub, high Spekboom covered less than the area of Spekboom in the intervened areas. The result shows that there was more occurrence of Spekboom in the intervened areas compared to Non-intervened areas.

Table 9. Land cover composition in intervened and non-intervened with focus on Spekboom class

Class	Intervened Area		Non-Intervened Area	
	Area (ha)	Area (%)	Area (ha)	Area (%)
Dense shrub, high Spekboom	10	0.12	5367	5
Dense shrub, low Spekboom	228	3	823	0.8
Open shrub, high Spekboom	841	10	923	0.9
Open shrub, low Spekboom	313	4	3698	4
Others	7058	84	86989	89

Figure 6 and Figure 7 shows the spatial distribution of the thicket cover classes in non-intervened area and intervened area. Open shrub, high Spekboom occupied 10 % with 841 ha of intervened areas whereas 923 ha of Non-intervened area where it covers only 0.9%

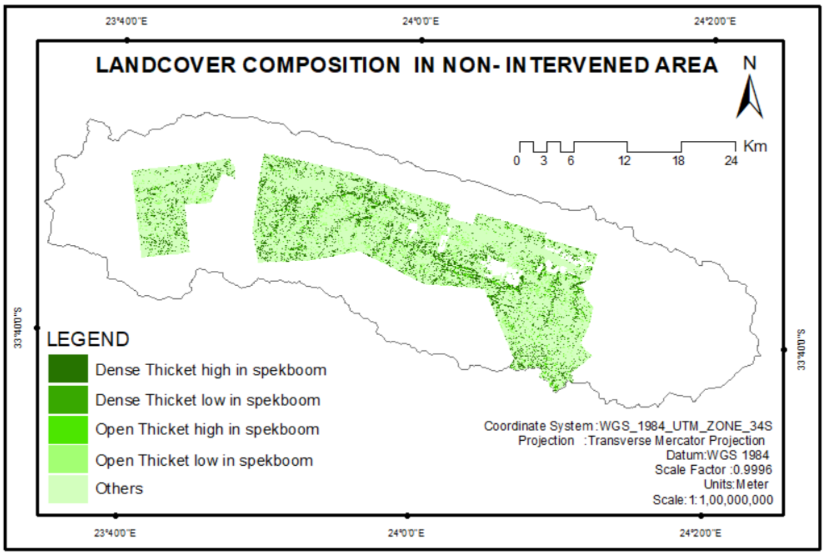


Figure 6. Land cover map showing the composition in non-intervened areas

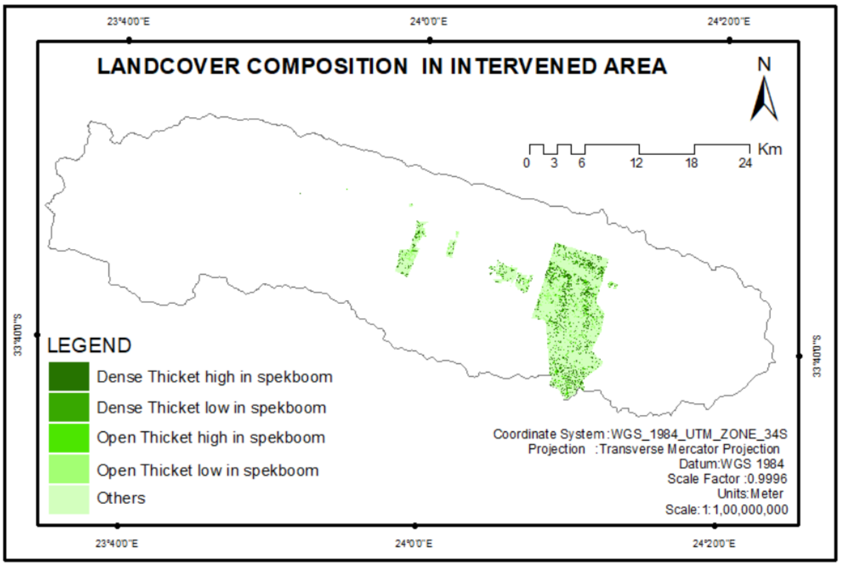


Figure 7. Land cover map showing the composition in intervened areas

Table 10 shows the percentage of Spekboom classes under five restoration type. It was apparent that under Fenced/Revegetation/Livestock exclusion Dense shrub, high Spekboom covers higher percentages with 29% while in other restoration types it does not perform well. Moreover, Open shrub, low Spekboom with 22% occupies higher percentage in Revegetation intervention type while 24% cover of Open shrub, low Spekboom dominated Revegetation/Livestock Exclusion restoration type.

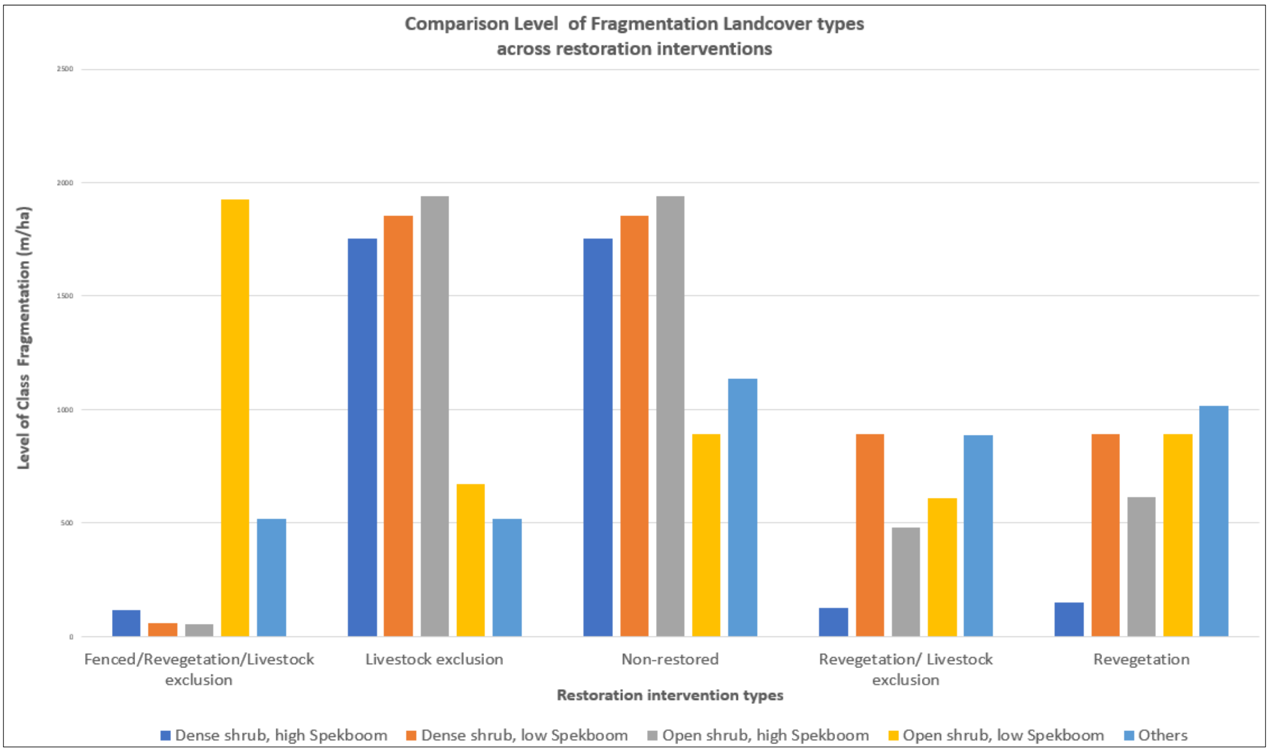
Table 10. Land cover percentage under different restoration type

CLASS	Fenced/Revegetation/Livestock Exclusion		Livestock exclusion		Revegetation		Revegetation/ Livestock exclusion		Non-restored area	
	Area (ha)	Area (%)	Area (ha)	Area (%)	Area (ha)	Area (%)	Area (ha)	Area (%)	Area (ha)	Area (%)
Dense shrub, high Spekboom	2	29	6732	21	624	21	362	21	35026	22
Dense shrub, low Spekboom	1	12	5992	19	556	19	324	21	30629	19
Open shrub, high Spekboom	1	18	6105	19	554	19	299	19	30750	19
Open shrub, low Spekboom	2	23	6486	21	634	22	365	24	33446	21
Others	1	18	6313	20	577	20	347	22	31487	20
Total	7		31628		2945		1697		161338	

The percentage of Spekboom classes under the four restoration types plus non-restoration types are presented in Table 10. It is apparent from Table 10 that under Fenced/Revegetation/Livestock exclusion the Dense shrub, high Spekboom class occupy higher percentages with 29% while in other restoration types such as Livestock exclusion, Revegetation, Revegetation and Livestock exclusion and Non-restored it does not perform well. Moreover, Open shrub, low Spekboom occupies higher percentage (22%) in Revegetation intervention type while Open shrub, low Spekboom dominated Revegetation/Livestock Exclusion restoration type (24%). The ANOVA test results show with 95% confidence that there is a significant difference in the percentage cover of Dense shrub, high Spekboom across the restoration types (p=0.001).

A comparison of land cover class fragmentation accross restoration interventions (Figure 8) shows that Open shrub, low Spekboom is highly fragmented under Fenced/Revegetation/Livestock Exclusion restoration intervention. Dense shrub, high Spekboom, Dense shrub, low Spekbom, Open shrub, high Spekboom are more clustered in the Fenced/Revegetation/Livestock Exclusion restoration intervention compared to other restortion interventions. Among the 5 restoration types, it is apparent that Livestock Exclusion and non-restored intervention showed high fragmentation for all land cover class across restoration type.

Figure 8. The level of land cover class fragmentation under different restoration type



The ANOVA test was conducted to determine whether there was a significant difference in the fragmentation of Spekboom across different intervention types was positive. It showed that there was a significant difference in the level of fragmentation across interventions at the 95% confidence level ($p=0.02$). The null hypothesis which stated that there is no significant difference between the level of fragmentation across intervention type, was therefore rejected. In addition, the same method was used to investigate a difference in the percentage cover of Open shrub, low Spekboom in farms across restoration types. The results show that there is no significant difference in the percentage cover of Open shrub, low Spekboom in farms across restoration types ($p=0.06$).

The results of Post hoc comparison (Table 10) using the Turkey HSD test at 95 % confidence level, specifically investigated the intervention types to determine which intervention had a significantly different degree of Spekboom fragmentation and percent land cover.

Table 11. Post hoc tests showing the variation in the level of land cover fragmentation across different restoration types, and the difference in percentage cover of dense shrub, high Spekboom

Restoration Types	Restoration Types (N=5)	% cover of Dense shrub, high Spekboom (P value)	Fragmentation level (P value)
Fenced	Livestock exclusion	.01	.02
	Non-restored	.00	.01
	Revegetation	.00	.44
	Revegetation/ livestock exclusion	.00	.82
Livestock exclusion	Fenced	.01	.02
	Non-restored	.82	.65
	Revegetation	.36	.09
	Revegetation/ livestock exclusion	.50	.03
Non-restored	Fenced	.00	.01
	Livestock exclusion	.82	.65
	Revegetation	.12	.04
	Revegetation/ livestock exclusion	.25	.01
Revegetation	Fenced	.00	.44
	Livestock exclusion	.36	.09
	Non-restored	.12	.04
	Revegetation/ livestock exclusion	.89	.59
Revegetation/ livestock exclusion	Fenced	.00	.82
	Livestock exclusion	.50	.03
	Non-restored	.25	.01
	Revegetation	.82	.59

The post hoc test reveal that the % cover of Dense shrub, high Spekboom in the Fenced intervention is significantly higher compared with the % cover of Dense shrub, high Spekboom in the other interventions at the 95% confidence level. Also, the fragmentation in the fenced intervention is lower compared to other interventions, and significantly lower ($p < 0.05$) compared to the fragmentation in the Livestock exclusion and Non-restored interventions at the 95% confidence level. In the case of the Livestock exclusion, the % cover of Dense shrub, high Spekboom is lower compared to the Non-restored intervention, and higher than in the Revegetation and Revegetation/ livestock exclusion interventions. However, these differences are not significant. The level of fragmentation under Livestock exclusion is lower compared to the Non-restored, and higher compared to the Revegetation and Revegetation/ livestock exclusion interventions. Nevertheless, the fragmentation in Livestock exclusion is only significantly higher than the fragmentation in the Revegetation/ livestock exclusion at the 95% confidence level. For the Non-restored area, the % cover of Dense shrub, high Spekboom is higher compared to the Revegetation and Revegetation/ livestock exclusion interventions. Still, the difference is not significant. The fragmentation in the Non-restored area is higher than the fragmentation in the intervened areas but this higher fragmentation in the Non-restored areas is only significant in the case of Fenced, Revegetation and Revegetation/ livestock exclusion interventions. The % cover of Dense shrub, high Spekboom in the Revegetation intervention is lower compared to all other interventions, and significantly lower compared to the cover in the Fenced intervention at the 95% confidence level. The Revegetation intervention is less fragmented compared to Livestock exclusion Non-restored interventions, but more fragmented compared to the Fenced and Revegetation/ livestock exclusion. The % of Dense shrub, high Spekboom cover in the Revegetation/livestock exclusion is lower compared to the Fenced, Livestock exclusion and Non-restored areas, and significantly less fragmented compared to Livestock exclusion and Non-restored areas $p<0.05$.

4. DISCUSSION

This section discusses the results of the study with relevant scientific literature. The section is divided into three subsections with focus 1. Restoration impact in the Baviaanskloof, 2. Reflection on Methods, 3. Land cover mapping to assess restoration impact

4.1.1. Restoration impact in the Baviaanskloof

Land managers need sound, evidence-based information about land degradation patterns and about the effectiveness of their management responses towards land restoration. One of the major aims of this study was to explore the use of remote sensing to evaluate the performance of restoration interventions, as an objective means of guiding sound decision making by the Common Lands. An interesting finding in this study is the relationship between intervention types and the land cover fragmentation. The significantly higher percent cover of Dense shrub, high Spekboom, and the significantly lower fragmentation in the Fenced compared to other interventions mean that the fenced intervention is performing better. This is evident from the field work survey conducted. Some farmers who allotted a portion of their land for the implementation of Fenced/Revegetation/Livestock exclusion experienced less fragmentation. Moreover, in the case of Zandvlakte farm where an entire land was allotted for restoration under Fenced/Revegetation/Livestock exclusion, Spekboom grows more than 4-5 meters tall with very low fragmentation. In addition, to the performance of Spekboom in this intervention, other vegetation types also thrived well. Some interventions may have impact but not as evident when compared to Fenced/Revegetation/Livestock exclusion. Although the classification accuracies obtained in this study are relatively low. The study provides stakeholders with an insight into the performances of intervention types. Also, the study provides foresight on the main vegetation classes relevant for monitoring restoration intervention in the area. However, among the overall intervention only Fenced/Revegetation/Livestock exclusion intervention measure is giving better results.

4.1.2. Reflection on Methods

Remote sensing has been widely used for monitoring due to its wide coverage. It has become one of the important sources of acquiring accurate and regular information on the ecosystem (Otukei & Blaschke, 2010). Land cover mapping methods depend mostly on the variations in spectral characteristics of the landscape to distinguish vegetation types (Feleke, 2003). Obtaining such information is difficult and costly with only field work particularly if the area to be monitored is large. This work corroborates the works of (Meroni et al., 2017; Norman et al., 2014), advocating for the capability of remote sensing to provide accurate and up to date information on the performance of management activities. The Supervised image classification using maximum likelihood algorithm was used in this study. Although, the Maximum Likelihood is good as has been supported by studies Bakx et al., (2013), Bailey et al., (2016) , this classifier needs a large amount of field data for proper classification which was not the case for all cover types in this study. Several studies have shown the benefits of using Supervised classification utilizing Maximum likelihood algorithm.

The accuracy of the classification is however dependent on the number of training samples, the spectral distinctness of the classes and the skill of the individual processing the image. If the training data is poor or not well representative of each cover class, the classification results will also be poor, and these can be observed in some of the classes that are not well represented during image classification using different band combinations with more than 5 classes.

Vegetation stratification needs to be done prior to field work and concluded after field work, with enough data to validate it. On the other hand, the vegetation structure classification utilized visual estimates or cover estimates. In line with the work of De Oto (2017), the vegetation classification structure in this study was based on percentages of different land cover classes. However, the structural stratification was very detailed, but the field data to support the classification was limited and could be blamed for the low classification accuracies recorded.

The image for the dry season was taken in August 2018 and for wet season an image was captured in March 2018 and used as basis for land cover mapping. Six designs were performed systematically to classify the image using several band combinations in an attempt to differentiate various land cover classes accurately. The results show that seasons influence the accuracy of image classification. During dry season 52% overall accuracy were obtained while in wet season the accuracy produced was 34% using 5 band combinations Band 11, 2,3,4 and 8 with 11 classes to obtain better accuracy result. Comparing the individual performance of land cover classes during wet season, confusion between Low Mixed vegetation, Forest, Lavandin, Irrigated grass, Open shrub, low Spekboom, Open Fynbos and Open Thicket becomes apparent as the classes are mis-classified into other classes due to similarity in spectral reflectance. According to the study of Jacob, Bonnell, Dowhaniuk, & Hartter, (2014) and Schmidt & Skidmore (2003) if there are more than two vegetation types having the same biochemical structure this will result to overlapping of light absorption and reflectance features making it more difficult to discriminate during image classification.

However, the classified land cover maps for wet and dry season were the basis for determining land cover types affected by seasonal variation. For this reason, and due to the fact that Spekboom is the main focus of the intervention, this study zoomed into the Spekboom class: Dense shrub, high Spekboom, Dense shrub, low Spekboom, Open shrub, high Spekboom and Open shrub, low Spekboom. The classification accuracy consequently increased drastically to 85%. The increase may be attributed to the reduction in the number of land cover classes and the use of 10 band image, obtained by combining bands from the wet and dry seasons.

The result from integrating the 10-band from wet and dry season of Sentinel 2 provides better result compared to 5 band combinations (Figure 7). The combination of image bands from wet and dry seasons must have enhanced the differentiation in land cover classes as would have been the case when using multi-temporal images. This is in line with the assertion of Gašparović & Jogun (2018) that the combination of Sentinel 2 bands images improves the overall classification accuracy, particularly in pixel-based classification relative to land cover classification.

To analyse the difference in land cover composition across restoration types, an ANOVA test was performed. The results show a significant difference in the % cover fragmentation of Dense shrub, high Spekboom across interventions at the 95% confidence level. In line with a priori expectations, this result mean that the different interventions performed relatively differently, in terms of cover extent, and the level of fragmentation. Also, the Tukey's honestly significant difference (HSD) Post Hoc test was performed to investigatetest the best performing restoration interventions. The significantly higher % cover of the Dense shrub, high Spekboom, and lowest fragmentation values in the Fenced intervention compared to the others means it performs the best.

To further understand the spatial relationship of Spekboom across different restoration type implemented in Baviaanskloof, Landscape metrics were calculated using FRAGSTAT. The result of this study shows that using patch metrics of FRAGSTAT provides information on which patch type are fragmented across the restoration interventions. The analyses produced information that engendered a better understanding on the complexity of changing landscapes due to development, which causes biodiversity loss relative to land use and land cover change.

This study was able to look at the performance of interventions based on extent of fragmentation. This is an important quality that describes ecosystem functioning. From this analysis, it was possible to deduce that the fenced intervention restores the area both in percent cover and also in function, since fragmentation was very low.

The results of this study revealed the influence of season on the classification accuracy of land cover classification, with dry season enhancing classification accuracy more than the wet season. Although the study of Liu et al., (2016) used Landsat imagery, he demonstrated that classification of dry season images results in better accuracies compared to wet season images. He further reported that time series data could improves the overall accuracy compared to single data images taken in dry season and wet season. This is in line with the present study which combined image bands from wet and dry season and got a better accuracy. However, this study did not use multitemporal data. Vuolo et. al., (2018) used Sentinel 2 images for vegetation classification and noted that, the highest overall accuracy of 95% was achieved with images taken in July, when summer crops are at full growth development. There is a possibility that the time of image capture in this study is not appropriate for distinguishing the characteristic restoration species in Baviaanskloof.

The results of this thesis, however, contributes to the understanding of Sentinel-2 imagery capabilities for monitoring land cover change to evaluate restoration interventions. Nevertheless, higher resolution images could produce better results. The integration of UAV and satellite information could also be a promising alternative which can be considered for future use. There are still unanswered questions about this study, for instance, if the inclusion of Red Edge position Bands 5, 6 and 7, utilization of other algorithm method for image classification, and time series of Sentinel-2 data might significantly influence the accuracy of land cover classification.

4.1.3. Land cover mapping to assess restoration impact

Land managers need sound, evidence-based information about land degradation patterns and about the effectiveness of their management responses towards land restoration. Obtaining such information is particularly difficult if the area to be monitored is large and conducting field validation survey is time consuming. One of the major aims of this study is to evaluate the performance of restoration interventions, as an objective means of guiding sound decision making by the Common Land. The results corroborates the works of (Meroni et al., 2017; Norman et al., 2014), advocating that remote sensing has the capability of providing accurate and up to date information on the performance of management activities.

Using multispectral data, the work of Nagler, Glenn, & Huete, (2001) showed that vegetation indices are most simply related to the % of vegetation cover, and could be good to evaluate changes in the pattern of greenness of riparian area, as a measure of the effectiveness of intervention activities. However, this study explored band combinations and reveals their utility and effectiveness in evaluating the performance of restoration activities. In addition, this work exposes the dimension of restoration success in terms of vegetation cover and fragmentation extent as a proxy to biodiversity and ecosystem function restoration. Such a result will guide stakeholders as to which intervention produces more biodiversity and ecosystem functions, as well as which areas are most suitable for the different vegetation types used in the restoration interventions.

The study can be used as a basis for the farmers and stakeholders project implementors to select the best method or technology that can be effectively implemented in the degraded thicket. This will also pave the way to understand the range of degradation of land cover in intervened and non-intervened areas which are fundamental in restoring fragmented ecosystem. Spekboom is a keystone species in the area that gives habitat for many organism and is being used as key species for restoration intervention.

The result shows that the restoration type adopted affects the land cover composition, with reference to the Dense shrub, high Spekboom and Dense shrub, low Spekboom. Moreover, the result reveals that the extent of fragmentation in Fenced/Revegetation/Livestock exclusion is significantly lower compared to fragmentation in Revegetation and Revegetation/Livestock exclusion. Fragmentation in Non-Restored area is significantly higher compared to other restoration types. This can be attributed to the characteristic of the intervention type such as constructing fences to protect from animal and human intrusions, planting of spekboom and removing of livestock in the area.

In addition, if the magnitude of fragmentation is higher, this will result to less favourable environment making the habitat unfavorable for some organism. This ascertain that there is a relationship between the restoration type implemented and the fragmentation of land cover class across restoration types. Among five restoration type implemented Fenced/Revegetation/Livestock exclusion is considered to be effective, however, the probability of poor soil condition, the presence of rocks and the aspect influenced the growth development of Spekboom as observed during field work validation and this manifested in an area located at Damsedrief were the survival of Spekboom is low. Harris et. al, (1996) cited that there were several factors that may attribute to the failures of restoration interventions such as (1) low cost/benefit ratio in the short-term; (2) unfavourable climatic and physical factors; and (3) absence of proven techniques that land users can refer to. For that reason, implementing alternative methods to regenerate the ecosystem apart from planting Spekboom, Lavandin and Rosemary needs to be explored in the future.

5. CONCLUSION AND RECOMMENDATION

This study sets out to map and analyse land cover in the Baviaanskloof based on cover classes that are relevant for evaluating restoration success. This was done through using a Sentinel-2 band satellite imagery with field data. The results reveal that freely accessible and relatively high-resolution Sentinel-2 imagery has adequate capability for mapping land cover for evaluating restoration success., with a classification accuracy of up to 85%. The key findings are presented below.

1. There were 17 land cover classes identified in Baviaanskloof, out of which six classes were used for restoration intervention. The land cover types used in the interventions include: Dense shrub, high Spekboom, Dense shrub, low Spekboom, Open shrub, high Spekboom, Open shrub, low Spekboom, Lavandin and Rosemary. However, for design F, the image classification gives emphasize on Spekboom class. Spekboom is a keystone species in the area, as it provides habitat for many organism and is being used as key species for restoration intervention. On the other hand, Lavandin and Rosemary were used as alternative livelihood for farmers in exchange for implementing restoration interventions.

2. In identifying the current spatial distribution in the area, there were six design types systematically implemented for image classification, to assess the possibility of accurately differentiating different land cover classes within the study area. However, 3 bands and 5 band combinations generated lower accuracy whereas the combination of 10 bands from wet and dry season produced higher overall accuracy of 85 % with focus on Spekboom class such as: Dense shrub, high spekboom, Dense shrub, low spekboom, Open shrub, high Spekboom and Open shrub, low Spekboom.

3. The period of dry season spans from May to August; with May being the driest month with the lowest precipitation recorded. On the other hand, the wet season commenced in October and ended in April, but the wettest month, during which precipitation trend is most consistent is March.

4. The result of this study shows that seasons influence the accuracy of the image classification. In the dry season the classification accuracy was 52% while in wet season it decreased to 32%.

5. The land cover classes that can best be distinguished during dry season are Dense Fynbos, Forest, Irrigated grass, Lavandin and Rosemary while in wet season only Forest and Dense Fynbos were effectively distinguished.

6. The result of this study shows that there were more occurrence of different land cover type in the non-intervened area compared to intervened area. As such, land cover diversity was greater in the non-intervened areas. In design F, with focus more on Spekboom, the land cover which did not focus on Spekboom were merge into 'Other' class. Evidently, the "other" class amounted to a total of 86989 ha in the in non-intervened (89%), whereas its extent amounted to only 7058 ha in the intervened area (84%).

7. Further studies may still be necessary in order to improve the quality of the results of this research. It may be necessary to explore the potentials of the red edge bands of Sentinel-2 to improve the precision and accuracy of the land cover classification. Also, other land cover classification algorithms like, Random forest, Random Tree or Support Vector machine classifiers and time series of Sentinel-2 data may be assessed to determine whether they can improve accuracy with minimal investment in field data and time.

LIST OF REFERENCE

Andres, L., Boateng, K., Borja-Vega, C., & Thomas, E. (2018). A review of in-situ and remote sensing technologies to monitor water and sanitation interventions. *Water (Switzerland)*, *10*(6). https://doi.org/10.3390/w10060756

Bailey, K. M., McCleery, R. A., Binford, M. W., & Zweig, C. (2016). Land-cover change within and around protected areas in a biodiversity hotspot. *Journal of Land Use Science*, *11*(2), 154–176. https://doi.org/10.1080/1747423X.2015.1086905

Bakx, W., Janssen, L., Schetselaar, E., Tempfli, K., Tolpekin, V., & Westinga, E. (2013). Image Analysis. In *The Core of GIScience a system-based aproch* (pp. 205–225). Enschede, Netherlands: Faculty of Geo-Information Science and Earth Observation (ITC), UNiversity of Twente. https://doi.org/10.1016/B978-0-12-385889-4.00013-2

Boshof, A., Cowling, R., & Kerley, G. (2000). *The Baviaanskloof Conservation Area*. Port Elizabeth, South Africa: Terestial Ecology Research Unit. Retrieved from http://ace.mandela.ac.za/ace/media/Store/documents/Technical reports/TERU-Report-27-Boshoff-et-al-2000-Baviaanskloof-Mega-reserve-booklet.pdf

Boshoff, A. (2008). *The Baviaanskloof Mega-Reserve: From Concept to Implementation*. Port Elizabeth: African Center for Conservation Ecology (ACE). Retrieved from http://ace.mandela.ac.za/ace/media/Store/documents/Technical reports/ACE-Report-58-Boshoff-AF-2008-Baviaanskloog-Mega-reserve-booklet.pdf

Chhabra, A., Geist, H., Houghton, R. A., Haberl, H., Braimoh, A. K., Vlek, P. L. G., … Lambin, E. F. (2006). Multiple Impacts of Land-Use/Cover Change. In *Land-Use and Land-Cover Change* (pp. 71–116). Berlin, Heidelberg: Springer Berlin Heidelberg. https://doi.org/10.1007/3-540-32202-7_4

Conservation South Africa. (2012). *Conservation South Africa Strategy 2012 - 2017*.

Cordell, S., Questad, E. J., Asner, G. P., Kinney, K. M., Thaxton, J. M., Uowolo, A., … Chynoweth, M. W. (2017). Remote sensing for restoration planning: how the big picture can inform stakeholders. *Restoration Ecology*, *25*, S147–S154. https://doi.org/10.1111/rec.12448

Cunha, A. P. M., Alvalá, R. C., Nobre, C. A., & Carvalho, M. A. (2015). Monitoring vegetative drought dynamics in the Brazilian semiarid region. *Agricultural and Forest Meteorology*, *214–215*, 494–505. https://doi.org/10.1016/J.AGRFORMET.2015.09.010

De La Rocque, S., Michel, V., Plazanet, D., & Pin, R. (2004). Remote sensing and epidemiology: examples of applications for two vector-borne diseases. *Comparative Immunology, Microbiology and Infectious Diseases*, *27*(5), 331–341. https://doi.org/10.1016/j.cimid.2004.03.003

Department of Rural Development and Land Reform. (2017). *South African Land Cover Classes and Definitions Approved in terms of spatial Data Infrastructure Act No 54, 2003*. Capetown, South Africa. Retrieved from http://www.ruraldevelopment.gov.za/

ESA. (2007). *GMES Sentinel -2 Mission Requirements Documents*. Retrieved from https://earth.esa.int/pub/ESA_DOC/GMES_Sentinel2_MRD_issue_2.0_update.pdf

ESA. (2015). *SENTINEL-2 User Handbook*. https://doi.org/GMES-S1OP-EOPG-TN-13-0001

European Commission. (2018). The Consultation Process – Mid-Term Evaluation of the EU's GSP. Retrieved August 27, 2018, from http://www.gspevaluation.com/consultation/the-consultation-process/

Fan, C., Zhang, P., Sun, Y., Liu, C., & Shi, X. (2012). Natural disaster information statistics study based on stratified random sampling survey statistical methods. *2012 IEEE International Conference on Granular Computing*, *00*, 1–4. https://doi.org/10.1109/GrC.2012.6468679

Feleke, A. K. (2003). *Land Use and Land Cover in Relation to Chromolaena odorata Distribution Mapping and Change Detection In ST. Lucia wetland area, South Africa*. Retrieved from https://library.itc.utwente.nl/papers_2003/msc/nrm/abaye.pdf

Forkuor, G., Dimobe, K., Serme, I., & Tondoh, J. E. (2018). Landsat-8 vs. Sentinel-2: examining the added value of sentinel-2's red-edge bands to land-use and land-cover mapping in Burkina Faso. *GIScience & Remote Sensing*, *55*(3), 331–354. https://doi.org/10.1080/15481603.2017.1370169

Gašparović, M., & Jogun, T. (2018). The effect of fusing Sentinel-2 bands on land-cover classification. *International Journal of Remote Sensing*, *39*(3), 822–841. https://doi.org/10.1080/01431161.2017.1392640

George, M. R. (2018). Mediterranean Climate - UC Rangelands Archive. Retrieved from http://rangelandarchive.ucdavis.edu/Annual_Rangeland_Handbook/Mediterranean_Climate/

Godínez-Alvarez, H., Herrick, J. E., Mattocks, M., Toledo, D., & Van Zee, J. (2009). Comparison of three vegetation monitoring methods: Their relative utility for ecological assessment and monitoring. *Ecological Indicators*, *9*(5), 1001–1008. https://doi.org/10.1016/j.ecolind.2008.11.011

Grounded. (2016). Baviaanskloof. Retrieved August 10, 2018, from https://www.grounded.co.za/our-work/baviaanskloof/

Haque, M. I., & Basak, R. (2017). Land cover change detection using GIS and remote sensing techniques: A spatio-temporal study on Tanguar Haor, Sunamganj, Bangladesh. *Egyptian Journal of Remote Sensing and Space Science*, *20*(2), 251–263. https://doi.org/10.1016/j.ejrs.2016.12.003

Harris, J. A., Birch, P., & Palmer, J. P. (1996). *Land restoration and reclamation: principles and practice*. Harlow, UK: Addison Wesley Longman Ltd. Retrieved from www.cabdirect.org/cabdirect/abstract/19961906920

Heumann, B. W. (2011). Satellite remote sensing of mangrove forests: Recent advances and future opportunities. *Progress in Physical Geography*, *35*(1), 87–108. https://doi.org/10.1177/0309133310385371

Jacob, A. L., Bonnell, T. R., Dowhaniuk, N., & Hartter, J. (2014). Topographic and spectral data resolve land cover misclassification to distinguish and monitor wetlands in western Uganda. *ISPRS Journal of Photogrammetry and Remote Sensing*, *94*, 114–126. https://doi.org/10.1016/J.ISPRSJPRS.2014.05.001

Jansen, H. C. (2008). Water for food and ecosystems in the Baviaanskloof Mega Reserve : land and water resources assessment in the Baviaanskloof, Eastern Cape Province, South Africa. Alterra-report 1218, 80. https://doi.org/Alterra-report 1812

Kertész, Á. (2009). The global problem of land degradation and desertifi cation. *Hungarian Geographical Bulletin*, *58*(1), 19–31.

Kishk, A. M. (1990). Conceptual Issues in Dealing with Land Degradation/Conservation Problems in Developing Countries. *GeoJournal*, *20*(3), 187–190. Retrieved from https://link.springer.com/content/pdf/10.1007%2FBF00642983.pdf

Klemas, V., & Klemas, V. (2014). Using Remote Sensing to Select and Monitor Wetland Restoration Sites : An Overview Using Remote Sensing to Select and Monitor Wetland Restoration Sites : An Overview, (July 2013). https://doi.org/10.2307/23486563

Kottek, M., Grieser, J., Beck, C., Bruno, R., & Rubel, F. (2006). World map of the Köppen-Geiger climate classification updated. *Meteorologische Zeitschrift*, *15*(3), 259–263. https://doi.org/10.1127/0941-2948/2006/0130

Kruse, B. S., & Groninger, J. W. (2003). Vegetative Characteristics of Recently Reforested Bottomlands in the Lower Cache River Watershed, Illinois, U.S.A. *Restoration Ecology*, *11*(3), 273–280. https://doi.org/10.1046/j.1526-100X.2003.00178.x

Lang, Y., Song, W., & Deng, X. (2018). Projected land use changes impacts on water yields in the karst mountain areas of China. *Physics and Chemistry of the Earth*, *104*(September 2017), 66–75. https://doi.org/10.1016/j.pce.2017.11.001

Liu, J., Heiskanen, J., Aynekulu, E., Maeda, E., Pellikka, P., Liu, J., … Pellikka, P. K. E. (2016). Land Cover Characterization in West Sudanian Savannas Using Seasonal Features from Annual Landsat Time Series. *Remote Sensing*, *8*(5), 365. https://doi.org/10.3390/rs8050365

Living Land. (2016). Who We Are. Retrieved August 2, 2018, from https://livinglands.co.za/who-we-are/

Lu, D., Mausel, P., Brondízio, E., & Moran, E. (2004). Change detection techniques. *International Journal of Remote Sensing*, *25*(12), 2365–2401. https://doi.org/10.1080/0143116031000139863

Mahmood, R., Pielke, R. A., Hubbard, K. G., Niyogi, D., Bonan, G., Lawrence, P., … Syktus, J. (2010). Impacts of land use/land cover change on climate and future research priorities. *Bulletin of the American Meteorological Society*, *91*(1), 37–46. https://doi.org/10.1175/2009BAMS2769.1

Markogianni, V., Dimitriou, E., & Kalivas, D. P. (2013). Land-use and vegetation change detection in Plastira artificial lake catchment (Greece) by using remote-sensing and GIS techniques. *International Journal of Remote Sensing*, *34*(4), 1265–1281. https://doi.org/10.1080/01431161.2012.718454

McCarthy, M. J., Colna, K. E., El-Mezayen, M. M., Laureano-Rosario, A. E., Méndez-Lázaro, P., Otis, D. B., … Muller-Karger, F. E. (2017). Satellite Remote Sensing for Coastal Management: A Review of Successful Applications. *Environmental Management*, *60*(2), 323–339. https://doi.org/10.1007/s00267-017-0880-x

McGarigal, K., Cushman, S., & Ene, E. (2012). FRAGSTATS v4:Spatial Pattern Analysis Program for Categorical and Continuous Maps. Retrieved January 5, 2019, from http://www.umass.edu/landeco/research/fragstats/fragstats.html

Meroni, M., Schucknecht, A., Fasbender, D., Rembold, F., Fava, F., Mauclaire, M., … Leonardi, U. (2017). Remote sensing monitoring of land restoration interventions in semi-arid environments with a before–after control-impact statistical design. *International Journal of Applied Earth Observation and Geoinformation*, *59*, 42–52. https://doi.org/10.1016/J.JAG.2017.02.016

MeteoBlue. (2019a). Climate Baviaanskloof Farming Community - Meteoblue. Retrieved November 4, 2018, from https://www.meteoblue.com/en/weather/forecast/modelclimate/baviaanskloof-farming-community_south-africa_1020788

MeteoBlue. (2019b). Weather Archive Baviaanskloof Farming Community. Retrieved August 15, 2018, from https://www.meteoblue.com/en/weather/forecast/archive/baviaanskloof-farming-community_south-africa_1020788?fcstlength=1m&year=2018&month=8

Nagler, P. L., Glenn, E. P., & Huete, A. R. (2001). Assessment of spectral vegetation indices for riparian vegetation in the Colorado River delta, Mexico. *Journal of Arid Environments*, *49*, 91–110. https://doi.org/10.1006/jare.2001.0844

Nichols, O. G., & Nichols, F. M. (2003). Long-Term Trends in Faunal Recolonization After Bauxite Mining in the Jarrah Forest of Southwestern Australia. *Restoration Ecology*, *11*(3), 261–272. https://doi.org/10.1046/j.1526-100X.2003.00190.x
Norman, L., Villarreal, M., Pulliam, H. R., Minckley, R., Gass, L., Tolle, C., & Coe, M. (2014). Remote sensing analysis of riparian vegetation response to desert marsh restoration in the Mexican Highlands. *Ecological Engineering*, *70*, 241–254. https://doi.org/10.1016/J.ECOLENG.2014.05.012
Nyamugama, A., & Kakembo, V. (2015). Estimation and monitoring of aboveground carbon stocks using spatial technology. *South African Journal of Science*, *111*(9–10), 1–7. https://doi.org/10.17159/sajs.2015/20140170
Oto, L. H. D. E. (2017). Exploring an alternative approach for deriving NDVI-based forage scarcity in the framework of index-based livestock insurance in East Africa Exploring an alternative approach for deriving NDVI-based forage scarcity in the framework of index-based livestoc. Retrieved from http://www.itc.nl/library/papers_2017/msc/nrm/deoto.pdf
Otukei, J. R., & Blaschke, T. (2010). Land cover change assessment using decision trees, support vector machines and maximum likelihood classification algorithms. *International Journal of Applied Earth Observation and Geoinformation*, *12*(SUPPL. 1), 27–31. https://doi.org/10.1016/j.jag.2009.11.002
Reif, M. K., & Theel, H. J. (2017). Remote sensing for restoration ecology: Application for restoring degraded, damaged, transformed, or destroyed ecosystems. *Integrated Environmental Assessment and Management*, *13*(4), 614–630. https://doi.org/10.1002/ieam.1847
Ruiz-Jaen, M. C., & Aide, T. M. (2005). Restoration success: How is it being measured? *Restoration Ecology*, *13*(3), 569–577. https://doi.org/10.1111/j.1526-100X.2005.00072.x
Rujoiu-Mare, M.-R., & Mihai, B.-A. (2016). Mapping Land Cover Using Remote Sensing Data and GIS Techniques: A Case Study of Prahova Subcarpathians. *Procedia Environmental Sciences*, *32*, 244–255. https://doi.org/10.1016/j.proenv.2016.03.029
Salinas, M. J., & Guirado, J. (2002). Riparian Plant Restoration in Summer-Dry Riverbeds of Southeastern Spain. *Restoration Ecology*, *10*(4), 695–702. https://doi.org/10.1046/j.1526-100X.2002.01050.x
Schmidt, K. S., & Skidmore, A. K. (2003). Spectral discrimination of vegetation types in a coastal wetland. *Remote Sensing of Environment*, *85*(1), 92–108. https://doi.org/10.1016/S0034-4257(02)00196-7
Schreuder, H. T., Ernst, R., & Ramirez-Maldonado, H. (2004). *Statistical Techniques for Sampling and Monitoring Natural Resources*. *Agriculture* (Vol. RMRS-126). Fort Collins, Colorado. Retrieved from http://www.treesearch.fs.fed.us/pubs/6287
SER. (2004). The SER International Primer on Ecological Restoration. *Society for Ecological Restoration International, Version 2*, 14. Retrieved from https://www.ctahr.hawaii.edu/littonc/PDFs/682_SERPrimer.pdf
Setegn, S. G., Srinivasan, R., Dargahi, B., & Melesse, A. M. (2009). Spatial delineation of soil erosion vulnerability in the Lake Tana Basin, Ethiopia. *Hydrological Processes*, *23*(26), n/a-n/a. https://doi.org/10.1002/hyp.7476
Sewell, A., Bouma, J., & Van Der Esch, S. (2016). *Investigating the Challenges and Opportunities for Scaling Up Ecosystem Restoration: Background Report Investigating the challenges and opportunities for scaling up Ecosystem Restoration*. The Hague.
Shackelford, N., Hobbs, R. J., Burgar, J. M., Erickson, T. E., Fontaine, J. B., Laliberté, E., … Standish, R. J. (2013). Primed for Change: Developing Ecological Restoration for the 21st Century. *Restoration Ecology*, *21*(3), 297–304. https://doi.org/10.1111/rec.12012
Singh, S. K., Mustak, S., Srivastava, P. K., Szabó, S., & Islam, T. (2015). Predicting Spatial and Decadal LULC Changes Through Cellular Automata Markov Chain Models Using Earth Observation Datasets and Geo-information. *Environmental Processes*, *2*(1), 61–78. https://doi.org/10.1007/s40710-015-0062-x
Snyman, H. A. (2003). Revegetation of bare patches in a semi-arid rangeland of South Africa: An evaluation of various techniques. *Journal of Arid Environments*, *55*(3), 417–432. https://doi.org/10.1016/S0140-1963(02)00286-0
Stringer, L. C., Dyer, J. C., Reed, M. S., Dougill, A. J., Twyman, C., & Mkwambisi, D. (2009). Adaptations to climate change, drought and desertification: local insights to enhance policy in southern Africa. *Environmental Science and Policy*, *12*(7), 748–765. https://doi.org/10.1016/j.envsci.2009.04.002
Talbot, M., & van den Broeck, D. (2015). *Shifting from Individual to Collective Action: Living Land's experience in the Baviaanskloof, South Africa*. *Land Restoration: Reclaiming Landscapes for a Sustainable Future*. Elsevier Inc. https://doi.org/10.1016/B978-0-12-801231-4.00008-2
TerrAfrica. (2013). What does SLM achieve? | Sustainable Land Management – Learning. Retrieved May 28, 2018, from http://terrafrica.org/sustainable-land-management-platform/what-does-slm-achieve
UNEP. (2015). *UNEP. United Nations Environment Programme (UNEP)*. https://doi.org/ISBN 978-92-9253-062-4
United Nations. (2015). Transforming our world: the 2030 Agenda for Sustainable Development : Sustainable Development Knowledge Platform. Retrieved August 26, 2018, from https://sustainabledevelopment.un.org/post2015/transformingourworld

Urbanska, K. M., Webb, N. R., & Edwards, P. J. (Eds.). (1997). *Restoration Ecology and Sustainable Development - Google Books*. Cambridge: Cambridge University Press. Retrieved from https://books.google.nl/books?id=TNtsGSJAVEMC&printsec=frontcover#v=onepage&q&f=false

Van Luijk, G., Cowling, R. M., Riksen, M. J. P. M., & Glenday, J. (2013). Hydrological implications of desertification: Degradation of South African semi-arid subtropical thicket. *Journal of Arid Environments*, *91*, 14–21. https://doi.org/10.1016/j.jaridenv.2012.10.022

Van Wyk, B.-E. (2011). The potential of South African plants in the development of new medicinal products. *South African Journal of Botany*, *77*(4), 812–829. https://doi.org/10.1016/J.SAJB.2011.08.011

Vanderhoof, M. K., & Burt, C. (2018). Applying high-resolution imagery to evaluate restoration-induced changes in stream condition, Missouri River Headwaters Basin, Montana. *Remote Sensing*, *10*(6). https://doi.org/10.3390/rs10060913

Vanderpost, C., Ringrose, S., Matheson, W., & Arntzen, J. (2011). Satellite based long-term assessment of rangeland condition in semi-arid areas: An example from Botswana. *Journal of Arid Environments*, *75*(4), 383–389. https://doi.org/10.1016/j.jaridenv.2010.11.002

Verma, J. P. (2013). One-Way ANOVA: Comparing Means of More than Two Samples. In *Data Analysis in Management with SPSS Software* (pp. 221–254). India: Springer India. https://doi.org/10.1007/978-81-322-0786-3_7

Vuolo, F., Neuwirth, M., Immitzer, M., Atzberger, C., & Ng, W.-T. (2018). How much does multi-temporal Sentinel-2 data improve crop type classification? *International Journal of Applied Earth Observation and Geoinformation*, *72*(June), 122–130. https://doi.org/10.1016/j.jag.2018.06.007

Walters, B. B. (2000). Local Mangrove Planting in the Philippines: Are Fisherfolk and Fishpond Owners Effective Restorationists? *Restoration Ecology*, *8*(3), 237–246. https://doi.org/10.1046/j.1526-100x.2000.80035.x

Waters, L. T., Indre, B., & Atcher, C. (2011). The potential of South African plants in the development of new medicinal products. *South African Journal of Botany*, *77*(4), 812–829. https://doi.org/10.1016/j.sajb.2011.08.011

Waters, L. T., Indre, B., Hatcher, C., Carter, G., & Alfred, C. (2016). Land Restoration in the Baviaanskloof, (February). Retrieved from http://cligs.vt.edu/wp-content/uploads/2016/05/Land-Restoration-in-the-Baviaanskloof_FINAL.pdf

Weiermans, J., & van Aarde, R. J. (2003). Roads as Ecological Edges for Rehabilitating Coastal Dune Assemblages in Northern KwaZulu-Natal, South Africa. *Restoration Ecology*, *11*(1), 43–49. https://doi.org/10.1046/j.1526-100X.2003.00026.x

Wilkins, S., Keith, D. A., & Adam, P. (2003). Measuring success: Evaluating the restoration of a grassy eucalypt woodland on the Cumberland plain, Sydney, Australia. *Restoration Ecology*, *11*(4), 489–503. https://doi.org/10.1046/j.1526-100X.2003.rec0244.x

World Bank. (2011). *The World Bank: Republic of South Africa for a Biodiversity Conservation and Sustainable Development Project*. South Africa.

World Meteorological Organization (WMO). (2015). *WMO. International Organization* (Vol. 16). https://doi.org/10.1017/S0020818300010924

Xie, Y., Sha, Z., & Yu, M. (2008). Remote sensing imagery in vegetation mapping: a review. *Journal of Plant Ecology*, *1*(1), 9–23. https://doi.org/10.1093/jpe/rtm005

Xing, S. (2015). *Machine learning course notes*. Retrieved from https://sux13.github.io/DataScienceSpCourseNotes/8_PREDMACHLEARN/Practical_Machine_Learning_Course_Notes.html

Zhao, J., Yang, Y., Zhao, Q., & Zhao, Z. (2017). Effects of ecological restoration projects on changes in land cover: A case study on the Loess Plateau in China. *Scientific Reports*, *7*(March), 1–12. https://doi.org/10.1038/srep44496

Zhou, P., Wen, A., Yan, D., Shi, Z., Guo, J., Ju, Z., & Zhang, Y. (2014). Changes in land use and agricultural production structure before and after the implementation of grain for green program in Western China — taking two typical counties as examples. *Journal of Mountain Science*, *11*(2), 526–534. https://doi.org/10.1007/s11629-013-2369-2

APPENDIX A: DATAFORM

Data Sheet for vegetation cover in Baviaanskloof				**Sample No:**		**Time:**	
Date:							
Observer Name:							
Coordinates	**Lat:**			**Long: -33.**		**Altitude (m)**	
Intervention Evidence	Planted Spekboom		Goat dung		Goat		
General Characteristics:							
General location:	Flat		Hill side		Top		
Aspect :	North facing		South facing		East facing	West facing	
	North East facing		North West facing		South East facing	South West facing	
Stone cover %							
Stone color and other Visual color :							
Bare Soil Color:							
Erosion level							
Erosion Intensity	Very High		High	Medium	Low	Very Low	
Erosion Type	Gulle		Rill	Sheet	None		
Layer/Strata	**Cover %**	**Dominant Species**					
		%	**%**	**%**	**%**	**%**	**%**
Tree (>3m)							
Shrubs (2-3 m)							
Low woody (<1m)							
Low non- woody (<1m)							
Bare soil							
Stones							
		Acacia	**Pappea**	**Euclea**	**Spekboom**	**Grewia**	**Rhus longispina**
Cheklist of Dominant Species		**Fynbos**	**Aloe**	**Natural grass**	**Seeded grass**	**Lavandin**	**Rosemary**
Non-identified species:		**Succulent Shrub**	**Shrub**	**Fynbos shrubs**	**Tree**	**Herbs**	
Spekboom Status:							
Notes:							