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Testing the use of the new generation multispectral data in mapping vegetation communities of Ezemvelo Game Reserve

A research report submitted to the Faculty of Science, University of the Witwatersrand, Johannesburg, in partial fulfilment of the requirements for the degree of Master of Science (Geographical Information Systems and Remote Sensing) at the School of Geography, Archaeology & Environmental Studies)

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Declaration

I, Sibongile Rose Madela, declare that this research report is my own unaided work. It is being submitted to the Degree of Master of Science in Geographical Information Systems and Remote Sensing to the University of the Witwatersrand, Johannesburg. It has not been submitted before for any degree or examination at any other University.

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Signature of candidate

__________day of ___20___.in __________.

Abstract

Vegetation mapping using remote sensing is a key concern in environmental application using remote sensing. The new high resolution generation has made possible, the mapping of spatial distribution of vegetation communities.

The aim of this research is to test the use of new generation multispectral data for vegetation classification in Ezemvelo Game Reserve, Bronkhorspruit. Sentinel-2 and RapidEye images were used covering the study area with nine vegetation classes: eight from grassland (Mixed grassland, Wetland grass, Aristida congesta, Cynadon dactylon, Eragrostis gummiflua, Eragrostis Chloromelas, Hyparrhenia hirta, Serephium plumosum) and one from woodland (Woody vegetation).

The images were pre-processed, geo-referenced and classified in order to map detailed vegetation classes of the study area. Random Forest and Support Vector Machines supervised classification methods were applied to both images to identify nine vegetation classes. The softwares used for this study were ENVI, EnMAP, ArcGIS and R statistical packages (R Development Core, 2012) .These were used for Support Vector Machines and Random Forest parameters optimization.

Error matrix was created using the same reference points for Sentinel-2 and RapidEye classification. After classification, results were compared to find the best approach to create a current map for vegetation communities. Sentinel-2 achieved higher accuracies using RF with overall accuracy of 86% and Kappa value of 0.84. Sentinel-2 also achieved overall accuracy of 85% with a Kappa value of 0.83 using SVM. RapidEye achieved lower accuracies using RF with an overall accuracy of 82% and Kappa value of 0.79. RapidEye using SVM produced overall accuracy of 81% and a Kappa value of 0.79.

The study concludes that Sentinel-2 multispectral data and RF have the potential to map vegetation communities. The higher accuracies achieved in the study can assist management and decision makers on assessing the current vegetation status and for future references on Ezemvelo Game Reserve.

Keywords

Random forest, Support Vector Machines, Sentinel-2, RapidEye, remote sensing, multispectral, hyperspectral and vegetation communities

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Abbreviations and Acronyms

ANN	Artificial neural network
GPS	Global Positioning System
MLC	Maximum likelihood
RF	Random Forest
RBF	Radial basis function
SVM	Support Vector Machines

Chapter 1: Introduction

1.1 Background of the study

Vegetation mapping is a vital tool for managing natural resources such as vegetation communities. It has an imperative role in worldwide environmental dynamics for all living creatures. It also gives valued data on quantifying vegetation, examining natural and semi natural environments from locally and globally (Xiao *et al.* 2004).

Natural resources such as vegetation can assist in reducing the negative impacts on global climate changes (Xiao *et al.* 2004). Vegetation recording enables better understanding of man-made and natural environment by quantification of vegetation cover on an extensive scale that is locally and worldwide. It is vital to get a recent state of vegetation cover so as to comeup with better ways of protecting vegetation and for restoration programs (Egbert *et al.* 2002; He *et al.* 2005).

The Ezemvelo Nature reserve is located to the north of the grassland biome in South Africa.. Ezemvelo is highly known as Rand Highveld Grassland (Mucina et al. 2005). It covers South Africa's productive area of grassland biome. The nature reserve is one of the most arable lands in South Africa for crop production and is also a major timber and dairy (Mucina et al. 2005). It consists of treats such as soil erosion, and acid rain due to sulphur dioxide from existing power stations as well as for gold and coal mines. (Neke & Du Plessis 2004). Due to these treats for the grasslands, mapping is vital. The Nature Reserve consists of different vegetation communities such as grassland and woodlands. These communities are dependent on their location and topography (Bredenkamp & Brown 2003)

Different methods have been previously used to map vegetation communities and have been classified using SPOT and Landsat TM images (Harvey and Hill 2001; Li *et al.* 2005). However, the utility of using multispectral data has been limited due to lack of spatial and spectral resolutions and lack of finances. Hyperspectral data is not easily found due to high costs (processing data and accessibility) (Goetz 2009). The acquisition of narrow bands contiguous and spectral channels allows detection of vegetation species level (Adam *et al.* 2010).

Multispectral data (Saatchi *et al.* 2008) and hyperspectral data sets have been used to map vegetation in different landscapes (Lawrence *et al*. 2006; Peerbhay *et al.* 2013). Field based procedures such as ground inspections for mapping vegetation are costly and, time consuming thereby making it difficult to get recent satellite images for vegetation cover (Nordberg *et al.* 2003). Remote sensing techniques provide cost-effective ways of studying changes in vegetation cover over large scale areas (Langley *et al.* 2001). Remote sensing images have been used regularly by scientists and professionals to outline vegetation cover on local to a large scale. This technique can be applied to different applications such as mapping underwater areas and land areas for environmental conditions in fresh water (Wolter *et al.* 2005). Remote sensing images of the past century used space borne and airborne sensors with spatial resolution ranging from sub-meter to kilometres (Navulur 2006).

As a comparison between the multispectral and hyperspectral imagery benefits and limitations, a collection of the recent images such as Sentinel- 2 (spatial resolution 10 m, 20 m and 60 m) and RapidEye (high spatial resolution images with 5 m) has begun over the last decade. RapidEye imagery is the optical earth observation that consists of five mini satellites (Rapid eye 2010) and five multispectral bands. The satellites are equally spaced in a single synchronous orbit with an altitude of 630 km. The sensor has a 5, 5 day temporal resolution and ground sampling distance of 6.5 m at nadir (Rapid eye 2010). The image was used in the context since it was designed for environmental resources and to monitor vegetation (RapidEye 2011).

Sentinel-2 which was launched on 23 June 2015, contains two satellites for land monitoring at worldwide level. The data has 13 spectral bands of new perspective of land and vegetation. It provides a global coverage of 10 days with one satellite and 5 days with 2 satellites (Topaglu *et al.* 2016). Sentinel-2 offers continuousness for the current SPOT and LANDSAT missions with a predictable lifetime of 7.25 years, over a 20 year period (Topaglu *et al.* 2016).

These images provide more details on vegetation mapping since their spectral and spatial resolutions have improved (Cho *et al.* 2012; Kleinschmit *et al.* 2012; Mutanga *et al.* 2014).The new generation sensors came with better (more bands) resolution which is perceived as an enhancement to multispectral imagery and on the other hand, it enables overcoming the limitation of hyperspectral data. The images such as RapidEye and Sentinel-2 have the red-edge bands that have been identified as key bands for predicting and mapping vegetation (Ramoelo *et al.* 2012).

1.2 Research problem statement

The 11 000 hectare (ha) Ezemvelo Nature Reserve contains habitat that comprises of the main unspoilt grassland in South Africa. It also contains savannah biomes of valuable biodiversity (of which some are endangered) .It also attracts up to 280 bird species. According to Showme (n.d.), it is a home of big and small mammals such as kudu, brown hyena and zebras.

The effective management of the game reserve lies on the latest spatial information on species diversity, vegetation quality and understanding of the feeding patterns of the wildlife (Adam *et al.* 2010). Proper management and planning are needed to stop degradation by factor such as alien species. The information obtained in this study will expand the knowledge for future management and decision makers of the Reserve. Assessing the geographic distribution of the vegetation is important for conservation efforts as it provides a habitat and pasture to biodiversity.

The old technique of using the field-based approach is currently used in the reserve for data collection. This method requires intensive labour and more time for vegetation mapping (Mutanga *et al.* 2004).For decision making and future plans to be successful, precise and latest spatial information on the vegetation is required. Remote sensing technique provides cost effective ways of studying changes in vegetation cover with big scale parts over a short period (Langley *et al.* 2001).

A remote sensing technique for vegetation mapping was established and uses multispectral and commercial data that is costly and disadvantages different applications. Sentinel-2 data was released by ESA that opened greater opportunities for any application in countries like South Africa to earth observation. Studies lack still in South Africa that is testing new generation (RapidEye and Sentinel- 2) in vegetation mapping of Ezemvelo Game Reserve.

Developing spatial patterns of the distribution of vegetation at the local scale would be of considerable benefit of scientists and environmental managers. The management will know the impacts on the biomes and habitat on the environment. Therefore, developing a methodology that aims to decrease the error in vegetation classification at the local scale is needed. Such methodology must focus on main problems: the spectral, radiometric suitability and classification methods of remotely sensed data sets used in thematic mapping at the local scale.

1.3 Aim and objectives

1.3.1 Aim

The main aim of the study is to examine the use of Sentinel-2 and RapidEye imageries with red edge band in mapping vegetation communities of Ezemvelo Game Reserve.

1.3.2 Objectives

The main objectives of this research are:

- To test the performance of the new-generation multispectral RapidEye and Sentinel-2 data in mapping vegetation communities using RF and SVM classifiers.
- To discover and evaluate the performance of different Sentinel-2 and RapidEye new bands on vegetation classification.
- To map vegetation communities using Sentinel-2 and RapidEye.

Chapter 2: Literature Review

2.1 Introduction

Vegetation mapping is a vital tool for managing natural resources such as vegetation. It has an imperative role in worldwide dynamics and in all living creatures. It also gives valued data onto quantifying vegetation, examining natural and semi natural environments from local to worldwide measures (Xiao *et al.* 2004).

2.2 The importance of mapping vegetation communities

The reserve caters different habitats and attracts different types of bird species. The updated spatial data is needed for proper management to check degradation by problems such as alien species. Assessing the geographic distribution of the vegetation is important to conservation efforts because they provide habitats and pasture to biodiversity (Mutanga *et al.* 2004). Fast changing vegetation plays a vital role in urban environments for climate changes scenarios (Ahamed *et al.* 2014).

The information or the results collected for this study will expand the knowledge for future management and decision makers of the Reserve. Studies in vegetation mapping have become a significant theme recently as they provide spatial information on conservation management (Cingolani *et al.* 2004). Mapping vegetation communities has been dependent on old studies that have been collected using image spectroscopy and field survey that is time consuming (Mutanga *et al.* 2004).The challenge to the field techniques is that they are expensive, difficult and can be carried out on areas with restricted access (Mutanga *et al.* 2012).

Remote Sensing is the best advanced tool that gives a clear picture about the spatial distribution of vegetation which is necessary to understand the distribution of species (Adam et al. 2010). The practice of this advanced tool decreases intensive field surveys required by traditional vegetation mapping techniques (Darvishzadeh *et al.*2008) by allowing for access to inaccessible areas (Running *et al.* 1993). Mapping of the distribution of foliar N from remotely sensed images also emerges patterns, which assist in understanding the dominant drivers causing vegetation patterns (Skidmore *et al.* 2010).

2.3 Mapping vegetation communities using multispectral data

Multispectral sensors contain additional distinctive bands that have given a chance of mapping vegetation communities on a huge area (Adam *et al.* 2015). SPOT and Landsat TM make remote sensing better techniques to old style that were used for mapping vegetation. Currently, the growth of multispectral high resolution devices such as IKONOS has carried distinctive chance of checking and classifying vegetation classes (Pu and Landry, 2012). These high spatial sensors contain bands such as blue, green, red and near infrared. A sensor doesn't precisely map vegetation communities in fragmented ecosystem if there is low spatial resolution.

When the spatial resolution is low, devices might not accurately map vegetation communities in a fragmented ecosystem (Foody 2002). Spectral resolution of multispectral data overcomes data limitations by giving contiguous wavebands and spectral data (Adam *et al.* 2015).

2.4 Mapping vegetation communities using Hyperspectral data

Hyperspectral sensors licence a detailed examination of earth surface topographies. The finer spectral resolution can increase vegetation classification by spotting physical changes in vegetation (Yamano *et al.* 2003). It separates the terrestrial landscapes into distinctive spectral signature. This is valued in classifying land topographies such as water and vegetation bodies (Shankar *et al.* 2014). Remote sensing datasets have limitations such as missing of data onto exact bands using spectral information.

Hyperspectral data has more bands that are within visible, near infrared and shortwave infrared region of the spectrum. They obtain data less than 10 nm bandwidths between visible and shortwave infrared (Shankar *et al.* 2014). The spectral and spatial resolution of medium resolution data bounds the accuracy of urban land classification (Ahamed *et al.* 2014). This data is progressively used to model, classify and map natural vegetation (Divya *et al.* 2014).

This data successfully mapped vegetation communities in the rangeland environments of South Africa at a local level because of their narrow bands. Several studies have confirmed the successful usage of hyperspectral data onto mapping vegetation communities. It was discovered in the study completed by (Mutanga *et al.* 2004) that the use of the continuum absorption has better approach than the band width approach to mapping vegetation communities in Kruger National Park of South Africa.

2.5 Mapping vegetation communities using new generation (RapidEye and Sentinel-2)

The introduction to new generation satellites consisting of suitable spatial resolution is perceived as an enhancement of hyperspectral and multispectral data for mapping vegetation communities (Mittapalli *et al.* 2014; Antonio 2014; Li *et al.* 2014). Multispectral sensors such as Sentinel-2 and RapidEye were designed recently with additional bands and high spatial resolution. The bands were designed to manage the restrictions of their spectral abilities over other multispectral sensors like Quickbird (Omer *et al.* 2015).

Both image to include the red-edge position which is sensitive to plant materials and very important to vegetation assessment (Ramoelo *et al.* 2015 a). The use of commercial satellites come with the limitation of cost which has resulted in their limited usage vegetation in larger areas for different applications (Ramoelo *et al.* 2015 a).

The effective management of conservation areas depends largely on the availability of well-timed accurate spatial datasets and identification of procedures that can be used to assess unlike conservation controlling practices at a national level (Zheng *et al.* 2015). The availability of Sentinel-2 MSI free of charge provides an opportunity to map vegetation communities because of its spectral and spatial characteristics and suitable for vegetation management on the regional level, which was not feasible before (Sentinel-2 2017).

In the previous studies RapidEye was used in vegetation mapping from high resolution satellite images of the heterogeneous arid environments of Socotra Island. An accuracy of 87% was achieved using Sequential maximum *a posteriori* (SMAP) and 66% while using Maximum Likelihood (ML) (Malatesta 2013).

Chapter 3: Materials and methods

3.1 Study area

The study area was conducted in Gauteng Province of South Africa (Figure.1). The study area lies along north of National road (N4) in Bronkhorstspruit. It is located between the latitudes of 25° 38’ 24’’ S and 25° 44’ 24’’ S and the longitudes of 28° 55’ 48’’ E and 29° 02’ 24’’ E. The Olifants River and Wilge River is the biggest rivers that flow through the Reserve. The extent of the Nature Reserve is approximately 11 000 hectares (ha).

Ezemvelo Game Reserve accommodates habitats such as savannah biomes and unspoilt grassland live in South Africa. The reserve contains birds, big mammals and predators. The life cycles of vegetation patterns are shaped by climate of factors such as temperature, rainfall, light and moisture. These factors can have positive and negative impacts on the vegetable’s life cycle (Schulze 2003).

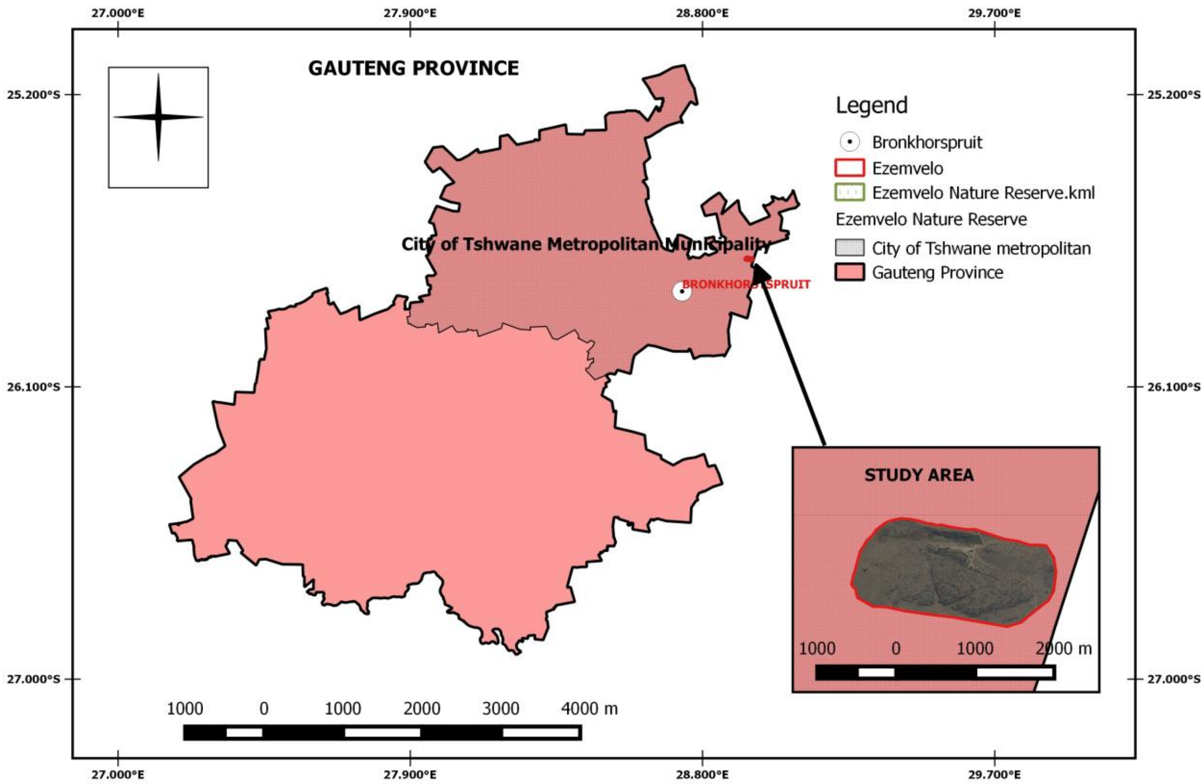

Figure 1: Study area for Ezemvelo Game Reserve from City of Tshwane Local Municipality (Google Earth and ArcGIS)

3.2 Materials

3.2.1 Research Material

The following materials were used in the study

1. Remotely sensed data: RapidEye and Sentinel-2 images for 2016 covering the study area (Ezemvelo Game Reserve)

2. Ground truth Data: Randomly selected points of Grassland *(Mixed grassland, Wetland grass, Aristida congesta, Cynadon dactylon, Eragrostis gummiflua, Eragrostis Chloromelas, Hyparrhenia hirta, Serephium plumosum)* and Woodland *(Woody vegetation)*

3. Hand held Trimble Global Positioning System (GPS) unit

4. Softwares used as follows: ArcGIS 10.3, ENVI 5.3, EnMAP, R statistical package and Google Earth.

3.2.2 Remote Sensing data

The initial step in the process of mapping vegetation communities was to acquire and identify a suitable sensor for the study in terms of spatial, spectral and temporal resolution. Remote sensing imageries have been acquired over the past century using spaceborne and airborne sensors (hyperspectral and multispectral). The sensors with the wavelength that ranges from visible to microwave, spatial resolution ranging from sub-meter to kilometre and temporal frequencies from 30 minutes to weeks or months (Malatesta 2013).

There are different types of satellite images that can be used to map vegetation communities. These include the commonly applied sensors such as Quickbird, Landsat TM, SPOT, IKONOS Aster and AVIRIS. Each satellite image has different temporal, spectral, spatial resolution and radiometric characteristics. The satellite sensors that have a medium spatial resolution such as SPOT and Landsat TM and SPOT while sensors with high spatial resolution include Quickbird and IKONOS and MODIS as lower spatial resolution are mostly used for vegetation mapping (Malatesta 2013). Choosing the satellite sensor is essential and depends on mapping objectives, image quality, interpretation and expected accuracy. High resolution images are required for vegetation mapping at small scale (Malatesta 2013).

Sentinel-2 and RapidEye images covering the study area were chosen and acquired at Southern Mapping Geospatial, Pretoria on the 3rd of January 2017. This date was selected based on the summer (rain season).

3.2.2.1 Sentinel-2

Sentinel-2 was launched in 23June 2015 and gives a full systematic coverage of land surface at worldwide level. Sentinel-2 consists of 13 bands that can add more advantages in mapping vegetation (Adam *et al.* 2014). It also provides a global coverage of 10 days (Raziye *et al.* 2016). Sentinel-2 assignment delivers continuousness for the current LANDSAT and SPOT (Topaglu *et al.* 2016). Sentinel-2 provides the medium to coarse spatial resolution images with (10 visible, 20 short infrared and 60 m atmospheric correction bands). Sentinel-2 is capable of mapping vegetation at a regional scale and at community level. The satellite covers a spectral range of 77 km (Table 1).

3.2.2.2 RapidEye

RapidEye is the profitable optical earth observation work with a gathering of five mini satellites (RapidEye 2010). The multispectral satellite was designed by MacDonald and launched on 29 August 2008 (RapidEye 2011). It consists of five multispectral bands that allow more accuracy for vegetation communities' representation and likewise spread out in one synchronous orbit with an elevation of 630 km (Eitel *et al.* 2007). The sensor has a 5, 5 day temporal resolution and ground sampling distance of 6.5 m at a nadir (Muntanga *et al.* 2014). RapidEye provides high spatial resolution images of 5 m (red and near infrared bands) which allows the selection of minimum cloud covers images of a short period (Eitel *et al.* 2007). RapidEye is capable of mapping vegetation at local to regional scale of community level (3.2). The satellite covers a spectral range of 290 km (Table1). Red edge band has been found with photosynthetic activity and insensitive to atmospheric noise and soil background (Eitel *et al.* 2007; Blackburn 1998). Red edge has been applied to the analysis of N status of grassland ad crops. The features explained above can contribute to the accurate map of vegetation communities (Malatesta *et al.* 2013).

The image has processed levels 1 B and 3 A. Level 3A receives geometric, radiometric and sensor correction. On the other hand, 1 B receives radiometric correction and receives data onto sensor (RapidEye 2011). RapidEye has red edge that monitors photosynthetic activity for vegetation (RapidEye 2011). The descriptions of bands are illustrated with Table 1 below. Table 1 below shows the description of bands spatial and spectral resolutions of images.

Table 1: Satellite imagery description

Sensor	Spectral Resolution	Spatial Resolution	Swath Width

Rapid Eye	Blue	(440-550) nm	5m	77 km
	Green	(520 – 590 nm)		
	Red	(630 – 685) nm		
	Red edge	(690-730) nm		
	Near-Infrared	(760 – 850) nm		
Sentinel-2	4 visible bands	(443–2190) nm	10 m	290 km
	6 red edge/ shortwave- infrared bands		20 m	
	3 atmospheric correction bands		60m	

3.2.2 Field data collection

Site visits was done to gather field data that was useful for verification and classification of the acquired satellite images on the 02 February 2017. There were 619 randomly selected ground reference points collected of different vegetation types namely eight Grassland *(Mixed grassland, Wetland grass, Aristida congesta, Cynadon dactylon, Eragrostis gummiflua, Eragrostis Chloromelas, Hyparrhenia hirta, Serephium plumosum)* and one Woodland *(Woody vegetation)* with a GPS. The collected data was in the form of reference data points. The co-ordinates were then converted from degree minutes and seconds to Decimals (Longitudes and latitudes). The co-ordinates were then converted to shape file formats using ArcGIS 10.3.

3.3 Image pre-processing

This process comprises all steps needed to improve the quality of the satellite image to be used for study. Image pre-processing is important to increase the quality of image and get rid of noise before vegetation extraction. The main aim of this process are to make images appear as if they were acquired using the same remote sensor (Hall *et al.* 1991).

The satellite sensors (RapidEye and Sentinel-2) were pre-processed. This was done for high precision of geometric and atmospheric correction (Lu *et al.* 2004). Sentinel-2 was not atmospherically corrected since the part of the study area was clear (without clouds) and was only performed to RapidEye. The resampled 5 m x 5 m spatial resolution of RapidEye Ortho product was delivered. The image was atmospherically corrected with an aim to retrieve surface reflectance using FLAASH (Fast line of sight atmospheric analysis hyper cubes) algorithm using Envi 5.3 software.

Geometric correction was applied to both image with an aim to establish the relationship between geographic co-ordinate system and image coordinate system using data (ground control points, altitude and calibration of the sensor). The collected GPS 182 points were projected Universal Traverse Mercator projection using WGS-84 Geodetic datum using ENVI 5.3 Remote sensing software. The images (RapidEye and Sentinel-2) were then georeferenced using the projected points.

3.4 Defining the vegetation classes

Vegetation classes were selected using Sentinel-2 and RapidEye images. Supervised classification tool of ArcGIS was used to select training and test datasets. Regions of interest were created by overlaying the ground data onto two images Sentinel-2 and RapidEye individually. Both classifiers used in randomly selected data that was divided into 70% (n=437) data onto training and 30% (n=182) data for accuracy as appear in (Table 2). The samples collected were eight Grasslands (*aristida congesta, cynadon dactylon, eragrostis chloromelas, eragrostis gummiflua, hyparrhenia hirta, serephium plumosum, mixed grassland, wetland grass) and one woodland (woody vegetation).*

Table 2: Training and test dataset collected for vegetation classes.

Vegetation class	**Vegetation type**	**Vegetation code**	**Training dataset (70 %)**	**Test dataset (30%)**	**Total**
Aristida congesta	Grassland	AC	42	17	59
Cynadon dactylon	Grassland	CD	35	14	49
Eragrostis Chloromelas	Grassland	EC	52	22	74
Eragrostis gummiflua	Grassland	EG	45	19	64
Hyparrhenia hirta	Grassland	HH	41	17	58
Mixed grassland	Grassland	MG	38	15	53
Serephium plumosum	Grassland	SP	48	20	68
Wetland grass	Grassland	WG	42	18	60
Woody vegetation	Woodland	WV	94	40	134

3.5 Image classification

Image classification is a process of extracting different classes such as vegetation from remotely sensed data (Xie *et al.* 2008). According to Palaniswami *et al.* (2006) defined image classification as the process that creates maps from satellite imageries.

There are different algorithms such as K-mean and ISODATA for unsupervised, maximum likelihood classification for supervised as traditional methods to image classification. Unsupervised classification always depends or relies on the pixel based statistics and automatically changes raw image data onto helpful data (Tso and Olsen 2005). Unsupervised has to be continual if new samples are extra (Xie *et al.* 2008). In supervised image classification, additional data has no impact on its standards as compared to unsupervised classification (Xie *et al.* 2008). Each sample unit contains interpreter variable measured and learning classification from training dataset (Lenka and Milan 2005).

Similar vegetation type of ground may possess similar and different spectral features of remote sensed data or images. Getting an image classifier with accurate, improved and better results is a research topic nowadays. Two image classifiers (RF and SVM) were discovered by Sluiter (2005) as better image classifiers compared to traditional supervised classifier (K-Mean). Sluiter also used spatial domain both per pixel and neighbouring pixel spectral information to analyse and classify remotely sensed imagery (Sluiter 2005). As mentioned above there are many images algorithm or classification methods established. In the study the combination of RF and SVM classifiers were used to map vegetation classes of Ezemvelo Nature Reserve. However, each images classifier was designed to solve the distinctive problem depending on successful extraction of pure spectral signature for each vegetation species (Asner and Heidebrecht 2002; Varshney and Arora 2004).

3.5.1 Signature creation

The dataset was divided into training 70% (n=437) and test 30% (n=182) for both images. Envi 5.3 was used to create signatures on Sentinel-2 and RapidEye images. The vector file from an image was loaded and overlaid images on Envi 5.3 where polygons were produced. The polygons were made around the points in signature creations. The region of interest tool was used to assign pixels with similar classes on vegetation (Table 2). Nine signature classes were created on Table 3

Table 3:Defined classes and classes codes for vegetation communities.

Class name	Class type	Class code
Aristida congesta	Grassland	AC
Cynadon dactylon	Grassland	CD
Eragrostis Chloromelas	Grassland	EC
Eragrostis gummiflua	Grassland	EG
Hyparrhenia hirta	Grassland	HH
Mixed grassland	Grassland	MG
Serephium plumosum	Grassland	SP
Wetland grass	Grassland	WG
Woody vegetation	Woodland	WV

3.5.2 Random forest (RF) classifier

In the study images were classified by means of supervised classification technique using Random Forest (RF) algorithm using ENVI software. RF is a collective learning method that was established by Breiman (2001) with advances trees and classification by putting together an amount of trees together. A single vote is contributed to the classifier to the input data onto the task of the common class. Random selection and bragging are the most powerful methods of the classifier (Lin *et al.* 2011).

A number of bootstrap samples are used to form various classification trees (ntree) from unique observations. The misclassification and variable importance is estimated by the total data. At every node a number of participation variables (mtry) are given that are randomly selected from separation of features.

The great split are calculated using this feature. No pruning and low bias is done in all trees of the forest to ensure lower match (Genuer et al. 2010; Lin et al. 2011). For better accuracy in classification, parameters need to be optimized (Breiman 2001; Mutanga *et al.* 2012). A 10 fold grid-search method based on the OOB approximation of mistakes is used to find the ideal grouping for these parameters (Tian *et al.* 2009).

3.5.3 Support Vector Machines (SVM) classifier

Support Vector machines classifier was originally proposed by Vapnik in 1979. It is a nonparametric supervised machine learning classifier that was first presented by Cortes and

Vapnik 1995 as a dual classifier (Cortes and Vapnik 1995). SVM is categorized by an effective hyperplane searching technique where minimal training area is used that takes a few times for processing. It avoids complications such as over fitting and requires no assumption of data type. It reduces misclassification and develops boundaries by splitting hyper planes (Vapnik 1995).

SVM works by classifying distance between each class of the data points correctly in training data onto decision boundary maximized. This minimises the misclassification obtained in training step (Tshilidzi *et al* 2007). The boundaries contain two support hyperplane that has data points on their edges called to support vectors that define the optimal hyperplane (Mountrakis *et al* 2011). The nonlinear algorithm is optimized using different methods such as the kernel that uses radial basis and is the mostly used method of remote sensing in most studies (Huang *et al.* 2002; Oommen *et al.* 2008). Two most parameters for tuning called sigma (*C)* and gamma (γ) were chosen for Radial basis method (Karatzoglou *et al.* 2006).

Previous studies show that SVM has high accuracy in image classifications (Candade *et al.* 2004; Foody *et al.* 2004; Shi *et al.* 2012). Foody and Mathur (Foody *et al.* 2004), confirmed that SVM multiclass can be useful and develop precise classification. Other methods such as decision trees, feed forward neural network were compared to SVM and discovered that SVM yielded higher accuracy (Foody *et al.* 2004).

The results were alike in a study carried out by Shi and Yang (Yang *et al.* 2012) that revealed that SVM do better than other classifiers such as MLC (Maximum likelihood), in terms of measurable accuracies. According to Candade and Dixon, SVM performs better than other classifiers as they used three SVM kernels such as Polynomial, RBF (Radial basis function) and linear kernel and the results were compared to ANN (Artificial neural network).

They revealed that there is a big difference between ANN and SVM the reason being ANN has the problem of over fitting while SVM shows better accuracy even while using small number of training samples (Candade *et al.* 2004). A Support Vector Machines classification tool was used in ENVI 5.3 for classification in this study.

After classification using Random Forest and Support Vector Machine using 70% training dataset, the results were taken for accuracy assessment using the remaining 30%. Both classifiers used the same data inorder to seeing the difference in the results.

3.6 Accuracy assessment and statistical analysis

The images after classification have errors due to noise, weakness of classifiers and spectral confusion (Liu and Cai 2012). Therefore, the quality of Sentinel-2 and RapidEye were assessed by post- classification which was meaningful (Lu *et al.* 2004). The remaining 30% (n=182) dataset was used to test accuracy and to assess the vegetation map by RF and SVM classifiers of new generation (Sentinel-2 and RapidEye). R statistical packages were used for Random Forest and Support Vector Machines parameters optimization (R Development Core, 2012).

Confusion matrix is used to measure the correspondence between field situation and image classification (Foody 2002). In order to evaluate the map of vegetation communities that was developed using RF and SVM classifiers on RapidEye and Sentinel-2 images, training dataset on Table 2 was used. Confusion matrix was then used to match assigned class and true class. The following accuracies were then obtained Producer's, User's Overall and the Kappa statistic (Congalton and Green, 2008).

Producer's accuracy shows the chance that the classifier has been properly categorized in an image pixel (Muntanga *et al.* 2014). Overall accuracy represents the likelihood that an accidentally nominated point is properly classified on the map. User's accuracy shows the chance that a pixel labelled as exact vegetation class on the map is the real class (Muntanga *et al.* 2014). A Kappa coefficient was also measured of the change in the real preparation of location data and the classifier used to achieve the classification versus the unexpected of arrangement between the reference data and a random classifier (Congalton *et al.* 1999). Kappa coefficient was done to check if it's closer or equal to 1 as this symbolises the strong agreement. The results of unsupervised algorithm were compared.

Chapter 4: Results

4.1 Tuning Random forest parameters

Random forest parameters were optimized inorder to developing the top parameters and to train the algorithm for classifying nine vegetation classes.

1. The results (Figure 2) of grid search produced lowest OOB error rate for a value of 14.0 % for Sentinel-2 achieved by many combinations of *ntree* value mtry values. While the lowest OOB error 16% was achieved in Sentinel-2 by the combination of mtry value 4 and ntree values of 6500 and 7000 (Figure 2). *Ntree* of 10000 and mtry of 3 were then used as optimum parameters to train RF on Sentinel-2 data, while ntree of 7000 and mtry of 4 were used for RapidEye data.
2. Figure 3 a and b indicates overlapping between the vegetation communities. The classes that are less separable from other vegetation communities are those achieved the highest user accuracy in
3. Table 4 and Table 5; *Eragrostis Chloromelas* and *Serephium plumosum. Mixed grassland* is evenly distributed among *Figure 3 b.*

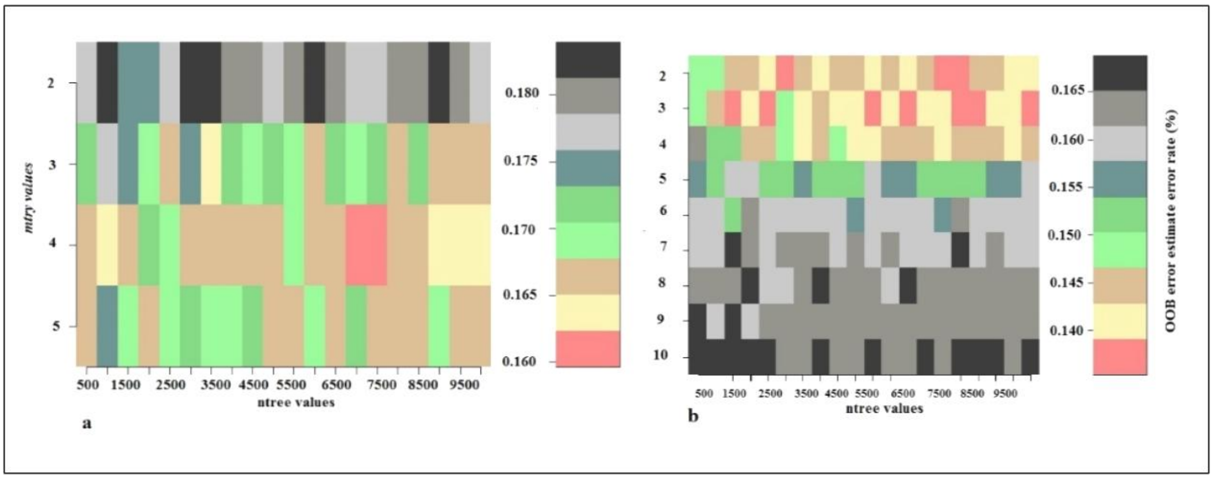

Figure 2: Optimization of Random forest parameters for RapidEye data (A) and Sentinel-2 data (B). The model was developed based on grid search method combined with OOB method to control the error rates of all dissimilar possible bands combinations (ntree and mtry).

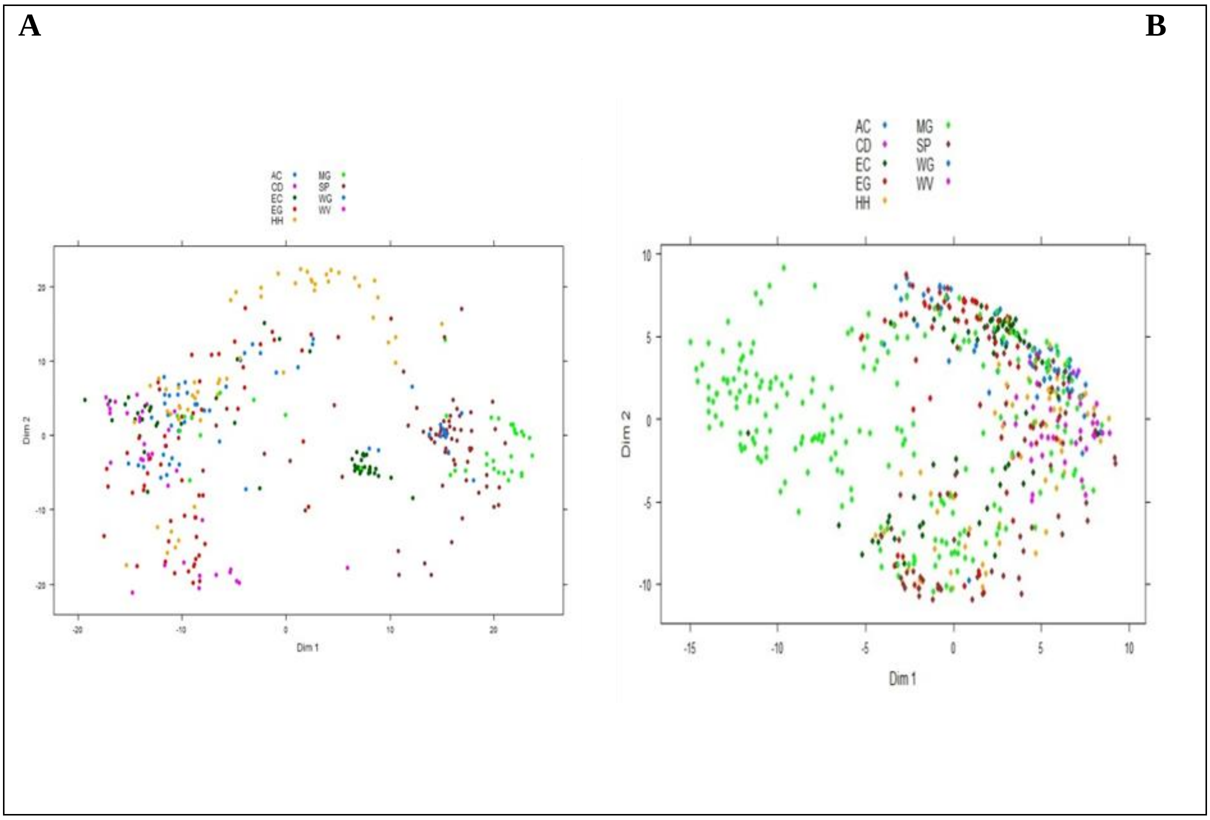

Figure 3: Scoter plot showing the classes separability for RapidEye image (A) and Sentinel-2 image (B). The separability analysis was done using Random forest classifier.

4.2 Variable importance measurements

Random forest provides a measure of the variables (RapidEye and Sentinel-2 bands) as a part of the classification process. The influence of RapidEye and Sentinel-2 were measured by optimum parameter settings as presented in (Figure 3).

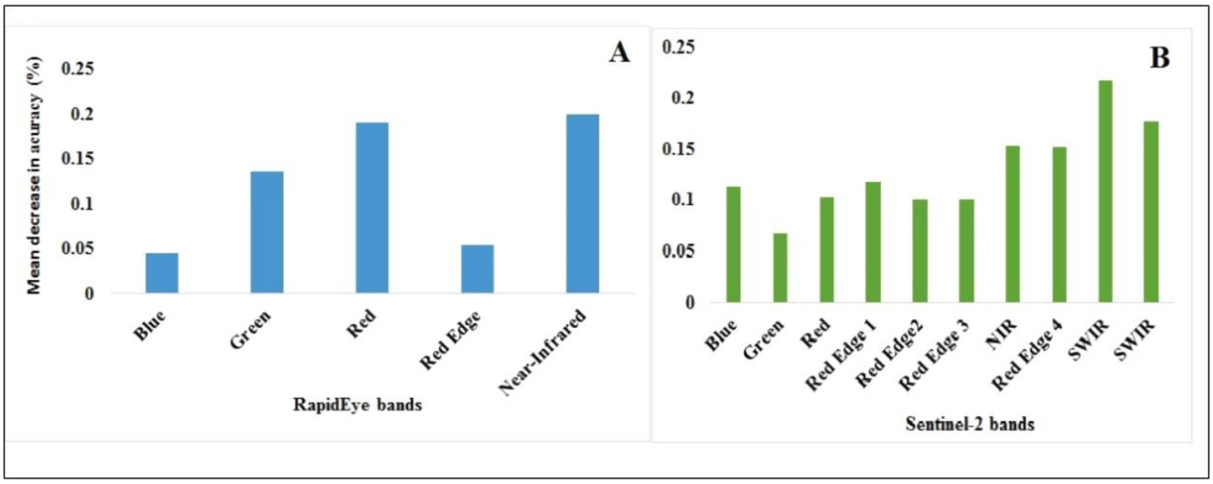

Figure 4: The significance and contribution of RapidEye bands (A) and Sentinel-2 bands (B) in the vegetation cover mapping. The importance measurement was calculated using mean decrease in accuracy.

A valuation of all RapidEye band (n=5) and Sentinel- 2 bands (n = 10) showed the red and NIR of RapidEye bands to be the most powerful in the classification procedure accuracy. While the SWIR bands and red Edge 4 was the most important Sentinel-2 bands in the mapping process. Researchers further evaluate the utility of each band of RapidEye and Sentinel-2 in mapping particular vegetation community (**Error! Reference source not found.**.

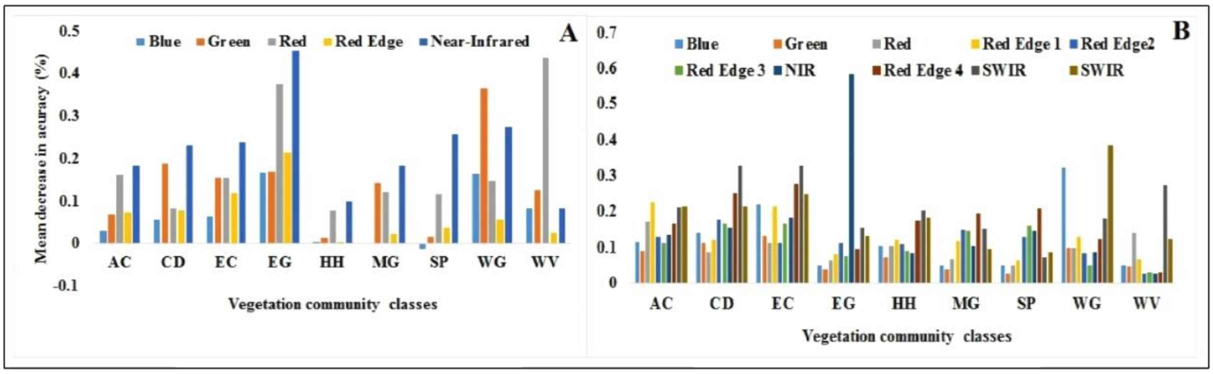

Figure 5: The importance of RapidEye bands (A) and Sentinel-2 bands (B) in mapping each individual vegetation community. The importance measurement was calculated using mean decrease in accuracy.

The important bands are those with the highest mean decrease in accuracy, in this classification were allocated at blue, yellow, grey bands (Figure 5). The utility of each band of mapping vegetation was evaluated where red and NIR bands of RapidEye have the highest contribution in mapping of different vegetation communities (Figure 5 A) such as the wetland vegetation

(WV) and *Eragrostis gummiflua* (EG). While SWIR, NIR, red edge 4 of Sentinel-2 bands have the highest contribution (Figure 5 B) in mapping of *Eragrostis gummiflua, Cynadon dactylon* (CD) and *Wetland Grass* (WG).

Likewise, vegetation mainly falls in the red and near infrared in RapidEye and Sentinel-2.

4.3 Tuning of SVM parameters

SVM parameters were optimized to define the best-input parameters to train the classification. The model was developed based on a radial basis kernel function. A 10-fold cross validation was used to calculate the classification error. The lowest classification error of 18.3% was achieved using the combination of gamma (γ) value of 0.1 and cost (C) value of 100 for both RapidEye and Sentinel-2 (Figure 6). These parameters were then used to classify the vegetation communities (n= 9).

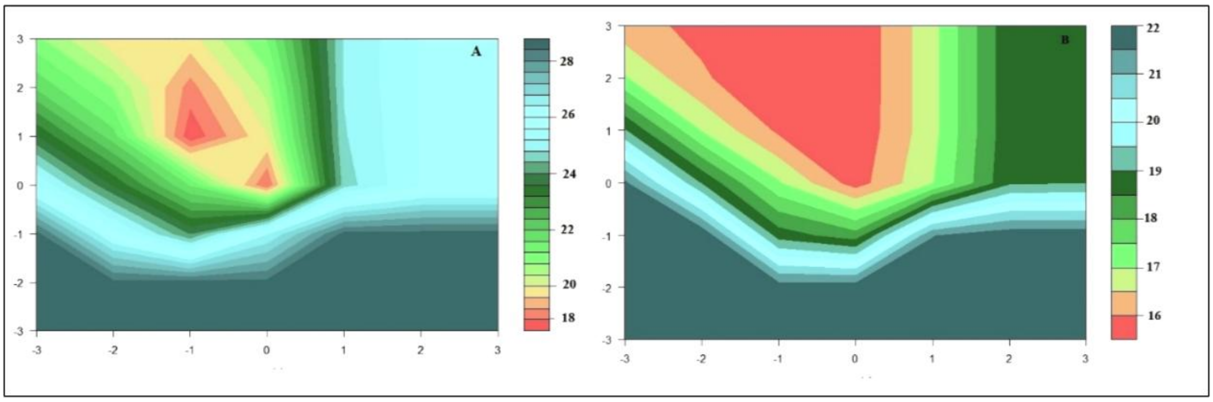

Figure 6: Optimizing of support vector machines parameters (C and γ) using the 10-fold grid search method. To determine the error rate for all the unlike combinations for RapidEye image (A) and Sentinel-2 image (B), the OOB sample was used.

Serephium plumosum class was confused with wetland grasses and *Aristida congesta* and therefore achieved the lowest user accuracy for both Sentinel-2 and RapidEye images. User accuracy calculated from RapidEye was less than 80% for *Serephium plumosum* and *Aristida congesta*. While the mix grass and *Serephium plumosum* had user accuracy less than 80% when Sentinel-2 was used. Scoter plot was generated using SVM to visualize the separability among the vegetation communities (Figure 7).

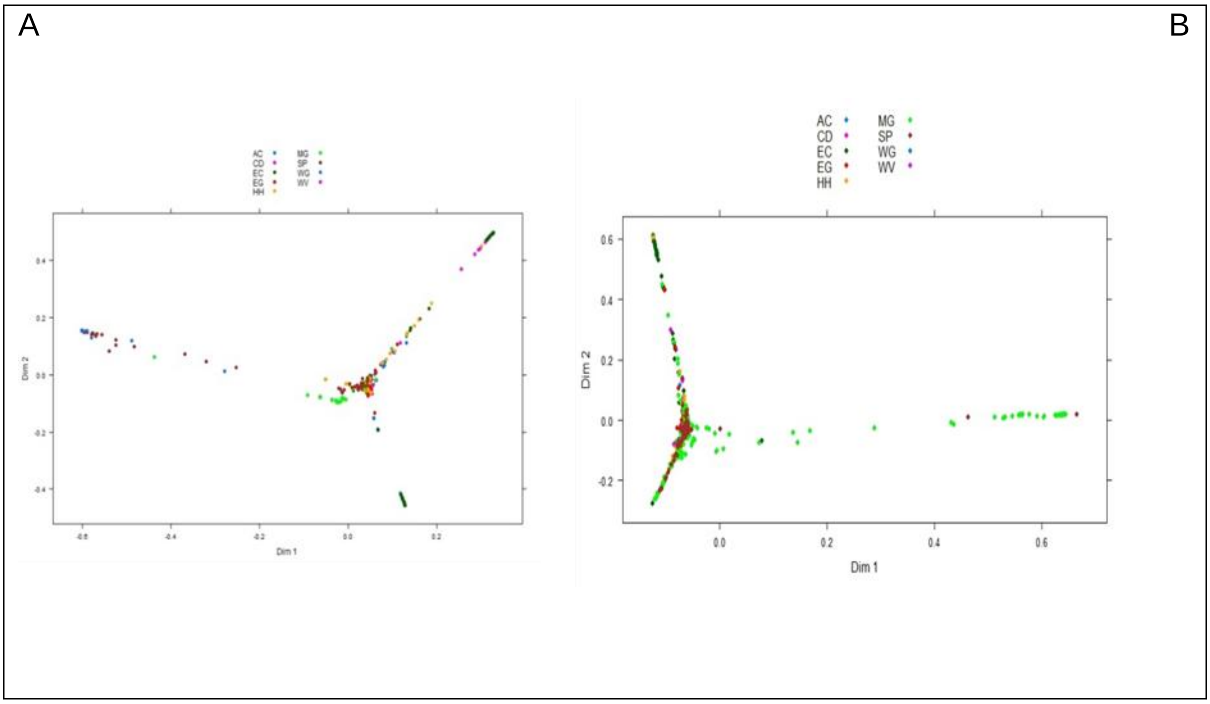

Figure 7: Scoter plot showing the classes separability for RapidEye image (A) and Sentinel-2 image (B). The separability analysis was done using Support Vector Machines classifier.

4.5 Accuracy assessment

4.5.1 Assessing the performance of Random Forest classifier

The error matrix was used with ground data, produced this should meet 85% level of accuracy and reliability (Anderson *et al.* 1976).

The test dataset (30%) was used to test the performance of RF algorithms. Table 3 and 4 shows confusion matrix for RF using RapidEye and Sentinel-2 images. The overall accuracy achieved by Sentinel-2 data was 86% and kappa value of 0.8422. This is slightly higher than the results achieved by RapidEye data, which produced an overall accuracy of 82.4% and kappa value of 0.80.

The highest user accuracies created by RapidEye and Sentinel-2 were 100 %, which were reported on *Eragrostis chloromelas* (EC) and AC (Aristida congesta) followed by (WG) wetland grass at 94.44%. The pixels of these above classes were labelled exactly and mapped as real classes. The lowest user accuracies achieved by the RapidEye and Sentinel-2 were 66.67% and 73.08 % for *Aristida congesta* (EG) and *Serephium plumosum* (SP) respectively (Table 3 and 4).

Table 4: Confusion matrix using RapidEye image and random forest classifier. The accuracies calculated using the test dataset (30%). These accuracies include overall accuracy (OA), user's accuracy (UA) and producer's accuracy (PA) and kappa.

Class	AC	CD	EC	EG	HH	MG	SP	WG	WV	Total	UA%	PA%
AC	8	0	2	1	1	0	0	0	0	12	66.66%	61.54%
CD	0	13	0	0	0	1	0	0	0	14	92.86%	92.86%
EC	0	0	15	2	2	3	0	0	1	23	65.23%	71.42%
EG	0	0	0	16	0	0	0	0	0	16	100.00%	76.19%
HH	1	1	0	0	15	0	0	0	0	17	88.23%	78.94%
MG	1	0	2	0	0	9	0	0	0	12	75.00%	56.25%
SP	2	0	2	1	0	1	19	0	1	26	73.08%	95.00%
WG	0	0	0	0	1	0	0	17	10	18	94.44%	94.44%
WV	1	0	0	1	0	2	1	1	38	44	86.36%	95.00%
Total	13	14	21	21	19	16	20	18	40	182		
OA= 82 %, Kappa= 0.7980												

Table 5: Confusion matrix using Sentinel-2 image and random forest classifier . The accuracies calculated using the test dataset (30%). These accuracies include overall accuracy (OA), user's accuracy (UA) and producer's accuracy (PA) and kappa

Class	AC	CD	EC	EG	HH	MG	SP	WG	WV	Total	UA%	PA%
AC	12	0	0	0	0	0	0	0	0	12	100.00%	70.6%
CD	0	13	0	0	0	1	0	0	0	14	92.86%	92.86%
EC	0	0	18	1	1	2	0	0	1	23	78.26%	81.81%
EG	0	0	0	16	0	0	0	0	0	16	100.00%	84.21%
HH	1	1	0	0	15	0	0	0	0	17	88.24%	88.24%
MG	1	0	2	0	0	9	0	0	0	12	75.00%	60.00%
SP	2	0	2	1	0	1	19	0	1	26	73.08%	95.00%
WG	0	0	0	0	1	0	0	17	0	18	94.44%	94.44%
WV	1	0	0	1	0	2	1	1	38	44	86.36%	95.00%
Total	17	14	22	19	17	15	20	18	40	182		
OA= 86 % ,Kappa= 0.8422												

4.5.2 Assessing the performance of Support Vector Machines classifier

Accuracy assessment was performed to validate the performance of SVM for both RapidEye and Sentinel-2 in mapping of the nine vegetation communities. The test dataset (30%) was used to test the performance of RF algorithms. Table 6 and 7 for SVM using RapidEye and Sentinel-2 images.

The test dataset (30%) was used to test the performance of SVM algorithms. Table 6 and 7 shows confusion matrix for SVM using RapidEye and Sentinel-2 images. The overall accuracy achieved by Sentinel-2 data was 85% and kappa value of 0.8304. This is slightly higher than the results achieved by RapidEye data, which produced an overall accuracy of 81% and kappa value of 0.79.

The highest user accuracies created by RapidEye and Sentinel-2 were 100 %, which were reported on *Eragrostis chloromelas* (EG) followed by (WG) *Wetland grass* at 94.44%. The pixels of these above classes were labelled exactly and mapped as real classes. The lowest user accuracies achieved by the RapidEye and Sentinel-2 were 66.67% and 73.08 % for *Serephium plumosum* (SP) and *Aristida congesta* (EG) respectively (Table 6 and 7).

Table 6: Confusion matrix using RapidEye image and Support Vector Machines classifier. The accuracies calculated using the test dataset (30%). These accuracies include overall accuracy (OA), user's accuracy (UA) and producer's accuracy (PA) and kappa.

Class	AC	CD	EC	EG	HH	MG	SP	WG	WV	Total	UA%	PA%
AC	8	0	2	1	1	0	0	0	0	12	66.67 %	61.53 %
CD	0	13	0	0	0	1	0	0	0	14	92.85 %	92.85 %
EC	0	0	15	2	2	3	0	0	1	23	65.21 %	71.42 %
EG	0	0	0	16	0	0	0	0	0	16	100%	72.72 %
HH	1	1	0	0	15	0	0	0	0	17	88.23 %	78.95 %
MG	1	0	1	0	0	10	0	0	0	12	83.33 %	58.82 %
SP	2	0	2	2	0	1	18	0	1	26	69.23 %	90.00 %
WG	0	0	0	0	0	0	1	17	0	18	94.44 %	94.44 %
WV	1	0	1	1	0	2	2	1	36	44	81.81 %	94.74 %
Total	13	14	21	22	19	17	20	18	38	182		
OA= 81 %, **Kappa**= 0.785838												

Table 7: Confusion matrix using Sentinel-2 image and Support Vector Machines classifier. The accuracies calculated using the test dataset (30%). These accuracies include overall accuracy (OA), user's accuracy (UA) and producer's accuracy (PA) and kappa

Class	AC	CD	EC	EG	HH	MG	SP	WG	WV	Total	UA%	PA%
AC	13	0	0	0	0	0	0	0	1	14	92.85	76.47

CD	0	14	0	0	0	1	0	0	0	15	93.33	100.00
EC	0	0	19	1	0	1	1	0	1	23	82.61	86.36
EG	0	0	0	16	0	0	1	0	0	17	94.12	84.21
HH	1	0	0	1	16	1	0	0	0	19	84.21	94.12
MG	1	0	2	0	0	11	1	1	0	16	60.75	73.33
SP	2	0	1	0	0	1	14	0	3	21	66.67	70.00
WG	0	0	0	0	0	0	1	17	0	18	94.44	94.44
WV	0	0	0	1	1	0	2	0	35	39	89.74	87.5
Total	17	14	22	19	17	15	20	18	40	182		
OA= 85 %,**Kappa**= 0.8304												

4.6 Production of vegetation Map

Vegetation maps were generated for the best classification accuracies achieved to display the spatial scattering of the vegetation communities for Ezemvelo Game Reserve. Extracting vegetation classes of satellite images are based on the interpretation of texture, colour and pixels information (Xie *et al.* 2008).The figures (Figure 8 and 9) below show the spatial distribution of the vegetation (Sentinel-2 and RapidEye) using RF and SVM algorithms. The maps produced were compared to the ground data collected in the research. All the nine classes were used for the comparison.

Sentinel-2 maps (Figure 8)

There is a slight difference in the vegetation pixels of two maps using Sentinel-2 (Figure 8). Based on the results, RF improved classification accuracy than SVM for Sentinel-2 in Figure 8 (image A is much clear than image B). Vegetation classes are truly represented and corresponding to the ground points (field data). Sentinel-2 achieved higher accuracies using RF with an overall accuracy of 86% and Kappa value of 0.84. Sentinel-2 also achieved overall accuracy 85% with a Kappa value of 0.83 using SVM.

RapidEye maps (Figure 9)

There is a slight difference in the vegetation pixels of two maps using RapidEye (Figure 9). Based on the results, RF improved classification accuracy than SVM for RapidEye in Figure 9 (both images are not clear, image A is much better than image B). Vegetation classes are not truly represented, some are invisible. This confirms that RapidEye achieved lower accuracies uses RF where it had overall accuracy of 82% and Kappa value of 0.79. RapidEye using SVM produced overall accuracy of 81% and a Kappa value of 0.79.

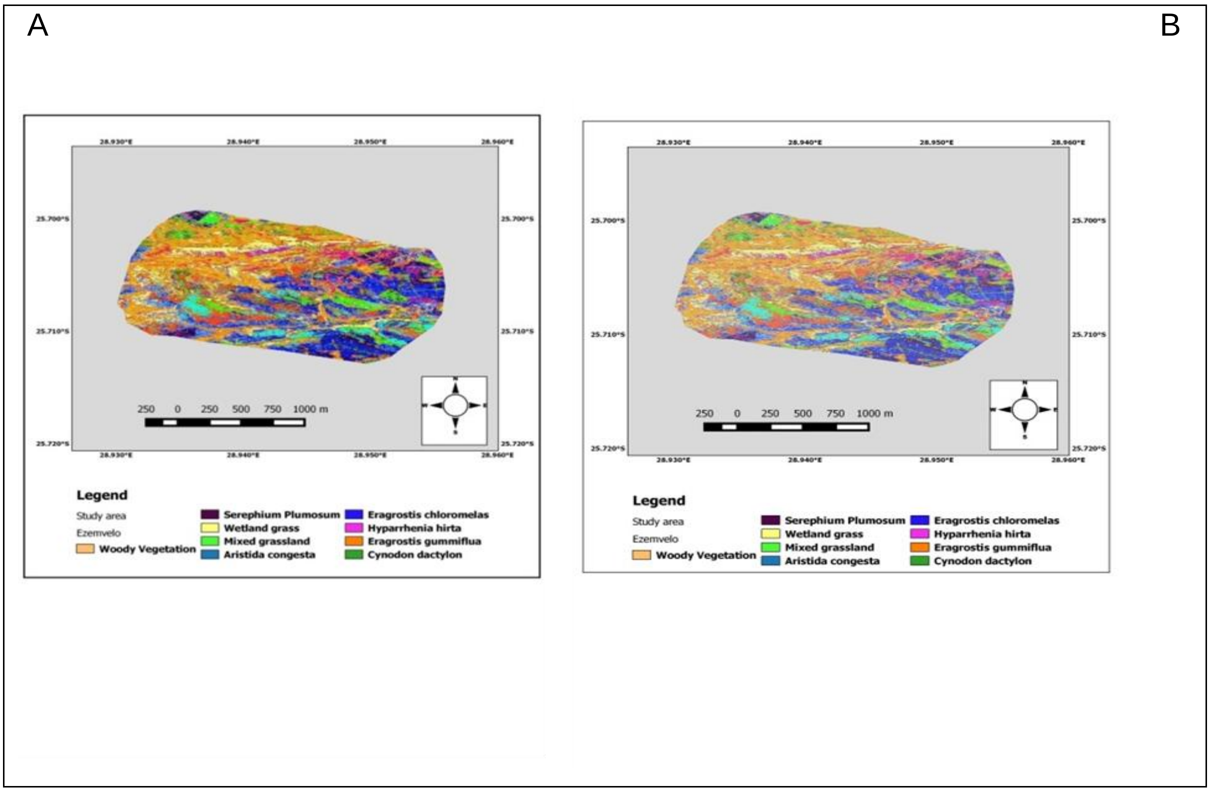

Figure 8: Vegetation community classification for Sentinel-2 image using Random Forest classifier (A) and Support Vector Machines classifier (B).

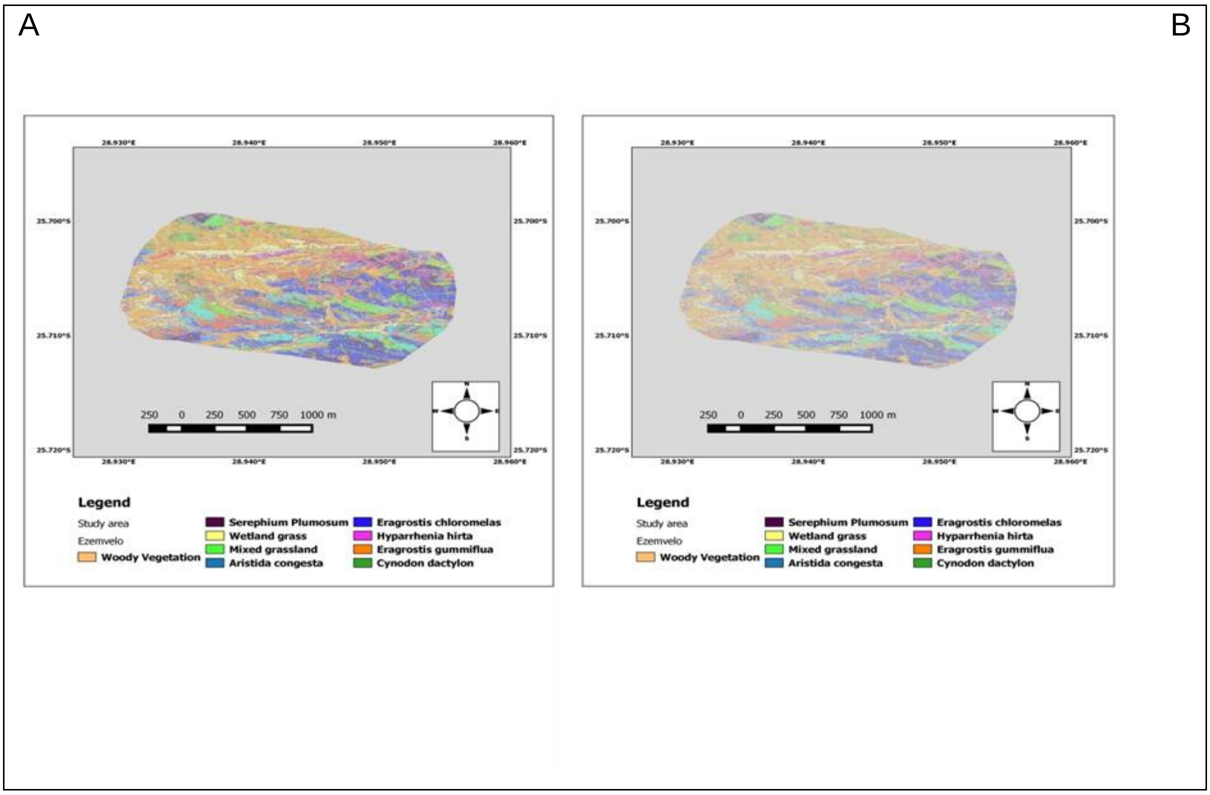

Figure 9: Vegetation community classification for RapidEye image using Random Forest classifier (A) and Support Vector Machines classifier (B).

Chapter 5: Discussion of Results

The availability of multispectral satellite data gives a great potential to map vegetation communities and give the recent information on effective management. The main aim of the study was to test the use of the new generation multispectral data onto mapping vegetation communities of Ezemvelo Game reserve. Support vector machines and Random Forest were used as image classifiers and the results showed that new generation multispectral images can map vegetation communities.

Shortly remote sensing images are key data sources for vegetation monitoring programs considering spectral, spatial and temporal resolution of the image (Nordberg and Evertson 2003). An up to date vegetation map can be produced at community level for future using remotely sensed images and image analysis. There are many studies that have used remote sensing images of mapping vegetation (Duchemin *et al.* 1999; Geerken *et al.* 2005; Nerry *et al.* 1998; Xavier *et al.* 2006). Remote sensing has more advantage because of its technology compared to traditional methods that were used in mapping vegetation communities (Xie *et al.* 2008). There are many challenges to mapping vegetation, one solution is to choose right satellite image (spectral, spatial and temporal resolution) taken by the right sensor (Cingolani *et al.* 2004).

Sentinel-2 has multispectral capabilities and high resolution that delivers unpredictable details of vegetation change. It delivers timely data onto different applications such as health and mapping vegetation commuters and informed decision can be made from the results (Sentinel-2 2015). The capabilities mentioned above, Sentinel-2 data will be an advantage in land management, food security and disaster control e.g., Landslides and floods (Baillarin 2012). According to Baillarin 2012 the results of computing process and quality presentation were encouraging, so different countries like South Africa. High resolution satellite data provides a great potential to achieve better results of mapping vegetation communities in arid environments using field spectrometry data (Mureriwa *et al.* 2016). The high overall and individual classification achieved in this study (Table 4 and 5) shows the capability of high spectral and spatial resolution of Sentinel-2 sensor to map vegetation communities. The higher accuracies achieved in the study can make the management and decision makers rely on basis of assessing the current vegetation status and for future reference on Ezemvelo Game Reserve.

Image classifiers are not uniformly applicable to all applications such as vegetation. This is a main topic nowadays to researchers mainly to create new classifiers suitable for specific application (Foody 2002; Xie *et al.* 2008). Two image classifiers (RF and SVM) were discovered by Sluiter (2005) as better image classifiers compared to traditional supervised classifier (K-Mean). A number of authors have preferred SVM or RF as algorithms which are faster with high accuracies (Petropoulos *et al.* 2012).According to (Sluiter & Pebesma 2010) SVM produced good results compared to other image classifiers (Sluiter & Pebesma 2010). Findings by Burai *et al.* (2015) state that SVM outperforms RF (Burai *et al.* 2015), though other report that SVM and RF classifiers performs similar results (Ghosh *et al.* 2014).

The previous study of (Burai *et al.* 2015), was classifying herbaceous vegetation using airborne hyperspectral data (Burai *et al.* 2015). The overall accuracies result given by individually Support Vector Machines and Random Forest classifiers improved a little bit while increasing training pixel number. It was also discovered that both classifiers overall accuracies were low. RF had an overall accuracy of 72.89 % and also achieved 72.84 % using SVM for 30 training pixels. Once training pixels decreases to 10 the RF decrease to 70.95 % and 70.44 % using SVM (Burai *et al.* 2015). Even for this study Support Vector machines and Random Forest were used for image classification. Comparing both classifiers, results showed similarity, but RF performed better than SVM. RF can be used to map vegetation communities due to high overall accuracies (86 % and 82%) while SVM (85% and 81%).

Thematic mapping produced from remote sensing data is based on image classification. This can be achieved by computer or visual (Foody 2002). The visual inspection of vegetation is not accurate (Xie *et al.* 2008), percentage of vegetation classes in the study area was used. Vegetation maps derived from image Sentinel-2 using Random Forest was considered as accurate as it represents true and real classes of the study area. The ground data and classes on the vegetation map are corresponding and relatively high overall and individual classification accuracy obtained in this study (Table 4, 5, 6 and 7) shows the capability of the Sentinel-2.

Sentinel-2 shows the high spectral and spatial that consists of 13 bands that can add more advantages in mapping vegetation (Adam et al. 2014). The results show, however, that the 13 band multispectral sensor of Sentinel-2 is suitable to map vegetation communities of Ezemvelo Nature Reserve.

Sentinel-2 achieved higher accuracies using RF with an overall accuracy of 86% and Kappa value of 0.84. Sentinel-2 also achieved overall accuracy 85% with a Kappa value of 0.83 using SVM. RapidEye achieved lower accuracies using RF where it had overall accuracy of 82% and Kappa value of 0.79. RapidEye uses SVM produced overall accuracy of 81% and a Kappa value of 0.79. RF and SVM advanced algorithms were used for testing and training in the study, RF and SVM classifiers to map vegetation communities were used, and both classifiers produced high overall accuracies. RF produced higher classification accuracy than SVM by 4%.

There is a slight difference in the vegetation pixels of two maps using Sentinel-2 (Figure 8). Based on the results, RF improved classification accuracy than SVM for Sentinel-2 in Figure 8 (image A is much clear than image B). Vegetation classes are truly represented and corresponding to the ground points (field data).

The aim and objectives of the study have been met and due to higher accuracies achieved in the study and shows that new generation multispectral data can be used to map vegetation communities. The new generation including Sentinel-2 and RapidEye can reduce cost while giving high accuracy level in mapping vegetation communities. It remains unclear whether the high accuracies achieved in the mapping were because of the SWIR bands and Red Edge in Sentinel-2. Further research needs to be done using other image classifiers like Maximum Likelihood.

While the SWIR bands and red Edge 4 were the most important Sentinel-2 bands in the mapping process

Chapter 6: Conclusion, recommendations and limitations

The study was conducted to test the performance of new generation RapidEye and Sentinel-2 in mapping vegetation communities using advanced classifiers Random Forest and Support Vector Machine of Ezemvelo Game reserve.

Support vector Machine classification performed using kernel function selection of specific datasets. Random forest provided band importance and variable for each of Sentinel-2 and RapidEye bands as well as vegetation classification.

Random forest classification outperformed Support Vector Machines as it has higher overall accuracy. Random forest issued variable importance ranking for RapidEye and Sentinel-2 bands as well as vegetation classification. SWIR band appear as the most important band used for vegetation classification. These results led to conclude that the spatial resolution and unique bands of Sentinel-2 have contributed most. A map for vegetation communities was accumulated of the study area, for reference in the upcoming years.

Results of this study also provide new insights on the performance of Sentinel-2 imagery in mapping vegetation cover in species level. This has potential to help environmental managers in focusing existing monitoring and control efforts of areas of priority. Such monitoring efforts allow rapid assessment and proactive adoption of the most appropriate intervention in the control of the invasive alien plants. The misclassifications seen in this study could be attributed to the spectral variation in the same class and the image's high spatial resolution. Consequently, alternative approaches such as object-based classification should be further explored.

6.1 Recommendations

Sentinel-2 is medium to coarse spatial resolution images of (10 visible, 20 short infrared and 60 m atmospheric correction bands. This sensor is capable of mapping vegetation at a regional scale of community level. The public sector and government can save money as it is available at no cost. This new generation has got unique additional bands that can better the mapping of different classes of high quality.

Further research has to be conducted to widen the use and integration of new generation multispectral data (RapidEye and Sentinel-2) in mapping vegetation. Furthermore, the collected data can be tested using object based image classification as one of the advanced classifiers.

6.2 Limitations

Atmospheric correction was applied to RapidEye image using Envi 5.3 software due to clouds that was covering the study area. Due to limitation of spatial resolution, Sentinel-2 can map vegetation at community level. The sensor provides a global coverage of 10 days temporal resolution (revisit the last location) (Topaglu et al. 2016). It becomes a challenge to vegetation mapping especially in rainy days (summer season) as high volume of clouds decrease image quality (Malatesta 2013).

For better results or accurate vegetation mapping, Sentinel-2 can be used with other remotely sensed image due to its spatial and temporal resolution. Currently, there is a shortage of previous studies using new generation of vegetation mapping. However, more studies have to be conducted to collect more dataset (test and training) for testing the new generation (Sentinel-2 and RapidEye).

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