

CHAPTER THREE: LAND COVER CLASSIFICATION

3.1 Introduction

“Remote sensing is indispensable for ecological and conservation biological applications and will play an increasingly important role in the future.” (Kerr & Otrovsky, 2003)

Remote sensing allows ecologists to recognise large-scale on-going processes and patterns within ecosystems (Roughgarden *et al.*, 1991), and has been useful in the study of various ecological matters such as mapping, studying and identification of land cover classes (Anderson *et al.*, 1976; Rogan & Chen, 2003; Pradhan *et al.*, 2010), hydrological and biogeochemical cycles (Hobbs & Mooney, 1991), biomass measurement (Lefsky *et al.*, 2002; Anaya *et al.*, 2009), forest fragmentation (Vogelmann, 1995), various landscape patterns (Wiens, 2002), as well as the monitoring and conservation of biodiversity (Stoms & Estes, 1993; Turner *et al.*, 2003).

Remote sensing instruments with passive sensors detect electromagnetic radiation that is emitted or reflected by objects on the Earth’s surface, and operates in the visible and infrared sectors of the electromagnetic spectrum (Cracknell & Hayes, 1991; Campbell, 2006; Wade & Sommer, 2006).

SPOT5 (*Le Système pour l’Observation de la Terra – Earth Observation System*) satellite images (CNES, 2007) were used in this study. SPOT satellite is best suited to provide data for land-use studies, assess geological and renewable resources, and execute cartographic work at scales of 1:50 000 – 1:100 000 (Campbell, 2006). The SPOT satellite consists of two High Resolution Geometrical (HRG) sensors (Spot Image, 2005), which may be operated in Panchromatic (PN) mode or Multispectral (XS) configuration, as well as a HRS instrument for acquiring stereopair imagery (Campbell, 2006). The SPOT5 images used in the study are the result of remote sensing using the Multispectral (XS) mode. Table 3.1 provides details on the spectral bands of SPOT5.

Table 3.1: Spectral band information for the SPOT 5 satellite (Spot Image, 2005).

Spectral resolution	
	Panchromatic: 0.48-0.71 μm
	Band 1: 0.50-0.59 μm
	Band 2: 0.61-0.68 μm
	Band 3: 0.78-0.89 μm
	Band 4: 1.58-1.75 μm
Satellite band specification	
	2 panchromatic: combined to create a 2.5 m resolution panchromatic image band.
	3 multi spectral bands: green, red, narrow infrared (10 m resolution).
	1 short-wave infrared band (10 m resolution).

3.1.3 Digital image classification

The output format of remotely sensed data includes images which are subsequently manipulated in some way using image processing software (Cracknell & Hayes, 1991) such as ArcView (ESRI, 2010a) and ENVI (Research Systems Inc., 2004). The classification procedure may be either supervised or unsupervised. Supervised classification requires identifying and specifying areas on the image according to samples that have known informational classes (reference data) (Lillesand & Keifer, 2000; Campbell, 2006). Unsupervised classification involves identifying natural groups or clusters within the multispectral data (Lillesand & Keifer, 2000; Campbell, 2006). Digital image classification encompasses the process of assigning classes to pixels (Lillesand & Keifer, 2000; Campbell, 2006). Pixels are assigned a digital number (radiance value) which corresponds to the average brightness or radiance of measures in each pixel. The amount of energy recorded by the sensor on a binary scale, dictated by the bit depth of the image, represents the measured radiance (Kearns, 2006). An eight-bit image allows a range of radiance values from 0-255. A value of 0 will be awarded to the darkest feature and 255 to the brightest (reflecting the most electromagnetic energy), with the rest of the feature radiances arranged in between. This procedure is executed for each multispectral band. Depending on the amount of spectral bands a sensor possesses, a specific ground location on the produced satellite image might have several different digital numbers for the corresponding pixel in each image band. Therefore, unique combinations of these different image bands, with subsequent different digital numbers, allow the image analyst to differentiate between different earth features, depending on the band combinations used (Lillesand & Keifer, 2000). Created land cover maps may subsequently be used as is, or as input for successive analysis.

The aim of this chapter is to describe the procedure of the land cover classification. The classification of the SPOT 5 satellite image into five land cover classes (namely water, trees, grass, soil, and urban) using GIS techniques is the first step towards quantifying urbanisation measures (*Chapter 4*) for the selected grassland fragments. These urbanisation measures eventually acted as indicators for certain anthropogenic processes and disturbances which may have an effect on the species composition and biophysical functioning of the grassland remnants.

3.2 Methods

For the land cover classification of the study area, the same procedure as described in Du Toit (2009) was followed. The study area is situated on the convergence of four SPOT 5 images (Figure 3.1). The information on the SPOT 5 images is provided in Table 3.2. Each of the SPOT 5 images were classified with ArcMap 10 software (ESRI, 2010a), using the Spatial Analyst extension. Spatial Analyst is a tool designed for spatial modelling and analysis (ESRI, 2010b). The initial input for the

creation of the classified land cover map were the four SPOT 5 satellite images, which combined two panchromatic (5m) bands to create a 2.5m spectral output (Spot Image, 2005). Possible RGB (red, green and blue) band combinations of the SPOT image's RGB composite raster were visually investigated in order to select the combination most suited for the satellite classification. This was executed for a smaller area, which was included in, and representative of the entire study area in order to enable faster and more effective selection of the best RGB band combination.

Table 3.2: Information on the four SPOT 5 satellite images that collectively represented the study area.

SPOT 5 satellite image	Image number	Geographic projection	Figure
a	130403421	GCS_WGS_1984	Fig. 3.1a
b	131403421	GCS_WGS_1984	Fig. 3.1b
c	131404421	GCS_WGS_1984	Fig. 3.1c
d	130404421	GCS_WGS_1984	Fig. 3.1d

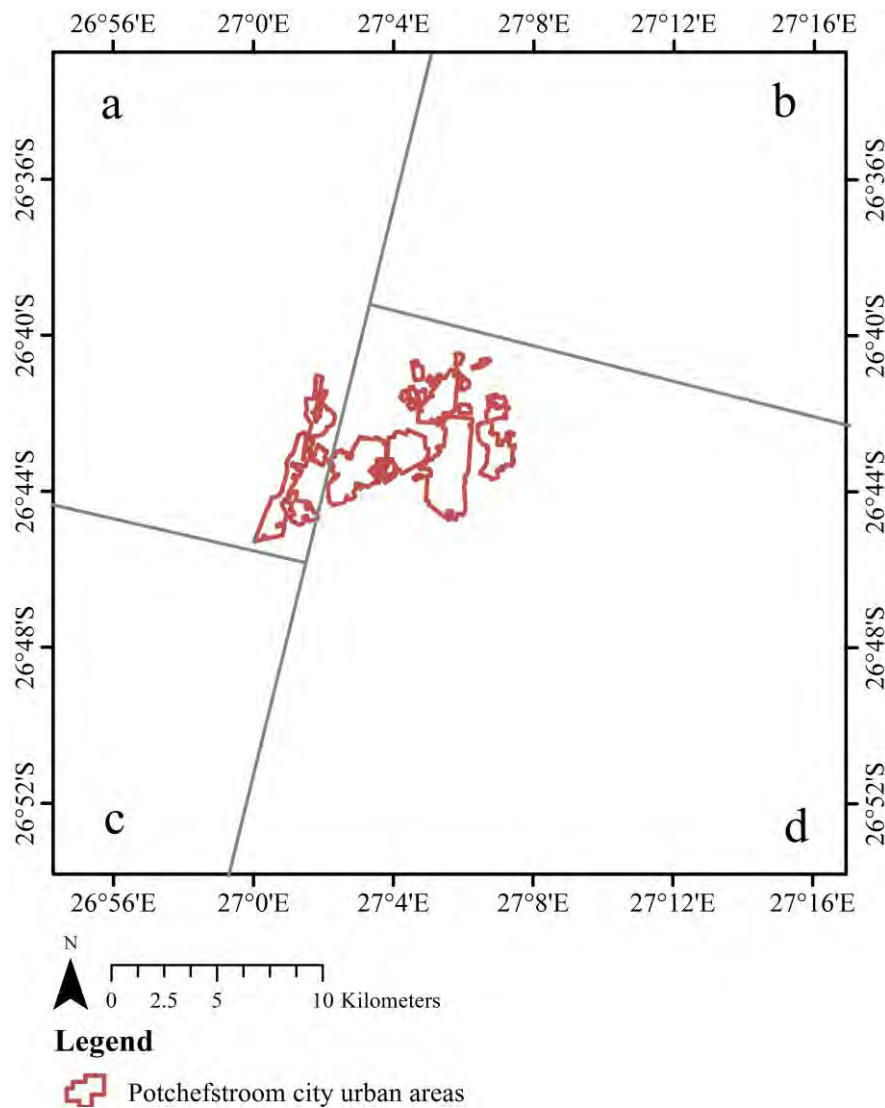


Figure 3.1: The Tlokwe Municipal area was situated at the convergence of four SPOT 5 (a, b, c and d) satellite images which were used in the land cover classification of the study area. The edge of each SPOT 5 image is indicated with grey lines, and the outline of the city of Potchefstroom is presented in red.

3.2.1 Classification procedure

The purpose of image classification in this study was to categorise the pixels in the SPOT5 RGB composite image into five land cover classes (Lillesand & Kiefer, 2000). The five land cover classes were water, trees, grass, urban, and soil (following Du Toit (2009) and Hahs & McDonnell (2006)). These land cover classes were selected as the basic requirement for patch classification towards subsequent metric quantification.

The classification procedure followed in this study was unsupervised. This involves comparing the post-classification image to ground reference data in order to verify the identity of the spectral clusters (Lillesand & Keifer, 2000). Unsupervised classification minimises the possibility of human error, and unique classes are recognised as discreet units (Campbell, 2006). The limitations of unsupervised classification are that classes which are spectrally similar do not necessarily correspond to the informational cluster of interest to the analyst, and spectral properties of features may change over time (Campbell, 2006).

The High Resolution Geometrical (HRG) sensor of the SPOT5 satellite senses four spectral regions: 1) red, 2) green, 3) narrow infrared and 4) short-wave infrared to produce a RGB composite image (Campbell, 2006; ESRI, 2008). ArcMap software can only display three spectral bands simultaneously in order to form a RGB composite image (ESRI, 2008). Therefore the analyst need to decide which bands should represent the RGB image in ArcMap. Twelve and fifteen classes of four possible combinations of the RGB compound of the multispectral bands were tested for each of the four SPOT 5 images in order to find the best possible combination for unsupervised satellite classification. These combinations were tested by Du Toit (2009) for the land cover classification of the Klerksdorp area and found to be the most accurate combinations for this specific SPOT 5 image classification procedure.

Signature files were created for the respective twelve and fifteen classes of each of the RGB band combinations using the Iso Cluster tool of the Spatial Analyst extension in ArcView (ESRI, 2010a). The signature files are needed to execute a maximum likelihood classification (MLC) which creates the classified rasters based on the specifications set by the Iso Cluster tool. The classified rasters were then reclassified into five classes (i.e. water, trees, grass, urban and soil) for final land cover classification using the Reclassify tool in Spatial Analyst.

3.2.2 Accuracy assessment

The accuracy of the classified images was tested with a classification error matrix which compares ground reference data and the classification results (Lillesand & Keifer, 2000). Fifty points of each of

the five land cover classes (as recommended by Lillesand & Keifer (2000)) were selected as reference data to be used in the error matrix, resulting in a total of 250 reference points. These 250 ground data points, overlain on the land cover map, were assigned values corresponding to the informational classes of the land cover map using the Extract Values to Points tool in the Spatial Analyst extension of ArcView (ESRI, 2010a). The error matrix compares the known reference data (ground data) and the corresponding results of the unsupervised classification on a category-by-category basis (Lillesand & Keifer, 2000).

3.3 Results and discussion

The best combination for this procedure was visually found to be the 421 RGB band combination (Figure 3.2). For SPOT images a and b (refer to Figure 3.1) 15 classes for the 421 RGB band combination was most accurate, whilst for SPOT images c and d (Figure 3.1) 12 classes for the RGB band combination was most accurate (Table 3.3).

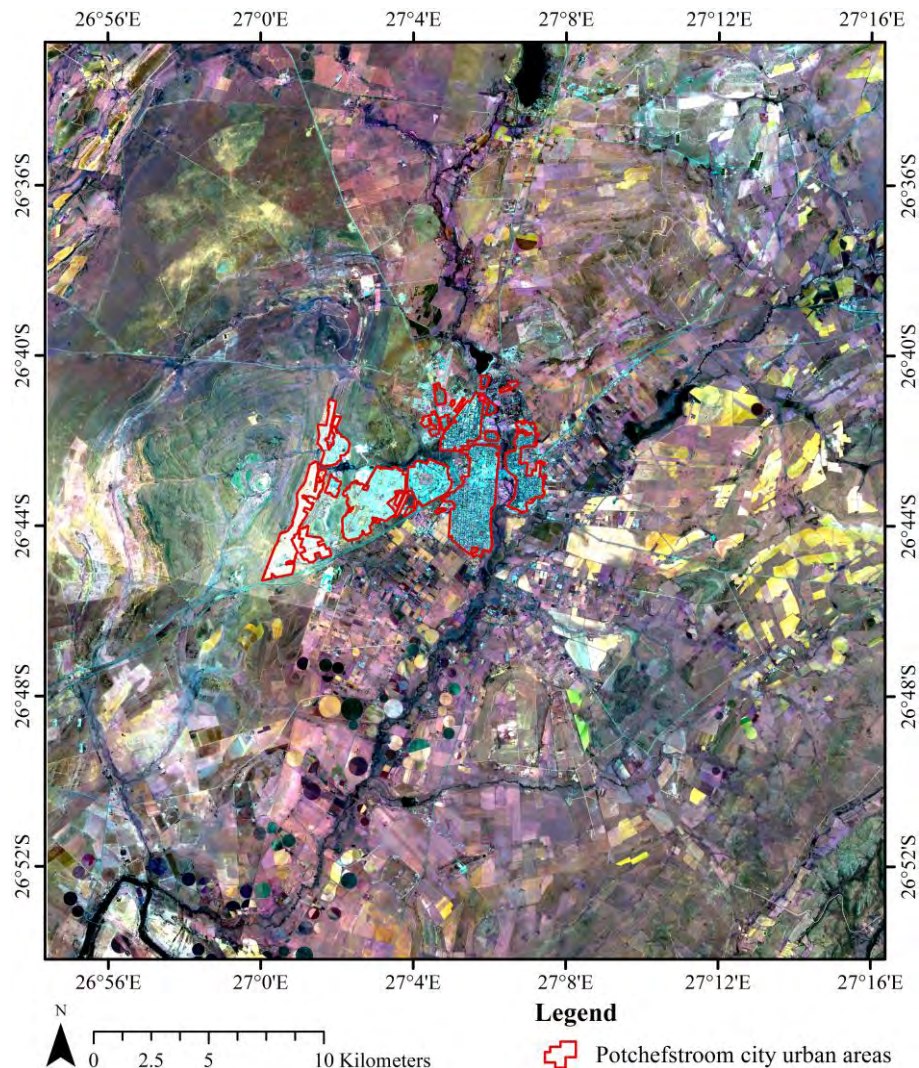


Figure 3.2: SPOT5 satellite image (421 RGB band combination) of the study site in the Tlokwe Municipal area. The red area represents the urban outline of Potchefstroom. This image was used for further classification of the land cover map.

Table 3.3: Output classes generated by the MLC classification procedure for 12 and 15 classes for the RGB band combinations of each of the four SPOT 5 images. The RGB band combination and number of classes indicated in green was visually estimated to be most accurate and used for the subsequent creation of the land cover map.

Image number		130403 (A)					131403 (B)					131404 (C)					130404 (D)				
RGB band combination		341					421					341					421				
No. of classes		12	15	12	12	15	12	15	12	15	12	12	15	12	15	12	12	15	12	15	15
Class																					
1	Water	Water	Water	Water	Water	Water	Water	Water	Water	Water	Water	Water	Water	Water	Water	Water	Water	Water	Water	Water	Water
2	Trees	Trees	Trees	Trees	Trees	Trees	Trees	Trees	Trees	Trees	Trees	Trees	Trees	Trees	Trees	Trees	Trees	Trees	Trees	Trees	Trees
3	Urban	Urban	Urban	Urban	Urban	Urban	Urban	Urban	Urban	Urban	Urban	Urban	Urban	Urban	Urban	Urban	Urban	Urban	Urban	Urban	Urban
4	Grass	Grass	Grass	Grass	Grass	Grass	Grass	Grass	Grass	Grass	Grass	Grass	Grass	Grass	Grass	Grass	Grass	Grass	Grass	Grass	Grass
5	Grass	Grass	Grass	Grass	Grass	Grass	Grass	Grass	Grass	Grass	Grass	Grass	Grass	Grass	Grass	Grass	Grass	Grass	Grass	Grass	Grass
6	Grass	Grass	Grass	Grass	Grass	Grass	Grass	Grass	Grass	Grass	Grass	Grass	Grass	Grass	Grass	Grass	Grass	Grass	Grass	Grass	Grass
7	Grass	Grass	Grass	Grass	Grass	Grass	Grass	Grass	Grass	Grass	Grass	Grass	Grass	Grass	Grass	Grass	Grass	Grass	Grass	Grass	Grass
8	Grass	Grass	Grass	Grass	Grass	Grass	Grass	Grass	Grass	Grass	Grass	Grass	Grass	Grass	Grass	Grass	Grass	Grass	Grass	Grass	Grass
9	Grass	Grass	Grass	Grass	Grass	Grass	Grass	Grass	Grass	Grass	Grass	Grass	Grass	Grass	Grass	Grass	Grass	Grass	Grass	Grass	Grass
10	Urban	Urban	Urban	Urban	Urban	Urban	Urban	Urban	Urban	Urban	Urban	Urban	Urban	Urban	Urban	Urban	Urban	Urban	Urban	Urban	Urban
11	Soil	Soil	Soil	Soil	Soil	Soil	Soil	Soil	Soil	Soil	Soil	Soil	Soil	Soil	Soil	Soil	Soil	Soil	Soil	Soil	Soil
12	Urban	Urban	Urban	Urban	Urban	Urban	Urban	Urban	Urban	Urban	Urban	Urban	Urban	Urban	Urban	Urban	Urban	Urban	Urban	Urban	Urban
13	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
14	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
15	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-

The 421 RGB band combination satellite images were chosen as the best band combination based on visual estimation. An accuracy assessment was executed on the merged classified land cover map (Table 3.4). The resulting error matrix of the land cover map indicates an overall accuracy of 87%, which, according to Herold *et al.* (2005), is acceptable.

Table 3.4: Error matrix for the land cover map of the Tlokwe Municipal area.

Classification data	Reference data					User's accuracy	
	Water	Trees	Grass	Urban	Soil	Row total	
Water	41	4				45	91%
Trees	8	45	7			60	75%
Grass		1	39	1		41	95%
Urban	1		4	44	1	50	88%
Soil				5	49	54	91%
Column total	50	50	50	50	50	250	
Producer's accuracy	82%	90%	78%	88%	98%		
						Overall accuracy	87%

The classification of the SPOT5 satellite image into five classes (water, trees, grass, urban and soil) was regarded “successful” (Figure 3.3). However, some misclassifications are inevitable due to spectral similarities of features. The agricultural land use areas are very heterogeneous in their spectral signatures, and could be ascribed to the presence of different types of crops differing in age. Consequently 1) some agricultural fields (predominantly maize) classified as trees; 2) agricultural land use areas classified as water which is possibly due to irrigation practices within the agricultural fields, and also burnt fields exhibited spectral signatures similar to that of water; 3) some agricultural fields classified in the soil class, these fields were most likely recently ploughed or resting with no or very little vegetation cover. The tree class might obstruct other classes such as the water and urban classes, as the canopy of trees may overlay rivers (water class) and roads (urban class). Unfortunately this may understate the extent of specifically the urban class. Informal settlements (on the western side of urban areas) were mainly characterised by soil land cover, due to the presence of dirt instead of tar roads, and small dwellings with traditional yards cleared of vegetation (Du Toit, 2009). The low spatial resolution (10 m) implicated that these small households on bare soil were classified as the land cover type comprising the majority of the grid cell (i.e. soil).

The created land cover map (Figure 3.3) was used to calculate selected urbanisation measures and quantify an urban-rural gradient within the study area (*Chapter 4*).

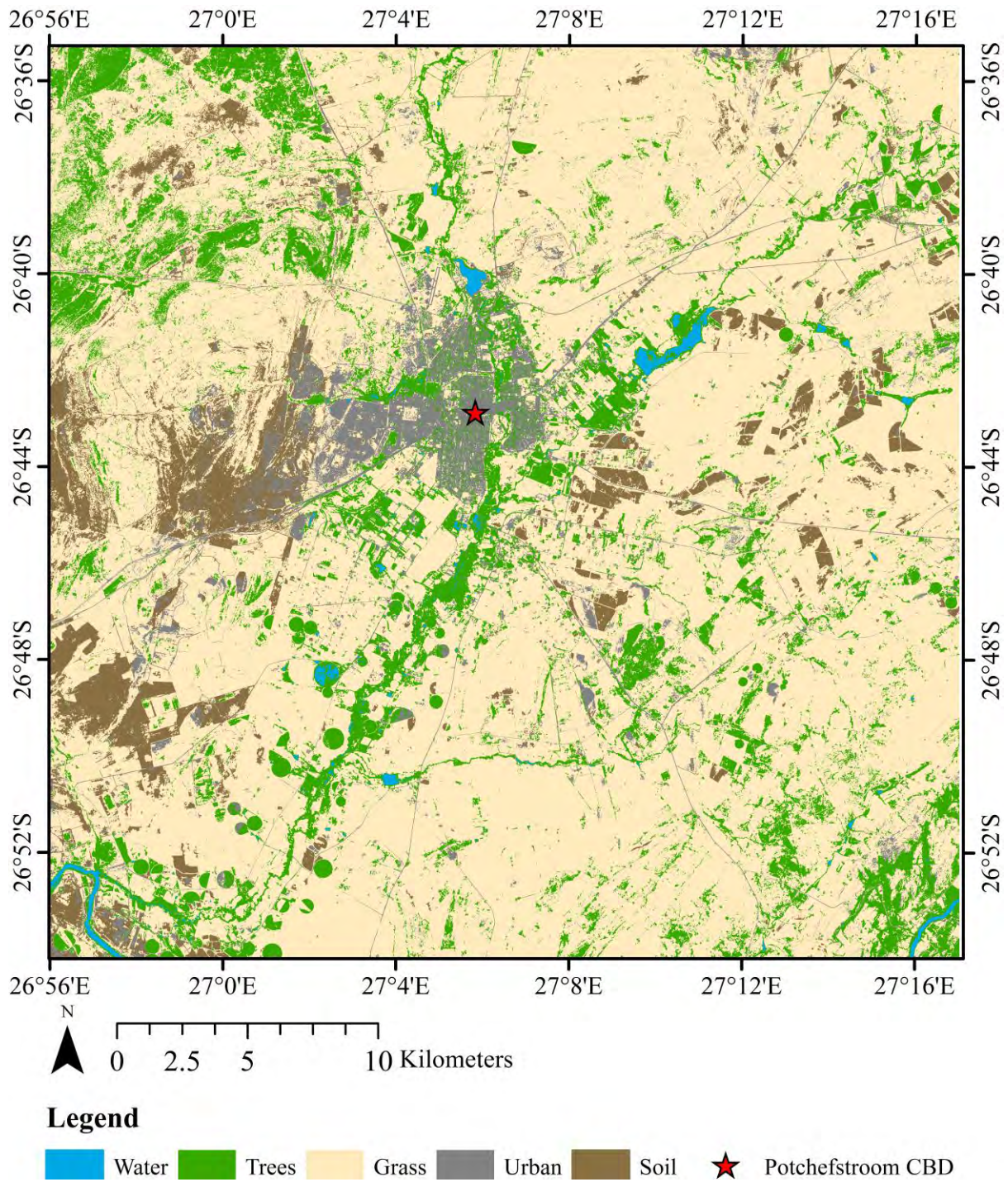


Figure 3.3: Land cover map of the study area in the Tlokwe Municipal area.

3.4 Summary

The aim of this Chapter was to:

1. Classify a SPOT5 satellite image of the study area into five land cover classes namely 1) water, 2) trees, 3), grass, 4) urban, and 5) soil.
2. Create a land cover map which will be used in *Chapter 4* to calculate various urbanisation measures in the process toward quantifying an urban-rural gradient for the Tlokwe Municipal area.

The SPOT5 satellite imagery was successfully classified into five land cover classes (water, trees, grass, urban and soil) using ArcView 10. Nevertheless, spectral similarities of features entailed that some misclassifications are expected (e.g. some agricultural fields classified in the water, trees or soil classes). The produced land cover map exhibited an overall classification accuracy of 87%, and is sufficient for subsequent use in calculation of certain urbanisation measures (Du Toit, 2009; Hahs & McDonnell, 2006), and thus classifying an urbanisation gradient for the Tlokwe Municipal area (*Chapter 4*).

3.5 References

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