Estimating Farm Dam Storage using SPOT Imagery

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In partial fulfillment of the requirements for the MSc degree in Environmental Management

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October 2011

Declaration

I hereby declare that this is my own work, that the work of others is accurately reported and that this thesis has not been submitted in any form for evaluation to another university.

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Abstract

South Africa is characterised by unevenly distributed rainfall patterns and experiences drought. There is a need to monitor water storage in dams that are not monitored or authorised. The objective of this study is to establish a methodology in which remote sensing can be used to support the monitoring of water resources. SPOT XS imagery and object oriented classification was used to identify farm dams and their surface area. Two equations applied to determining the capacity of dams were used to convert surface area to volume. The results showed a similarity between fieldwork and object-oriented classification data for surface area. Overall, there appears to be a strong positive correlation between object-oriented classification and unsupervised classification. The correlation between object-oriented classification and supervised classification ranged from strong positive association to little or no association. This study concludes that remote sensing is a useful tool in identifying water bodies and generating an estimate of volume stored.

Acknowledgements

The author wishes to acknowledge and thank the people and organizations who made this research possible.

I acknowledge The National Research Foundation and the Water Research Commission for funding this research.

I would like to thank the University of Cape Town for the opportunity to conduct this research. Special thanks to my supervisor, Dr. Winter, for his patience, advice, encouragement and for the reviewing of the dissertation.

I would like to thank Lesley Gibson, Zahn Münch, Jeanine Engelbrecht and Julian Conrad, of the WRC K5/1690 research team. I am grateful for the assistance and ideas contributing to this dissertation.

Thank you to Dr. van der Merwe of the University of Stellenbosch for allowing me to make use of their facilities.

I would like to thank my family members for their support. Thank you to Kyle Petersen for his much appreciated assistance in the field. Thank you to my aunt, Hilary DuToit, for her assistance and support.

Special thanks to Devon Wagner for his endless support, positive attitude and encouragement during the course of this research. I would not have made it this far without you.

NRF National Research Foundation

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List of Acronyms

AMSL	Above Mean Sea Level
CMA	Catchment Management Agency
CMS	Catchment Management Strategy
CNES	Centre National d'Etudes Spatiales
DAI	Deviation Area Index
DWA	Department of Water Affairs
EM	Electromagnetic
FAO	Food and Agriculture Organisation
IWRM	Integrated Water Resource Management
MIR	Mid-infrared
NDAI	Normalised Difference Area Index
NDVI	Normalised Vegetation Index
NIR	Near Infrared
NWA	National Water Act of 1998
NWRS	National Water Resource Strategy
RGB	Red Green Blue
SWIR	Short-wave Infrared
TIN	Triangulated Irregular Network
TIR	Thermal Infrared
TS	Training Sample
WRC	Water Research Commission

Chapter 1

Introduction

1.1. Background to the study

This dissertation forms part of a larger research project, *K5/1690*, funded by the Water Research Commission (WRC), entitled *"Remote Sensing – Quantification and Legal Compliance of Surface and Groundwater Use"*. The project team comprises members from the Agricultural Resource Council, Geohydrological and Spatial Solutions, Council for Geoscience and the University of Cape Town. The *K5/1690* WRC project is directed toward researching the usefulness and applicability of using Remote Sensing technologies as a tool for resource assessment and determination of the legal compliance of surface and groundwater use. The approach chosen to address this aim is to quantify the various components of the water balance equation. This thesis only addresses the storage component of the equation by attempting to determine the volume of water stored in farm dams. The thesis was initiated by the WRC project and contributes to the *K5/1690* study; however, it is independent of the WRC project.

South Africa is characterised by erratic, unevenly distributed rainfall patterns and often experiences drought. In 2007, South African Department of Water Affairs and Forestry (DWAF[1]) estimated that water used for irrigation amounted to 59 per cent of South Africa's total water yield. Furthermore, changes in land use, increasing and unevenly distributed population growth rates, and economic development are additional factors that make large demands on limited natural resources (Zietsman *et al.* 1996). There is a need to monitor water retention and storage of water in dams that are not monitored or authorised.

A study by Finch (1997) refers to "monitoring" as establishing the amount of water stored and assessing any declines in storage over time. Finch (1997) addresses water use in Botswana, where farmers in rural areas construct small dams with the capacity to contain anything between $1000m^3$ and $100\ 000m^3$, which in many cases are not monitored. The study explains the need for water resource managers to have useful information regarding the spatial distribution of these resources and suggests the use of remote sensing as an appropriate tool for doing so. Finch (1997) provides confidence in the use of remote sensing for identifying water bodies and determining the volume of water stored.

DWAF are responsible for obtaining water use information, such as dam storage and water supply, and to ensure compliance in water use regulations. Since stored water in dams no longer contributes to the Reserve, any stored water exceeding 10 000 cubic metres or where the water area at full supply level exceeds 1 hectare in total on land, must be authorised by a license issued by the Department of Water Affairs and Forestry.

[1] Name change to *Department of Water Affairs* in 2011.

Dams exceeding 10 000 m^3 not registered on the DWAF's inventory list are deemed to be illegal (DWAF, 2005).

Dams are monitored on a case-by-case basis but this is time-consuming and costly. The Department's Annual Report (2010) acknowledges the backlog of 1800 cases in water use authorisations. In addition, water managers have to deal with complex issues related to data-collection, staff capacity, communication and institutional fragmentation (Funke *et al.* 2007). The Annual Report further states that the target of 205 cases set for the issuing of water licences was not achieved due to capacity constraints. Only 25% of the 40% target of cases relating to compliance and enforcements identified were addressed. The reason for underachievement relates to the shortage of suitable personnel (DWAF, 2010).

DWAF's regulatory function used to be contained within various units reporting to different structures. This situation was improved with the establishment of the Chief Directorate: Regulation. However, the Water Services Regulation Unit still requires additional specialist (technical and scientific) capacity to accommodate for the ever increasing regulatory demand (DWAF, 2010). Illegal water use is a serious challenge in many parts of the country, both in terms of illegal abstraction mainly for agricultural use and mining. Unlawful water abstraction means that in some areas the demand for water will be higher than the availability especially during periods of poor rainfall or drought.

The main aim of this study is to establish a methodology in which remote sensing can be used to support the monitoring of water resources at catchment scale, by identifying farm dams and determining the volume of water stored in small dams.

Zietsman *et al.* (1996), Finch (1997) Sawunyama (2006) and Van de Giesen *et al.* (2004) all recognize that remote sensing is a tool suitable for monitoring agricultural water use since the technology allows for the regular collection of information about earth surface features at a spatial, spectral and temporal resolution. This study explores the use of remote sensing to identify farm dams in a catchment based on the spectral characteristics of water as captured by a satellite sensor in which image classification software is used to delineate the surface area of the dam. Surface area is a critical input in the water balance equation as an indicator of the storage volume. Gupta and Banerji (1985) proposed a method for estimating storage capacity of water bodies. Their findings suggest that there is a strong correlation between water surface area and water volume stored. This relationship is supported by the findings of Magome *et al.* (2003) where the method was applied in both Ghana and Japan.

1.2. Aims

This thesis aims to use remote sensing to determine the volume of water held in storage in farm dams. The objectives are:

- Identify agricultural dams in the study area from remotely sensed imagery;
- Determine surface area of dams;
- Determine the volume of water stored in farm dams using a storage volume equation; and
- Compare those dams identified using remotely sensed imagery with records in the DWAF WARMS database.

1.3. Research design

The study makes use of SPOT XS imagery that is freely available from the Satellite Application Centre. This imagery was chosen because of its high resolution properties and infrared band. The higher the resolution improves the accuracy of its surface area and volume calculation.

eCognition™ software is explored in attempt to provide a relatively simple, semi-automated means of classifying imagery and establishing the surface area of the water bodies. Surface area results can be used to determine the volume of water stored in the dams (Van de Giesen *et al.* 2004).

1.3.1. Scale and resolution

This study explores the relationship between area and volume of the impoundment of water at a quaternary catchment scale. Since slight changes in surface area of water bodies may translate to a relatively large change in volume, a certain level of detailed imagery is necessary for this study. As identified by the WRC K5/1690 project, high-resolution imagery, of less than 20m resolution, would be most practical to meet the above-mentioned aims. Since the near infrared (NIR) band is sensitive to water detection, multispectral imagery is critical for this study. Thomas (2008) assessed the use of various satellite datasets for water mapping. He opted to use SPOT data as he suggests that, given its resolution, is most appropriate for such an application. Furthermore, Chrysoulakis (2002) suggests that the use of SPOT infrared bands is best for discriminating between water and non-water features. This will be discussed in more detail in Chapter 2 and 3.

The study aims to measure farm dam storage. Therefore, the amount of water that is stored at full capacity i.e. an image captured in the rainy season would be most useful in determining the legal compliance of water storage.

1.3.2. Selection of imagery

SPOT 5 data were used for the study since it is high-resolution multispectral data. It has a reasonable temporal resolution of 26 days and is freely available for research purposes.

1.4. Study area

1.4.1. Piket-bo-berg

Piketberg is situated in the Swartland region, approximately 200km north of Cape Town in the South-Western Cape. It is an agricultural region where deciduous fruit farming is practiced on the slopes of the Piketberg Mountains and wheat farming in the valley. The farms selected for this study are located on the plateau of the Piketberg Mountain as shown in Figure 1. This area is known as Piket-bo-berg.

Field visits to the area indicated that agricutural activity in the region is largely commercial and grown for the export market. Piketberg produces 8% of South Africa's total nectarine and table grape production, 2% of the country's apple and pear production and 4% of the total apricot production (Louw & Fourie, 2003). These farms also influence the socio-economic status of the region since any shift in farm production will have a direct impact on local livelihoods. Approximately 4000 farm workers are dependent on agricultural activity in this area to sustain their livelihoods (Louw & Fourie, 2003).

Boucher (2008) indicates that the way in which rainfall patterns are likely to change in future will decrease the total amount of water available to rain-dependent farmers in the Swartland. The effects of rainfall changes, as a result of climate change, are likely to vary significantly between farmers, making it difficult to make generalisations (Boucher, 2008).

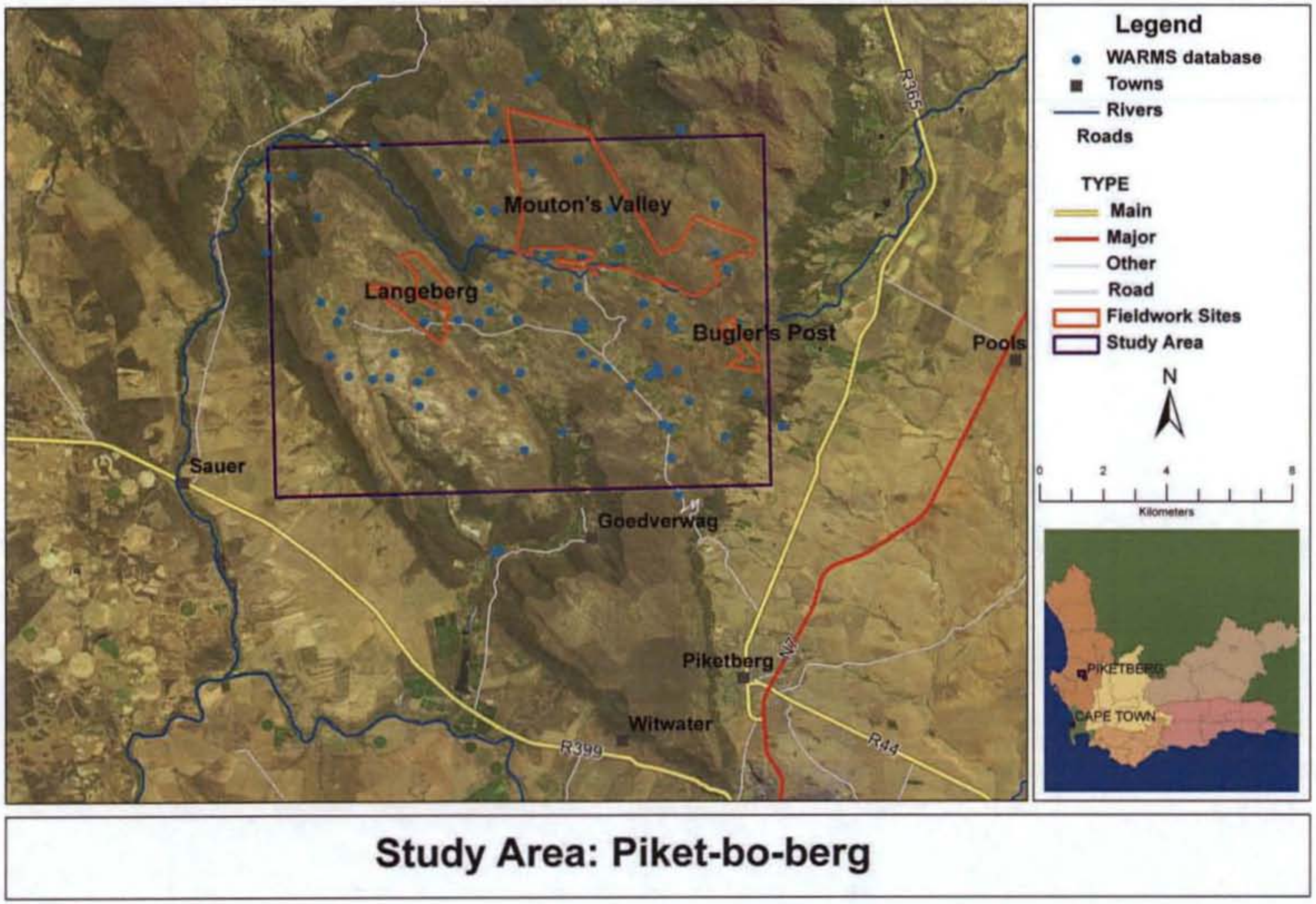

Figure 1: Study Area

1.4.2. Geology and Pedology

The geological characteristics of Piket-bo-berg forms part of the Cape System that is typically a thick layer of sandstone that rests on Malmesbury shale. The mountain consists of Table Mountain Sandstone and forms an intricate arrangement of fold lines, with the main drainage lines being along the folds (Boucher, 2008).

Linder (1976) conducted a preliminary study of soil types in Piket-bo-berg. The study revealed that the Glenrosa form is widespread on slopes in the area. The Glenrosa form is coarse sand with 5-10% silt and clay, and pH varying between 4.5 and 6.0. In the flatter lying areas on the mountain, the Fernwood form is commonly found. This soil type has similar pH to Glenrosa and consists of deep undifferentiated soil. Fernwood soil is suitable for cultivation. According to Linder (1976), a 10-50cm layer of clay soil can be found in certain areas, and is a sought after material for the construction of dams.

The marsh areas consist of the Champagne form, a very organic soil, rarely found in the area. Rich black alluvial soil was observed in the river valleys such as in Mouton's Valley and Agtervlei, but due to extensive cultivation at the time of study, the soil has not been studied in much detail (Linder, 1976). All the soil types, are derived from the Table Mountain Sandstone group, is coarse sand, and is known for its poor retention of water and being poor in nutrients.

1.4.3. Rainfall

The study area is in a Mediterranean climate that experiences winter rainfall. According to rainfall data collected at Heldervue, a farm in the Piket-bo-berg, the distribution of rainfall is largely irregular. Average rainfall, at an altitude of 800amsl (above mean sea level), is approximately 750mm per annum compared to 400mm in the town of Piketberg situated at an altitude of 300amsl (Linder, 1976).

1.5. Structure of thesis

Chapter Two discusses the history and current practice of water resource management in South Africa. The role of integrated resource management as a framework for resource management in South Africa is explored together with literature on monitoring water resources. In addition, the Chapter addresses literature that is relevant to the remote sensing component of this study in order to foreground the chosen methodology. Chapter Three describes the methodology. The findings are discussed in Chapter Four. The discussion includes an analysis of the results from digital and visual processing, compared with field data. The results are also compared to the existing WARMS database to assess the applicability thereof in terms of monitoring legal water use. Chapter Five concludes by discussing the applicability and reliability of remote sensing to calculate water storage in dams.

Chapter 2

Literature Review

2.1. Introduction

> "South Africa's water law comes out of a history of conquest and expansion. The colonial law-makers tried to use the rules of the well-watered colonising countries of Europe in the dry and variable climate of Southern Africa. They harnessed the law, and the water, in the interests of a dominant class and group which had privileged access to land and economic power" (Asmal in DWAF, 1997).

South Africa has made notable progress in reforming its national water law – now regarded as one of the most progressive in the world (Funke, *et al.* 2007). Under the old Water Act (Act 54 of 1956), property owners had riparian rights and could treat water as a private resource. The National Water Act of 1998 adopted a new approach that aims to achieve holistic and sustainable water management based on principles of Integrated Water Resource Management (IWRM). Integration, as emphasized in the NWA, seeks to ensure equity and sustainability, though:

- An integrated approach towards the management of water resources addresses ecological, social and economic concerns;
- A move from supply side water management towards demand management and conservation initiatives, involving all stakeholders; and
- Decentralised management with increased stakeholder participation (NWA, 1998).

Nomquphu *et al.* (2007) suggests that such integrated management must be supported by monitoring at national, regional (catchment) and local levels. According to these authors, monitoring that previously intended to support the development and operation of the national water infrastructure, should now attend to matters of compliance so as to meet resource quality objectives, management targets and water use licence conditions. For example, any attempt on the part of farmers to capture water in large quantities (over 10 000 m^3), now requires a license. Unregistered water use at this scale would then be deemed illegal. In 2005, DWA estimated that as much as 60% of water use in certain catchments could be illegal under the National Water Act. The responsible authorities will need to give great attention to the status of water resources and the effects of human activities and continually seek ways to improve and bridge any gaps in the monitoring and management of water resources. Illegal abstraction or the uncontrolled attenuation of water must be controlled so that downstream users have a fair means of acquiring water to meet their needs.

Before water resources can be effectively monitored and allocated equably, the resource has to be quantified – known as the Reserve. It is the DWA's responsibility to determine water availability, location and use but this is an incredibly challenging task in a country as vast as South Africa. Funke *et al.* (2007) highlights capacity and work load as a major problem in monitoring water resources. In terms of surface water monitoring, the views of Funke *et al.* (2007) is further exacerbated by any illegal entrapment of water such as dams and weirs, as it is excluded from the Reserve.

2.2. Water use legislation in South Africa

The National Water Act of 1998 states that the size of the water resource (the Reserve) must be quantified before water is allocated for any use. The Reserve consists of two parts: the Basic Human Needs Reserve and the Ecological Reserve (NWA, 1998). The Basic Human Needs Reserve is the water allocated for human consumption providing essential needs such as drinking water, personal hygiene and food preparation. The allocation from this Reserve is currently calculated at 25 litres per person per day to meet basic needs (NWA, 1998). The Ecological Reserve is the water required to protect and sustain aquatic ecosystems, and to secure ecologically sustainable development and water use (NWA, 1998). South African law places the obligation to manage water resources on the DWA. It is the Department's responsibility to determine the Reserve, monitor water quality, compliance, water availability, location and use. Monitoring of water resources incorporates licensing and target schemes, as well as water quality management at national, regional and local levels.

The decentralisation of water resource management has led to the development of a three-tier water management system. At a national level, Tier 1 involves the strategic development and planning of regulatory frameworks. It is the level at which the DWA takes responsibility for the design and coordination of monitoring programmes, development of appropriate technology for monitoring water resources, and assesses and audits these initiatives. However, DWA is at liberty to delegate all monitoring and assessment functions to local or provincial authorities (Nomquphu *et al.* 2007).

At a regional scale, Tier 2 focuses on the management of catchments. For this purpose, the country has been divided into 19 Water Management Areas wherein water use is regulated by Catchment Management Agencies (CMAs). The CMAs are responsible for water use licensing and registration of water use. One of the tools prescribed by the Act is the registration of water use. Schedule 1 of the Act lists activities that require the registration of water use by means of a license. Water storage, which is the focus of this thesis, is listed as one of these activities. The Act states that a license is required for "any person or body storing water for any purpose (including irrigation, domestic supply, industrial use, mining, aqua culture, fishing, water sport, aesthetic value, gardening, landscaping, golfing, etc.) from surface runoff, groundwater or fountain flow in excess of 10 000 cubic metres or where the water area at full supply level exceeds 1 hectare in total on land owned or occupied by that person or body and not in possession of a permit or permission" (DWA, 2007).

Finch (2007) claims that the construction of irrigation dams in some rural areas is largely unmonitored. Water Authorization and Resource Management System (WARMS) spatial decision support system is a database used to determine the demand for water in a catchment, storage and allocation decisions. The water user is expected to provide the location, nature and quantity of water use in the registration application process. If the water use is not registered, it is likely that DWA will be aware of the activity taking place until such a time that the area is reviewed. This is cause for concern in terms of establishing the Reserve and efficiently allocating water use to various sectors (DWA, 2007).

According to Funke *et al.* (2007), although the principles and objectives of national policy are promising, the implementation of the principles of IWRM shows little success. An example is the Mhlatuze catchment. The failure is attributed to the fact that data are scattered across sub-directorates, there are staff shortages and communication problems with external stakeholders (Funke *et al.* 2007). Inadequate staffing and sheer volume of work that DWA staff members have to deal with in the catchment makes it particularly difficult to deal with developments in an integrated way. The study by Funke *et al.* (2007) found that DWA officials are limited in planning, quantifying and monitoring because of staff capacity.

Additional problems arise with any illegal entrapment of water such as dams and weirs, as it is excluded, temporarily at least, from the Reserve and could compromise volume and quality. The Department will be far-stretched to manage thousands of illegal activities that might affect the Reserve. It is for this reason that the location and extent of farm dams must be known when calculating surface water Reserve. The licensing process is already underway in the Mhlatuze catchment to determine the Reserve. Mhlatuze was selected by DWA as the first catchment where compulsory licensing approaches were implemented to see if water users had registered their water use correctly; registered for water use to which they are not entitled; omitted to register uses to which they are entitled; or had not registered their water use at all (DWAF, 2005).

The Water Authorization and Resource Management System (WARMS) is a spatial decision support system. The database requires information regarding the size of the dam i.e. maximum wall height, crest of the wall, gross storage capacity and water surface area and depth at full supply. The dam basin shape and structure should also be disclosed in the registration form. Information about tolerances for accuracy is not provided. A problem with this approach is that it is not known if the volume of water registered is accurate. According to DWA (2007), if the water use is not registered, it is likely that DWA will be unaware of the activity taking place, until such a time that the area is reviewed. This is cause for concern in terms of establishing the Reserve and efficiently allocating water use to various sectors. Dams not licensed and registered to the DWA's inventory list would then be deemed illegal storage and should be addressed accordingly.

The Guide to Determine the Lawfulness of Existing Water Uses (DWAF, 2004) is being used by some regional offices for the validation and verification process. The Guide sets out a procedure to determine whether registered water use is under-, over-, or correctly registered. The steps provided by the Guide are given in Table 1. The methodology presented in this thesis speaks to steps 3 and 4.

Table 1: Procedure to determine the legal registration of dams

Step	Aim	Methodology
Step 1	Establish the scope of the investigation	Information gathering
Step 2	Prepare, compile and update the GIS	GIS data capture, SAPWAT modeling
Step 3	Identify water uses	Aerial photography/ satellite image interpretation & GIS
Step 4	Validate the registered water uses	GIS, SAPWAT, satellite image interpretations
Step 5	Determine whether the extent of the entitlement in know	GIS
Step 6	If the extent of the entitlement is known, establish the extent of the entitlement	GIS data capture, SAPWAT modeling
Step 7	Compare validated registered water use with entitlement	GIS
Step 8	If the extent of the entitlement is known, determine the extent of the existing lawful water use	Satellite imagery and SAPWAT
Step 9	Compare validated registered water use with existing lawful water use	GIS
Step 10	If it is necessary to verify the extent of an existing lawful water, request to register existing lawful water use	
Step 11	Compare the application with the existing lawful water use	
Step 12	Verification if application exceeds the determined existing lawful water use	
Step 13	Verification if application equal or is less that the determined existing lawful water use	

Source: DWAF, 2004

A guide to the validation and verification of water use was produced but there is no official methodology that is currently being implemented throughout South Africa. Consultants have various approaches to fit the available budgets (Gibson *et al.* 2006).
Experience in other parts of the world suggests that it is possible and feasible to use Remote Sensing for detecting water in dams.

2.3. The use of remote sensing for monitoring of agricultural water resources

Funke *et al.* (2007), argues that water resources need to be managed and monitored by improving the information available to the relevant officials and decision makers. This information needs to be accessible, reliable and measurable (Bartle, 2008). Zietsman *et al.* (1996) and Finch (1997), recognise remote sensing as a tool that is suitable for planning and monitoring of water resources because the technology allows for the regular collection of information about earth surface features at a spatial, spectral and temporal resolution.

Jha and Chowdary (2006), Zietsman *et al.* (1996) and Lourens (1990) all identify remote sensing as a cost-effective means of providing relevantly frequent, reliable data at regional and local scales. The repetitive coverage of remotely sensed data also allows for long-term water resource management. The primary concern of this is about the monitoring of stored water in rural areas; therefore, remote sensing might be a useful means of collecting data where areas are inaccessible. In this study, inaccessible farm dams or dams that have not been registered on the WARMS database, can be identified and studied using remotely sensed data.

Studies on the delineation of water bodies are fairly extensive. Gupta and Banerji (1985) proposed a method for estimating storage capacity of water bodies using Landsat MSS data. Their findings suggest that there is a strong correlation between water surface area and the volume of stored water. Similarly, Magome *et al.* (2003) proposed a method of estimating water storage in reservoirs in Ghana and Japan, based on digitized topographical data and satellite observations. The surface area of water bodies was used to determine the volume of water stored. Sawunyama *et al.* (2006) addresses a similar problem as presented in this thesis, where the author uses Landsat data extracted from images covering Zimbabwe to identify small reservoirs used for domestic purposes and farming. The authors concluded that remote sensing is a way to improve water resource management given the constraints of time and cost.

Remote sensing is currently undergoing huge advances in spatial and spectral resolution with the use of new sensors. According to Slonecker *et al.* (1998) the level of detail that can be extracted from satellite imagery is continually improving. For example, spectral imagery allows for the detection of details not visible to the human eye, and this offers numerous scientific advantages. However, it is important to note that despite progress in developing data collection, problems with data availability still exist (Zhen & Routray, 2003).

As previously mentioned, the Mhlathuze catchment was selected by DWA as the first catchment where compulsory licensing approaches were implemented to see if water users have registered their water use correctly. Remote sensing was used to identify irrigated land and overlaid with property cadastral data; while hydrological models were used to calculate the volumes of water used. The estimates of water use per property were calculated using a GIS based system and then compared to the WARMS registration, identifying unlawful water use. This method provided spatially referenced information on the extent, location and continued presence of cultivation activities in the catchment (Gibson *et al.* 2006). A comparative assessment of Landsat and SPOT 5 satellite imagery was used in the Mhlathuze study where it was found that Landsat was too coarse for field-level mapping however the use of the high-resolution SPOT 5 spectral imagery produced increased mapping accuracy.

According to the experiences from around the world that are noted here, remote sensing is a reliable means of identifying small farm dams. The information that can be gathered on a regular basis can be used to update and verify water resource databases to assist and improve water resource monitoring.

2.4. Physical properties of remote sensing

This section gives a brief description of technical details of remote sensing used in identifying water bodies. The benefit of using multi-spectral imagery is highlighted and the spectral behaviour of vegetation is included for comparison in the classification of imagery.

2.4.1. The electromagnetic spectrum

Remote sensing is the acquisition of information about the condition of an object without being in direct contact with the object. Electromagnetic (EM) waves that are reflected or backscattered from objects provide information such as physical, chemical or biological properties of water, vegetation, snow and lithology (Chuviego and Huete, 2010; McCloy 2006; Mather, 1999). Remote sensing information can also be used with other energy transformation forms to estimate soil moisture, photosynthesis and evapotranspiration.

The Electromagnetic spectrum is made up of various spectral regions. These regions are as follows:

1. **The visible region (0.4 to 0.7 µm).** This region of the spectrum is the portion of the spectrum that the human eye is capable of sensing. The visible region can be further divided into the three primary colours: blue (0.4 to 0.5 µm, green (0.5 to 0.6 µm) and red (0.6 to 0.7 µm).
2. **The near infrared (NIR) region (0.7 to 1.2 µm).** The human eye is incapable of sensing this portion of the spectrum. The NIR is useful for detecting green vegetation.
3. **The mid-infrared (MIR) region (1.2 to 8 µm).** This spectral region lies between the NIR and thermal infrared regions. From 1.2 to 3 µm the energy from the surface is reflected solar radiation and is known as the short-wave infrared (SWIR) region. From 3 to 8 µm there is solar-reflected and surface-emitted signal. From 1.3 to 2.5 µm is of use for soil and vegetation estimates and 3 to 5 µm is effective in detecting high-temperatures.
4. **The thermal infrared (TIR) region (8 to 14 µm)** is commonly used for detecting environmental pollution, clouds and vegetation stress.

5. **The microwave region (>1mm)** comprises very long wavelengths. Microwaves can penetrate clouds and forest canopies and are useful for soil moisture estimates and surface roughness analysis (Chuvieco and Huete, 2010; McCloy, 2006).

Since this study is concerned with identifying water bodies, the TIR and microwave regions will not be discussed here. For more information on these regions, refer to Chuvieco and Huete (2010) or McCloy (2006).

The electromagnetic energy signals received by sensors vary across the EM spectrum according to land cover type and characteristics. This is referred to as the spectral reflectance signature. Areas observed by sensors are likely to include different surface types such as water, vegetation and soil, in varying proportions. The next section explores how some surfaces behave over the above-mentioned spectral regions.

2.4.2. Spectral signatures in the solar spectrum

Remote sensing measurements do not always coincide with the reference signatures without uncertainty. For example, water has a low reflectance in the visible spectrum, yet shade/shadow caused by steep slopes or tall buildings appear as black regions in an image, the same as water bodies. The reference spectral signatures are a good indication of the optimal bands or combination of bands that best distinguishes between such features.

2.4.2.1. Water in the solar spectrum

Water bodies absorb most of the radiation they receive and therefore appear noticeably different to vegetation and soil in remotely sensed images. This means that the spectral reflectance of water shows a decrease in reflectance with increasing wavelengths (Mather, 1999). Reflectance patterns from open surface water may vary greatly. This may be as a result of surface reflectance, volume reflectance and base reflectance.

High reflectance occurs in the blue band, with gradual decreases in the NIR and SWIR regions. Reflectance may be influenced by its composition, such that sediment, the presence of chlorophyll and pollution all affect the level of reflectance. The effect of sediment depends on the reflectance characteristics of the sediment particles, the depth of the particulate layer and the density of the particles in the water. Increasing chlorophyll levels results in a decrease in reflectance in the blue band. The depth of the water body is another factor that may influence reflectance because absorption increases with increasing water depth (Mather, 1999).

The degree to which the volume reflection contributes to the total reflectance depends on the penetration depth of light (Liebe *et al.* 2005). This decreases from 10 m at 0.5–0.6 μm to less than 10 cm in the range between 0.8 and 1.1 μm. Base reflectance is also largely dependent on shorter wavelengths. Lastly, surface texture or roughness also affects reflectance as increases in texture increases reflectance (Liebe *et al.* 2005).

According to Chrysoulakis (2002), the optimal spectral wavelength to obtain bathymetric information is 0.48 μm. The presentation reiterates that the use of SPOT infrared bands is best for discriminating between water and non-water features. Furthermore, it is noted that the spectral response of water is influenced by the amount of sediment in the water as well as by the reflectance of any chlorophyll present. In a study by Singh *et al.* (1991), the authors reported on a comparison between reservoir spread and rainfall, where the reservoir extent was mapped using satellite images.

Whitman *et al.* (1999) used the spectral reflectance characteristics of water to extract surface water bodies in Landsat images. Although this study uses SPOT 5 data, the methodological approach used by Whitman and others is worth mentioning. Since surface water has a low reflectance in the NIR and SWIR regions, Landsat band 2 was divided by band 5, and according to the authors, a satisfactory result was obtained (Whitman *et al.* 1999). This ratio approach can be explored and modified for SPOT 5 bands.

Castano *et al.* (2000) presented a paper on wetland monitoring by integrating remotely sensed data in a GIS tool. The objective of their study was to implement a relatively simple method that automates the detection of water surfaces from Landsat5-TM satellite images. Water surface was identified using the following relationship:

$$\frac{Band4}{Band3} - \frac{Band4}{Band5} \geq 0.4$$

A coarse 30m resolution resulted in limitations in areas of shallow water where the water surface is underestimated and misclassified. The method is useful in determining trends with regard to wetland water surface area but the resolution imposed limitations.

The examples found in the literature reveal that remote sensing can be used to identify farm dams with confidence. The scale of the study and resolution of imagery is important when selecting imagery to be used for identifying water bodies.

2.4.2.2. Vegetation reflectance[2]

Vegetated areas are generally indicated by higher values due to their high reflectance in the near infrared and low reflectance in the visible red wavelengths. The NDVI uses the near infrared and the visible red bands in its calculations. It is not sensor dependent and can be used with any data containing these wavelengths. Values in the NDVI range from -1 to +1 where lower values indicate non-vegetated features such as water, barren land or clouds.

There are three main spectral domains that influence the optical properties of leaves; these are the VIS, NIR and SWIR regions. In the VIS region (0.4 to 0.7 μm) low reflectance occurs due absorption of leaf pigments (mainly chlorophyll, carotenoids and xanthophylls). The pigments absorb in the blue region of the EM spectrum (around 0.45

[2] For more information on reflectance of vegetation, including leaf structures and canopies, refer to McCloy (2006)

μm) but chlorophyll also absorbs in the red portion of the spectrum (around 0.65 μm). At 0.55 μm there is a region of less intensely absorbed radiation. This is known as the green reflectance peak that shows the green appearance of healthy leaves (Chuvieco and Huete, 2010).

The region between 0.7 and 1.1 μm is known as the NIR reflectance plateau. This is an area of very high reflectance with the exception of minor water related absorption bands (0.96 and 1.1 μm) that is dependent on internal leaf structures (Chuvieco and Huete, 2010). The NIR region is sensitive to leaf structure and reflectance decreases sharply from the NIR plateau to the SWIR region where there is strong absorption by leaf water.

The spectral behaviour of vegetation in the red and NIR portions of the EM spectrum forms the basis for vegetation indices. When multispectral images are available, vegetation indices are based on combinations of these bands using ratios and sums (Chuvieco and Huete, 2010).

A study by Yousfi (2000) sought to identify and evaluate agricultural surfaces in Algeria using SPOT data. Although not directly related to the objectives of this thesis, classification steps used by this author may be useful in refining the methodology of this study. For example, Yousfi (2000) uses a vegetation mask, Normalised Vegetation Index (NDVI), to eliminate non-vegetative classes. NDVI is the difference between NIR and red bands divided by their sums to create a biomass index. The value of dividing one band by another is to reduce the undesirable effects of noise.

$$NDVI = (NIR - R) / (NIR + R)$$

SPOT 5 imagery has greatly improved the identification of problematic features such as in water bodies (Forghani *et al.* 2003). In a local study of existing water bodies on the Cape Flats, historical data from topographical maps and aerial photographs in 2000 are compared to more recent SPOT 4 satellite imagery from 2007 (Thomas, 2008). The study reveals that the existence and extent of natural water bodies in this context is declining. However, relatively small water bodies and wetlands could not be easily identified due to the resolution of the imagery. The use of SPOT 5 imagery should overcome this constraint given its higher resolution. Thomas (2008) assessed the use of various satellite datasets for water mapping. He opted to use SPOT data as he suggests that, given its resolution, is most appropriate for such an application. The higher the resolution of the satellite data, the more accurate the surface area calculation will be and therefore render better volume calculation results.

2.6. Visual image processing

Visual interpretation of images uses criteria such as location, texture, colour and shape etc. making visual interpretation useful in discriminating land cover that may have similar spectral signatures. For example, when using digital interpretation a park in an urban area might have a similar spectral signature to irrigated crops due to their respective reflectance values. By providing context, visual interpretation can be used to distinguish between these features i.e. the geographic proximity of an urban park to tall buildings aids in differentiating between the land cover types. The following subsections discuss the criteria in more detail.

2.6.1. Brightness

Brightness is associated with spectral reflectance as it refers to the intensity of pixel radiance in a spectral band. Since reflectance is wavelength dependent, brightness differs in the different bands. For example, water and vegetation absorb the visible bands. However in the NIR band, water absorbs light, appearing dark and vegetation shows greater reflectance with light tones. In the SWIR green vegetation, dark soil and water all absorb light. So we see that the brightness criterion is a relatively simple way of distinguishing features across the spectrum.

2.6.2. Colour

The human eye perceives wavelengths between 0.4 and 0.7 µm and separates the energy into three components – the primary colours red, green and blue (RGB). Any colour can be derived from these components. When the components are arranged to a different order, false colour composites are formed which may be useful for interpretation. A well-known combination is applying RGB to NIR, R and G. In this case, dense vegetation would correspond with a red-magenta, white would be areas of little vegetation, bare soil or snow. Water would be displayed as dark blue to black.

2.6.3. Texture

Texture refers to the heterogeneity of an image i.e. if the tones are homogenous then the texture appears smoother. Factors affecting texture include the relation between the size of the object and the resolution of the sensor, the observation angle of the sensor and wavelength. The use of texture in interpretation is important when trying to distinguish between features that have similar spectral signatures e.g. different types of trees or water and shadow.

2.6.4. Spatial context

The location of an object is another means of classifying features. This means that when differing features have similar spectral signatures, one can differentiate between them by observing the surrounding features in the image. An example of this is the proximity of irrigated land to a water source such as a river or a dam.

2.6.5. Shape and size

The shape of an object can be used in image interpretation. Using this criterion, one can distinguish between natural and man-made features e.g. rivers versus channels. An interesting study by Dwivedi and Kandrika (2005) gives attention to the identification of aquaculture ponds by making use of the spectral response of water as well as the shape of these ponds. As will be discussed in section 2.9, eCognition™ software is able to make use of such parameters in its classification process. The authors mention the use of a rules-based approach to the SPOT data; however this is not elaborated upon.

Where features may be of similar shape with similar spectral signatures, one can then perhaps consider identifying the object in terms of their relative sizes.

The above criteria are all useful, intuitive means of interpreting images and are catered for in the eCognition™ environment.

2.7. Digital interpretation

Traditional classification methods have been divided into two groups: supervised and unsupervised classification. With supervised classification the user is familiar with the study area that aids in selecting samples for the different categories. Whereas, unsupervised classification is an automatic search for homogenous values in the image. Density slicing is another method that is used for classifying images. As discussed by Frazier and Page (2000), density slicing is used to map water bodies using a single band. However, multi-spectral classification was done for comparison and it was found that density slicing largely overestimates the area of water bodies in an image.

Thomas (2008) gives a useful account of the methods used for image classification. The SPOT image was orthorectified in PCI Geomatica 10.1.1 with reference to a digital topographical map for ground control points. A digital elevation model (SRTM 90) was used for geometric correction. A supervised classification was conducted to highlight regions of interest using ENVI™ software. The results of the supervised classification were mapped and compared to the historical data. Thereafter, an unclassified classification was achieved using ArcView™ Image Analysis Extension software. Both approaches revealed a decline in water bodies in the study area. The author further notes that unsupervised classification incorrectly mapped some shadows and roads as water bodies; resulting in a slight increase in total area of water for both years of study. The rule set that will be developed in eCognition™ will hopefully eliminate the classification error for shadows mentioned above. It must be noted that a degree of error exists in all image classification.

Both supervised and unsupervised classification has pros and cons. For example, supervised classification may be viewed as biased and unsupervised classifications give a result that is difficult to interpret. Spectral similarity does not necessarily imply homogeneity, as there may be variations within the same covers. Similarly, the same type of cover might have varying spectral characteristics.

In supervised classification, the user is familiar with classes that are present in the scene. The identified areas for the targeted categories are called training sites. The software defines the properties of the training sites and recognises the different categories. Basic statistics are computed for the training sites, which are later used for classifying the remaining pixels (Adams and Gillespie, 2006). It is therefore important that the identified training sites are good representatives of particular classes. Other aspects to consider for the different categories include, among others, type of soil, slope, and soil moisture.

Unsupervised classification tries to define spectral classes of an image by finding clusters with similar spectral characteristics. The software uses an algorithm that automatically organizes pixels values into groups. The K-means method is commonly used, where the user specifies the number of classes to be created. Once the amount of classes has been decided upon, the software performs the unsupervised classification. Clusters are created for as many classes assigned. The user would then have to identify the classes produced by the classification process (Adams and Gillespie, 2006).

This type of classification may be a starting point for investigating unfamiliar scenes but its value is limited where the user, as in this case, is familiar with the study area.

Since surface area of dams is of particular interest to this study, it is viewed more appropriate to make use of classification methods that are more sensitive to size and shape of features. This once again, reiterates the preferred use of multispectral data and not using density slicing as a method of classification. Although not the primary means of classification for this thesis, supervised and unsupervised classification have been included, to a certain extent, for comparative reasons.

2.7.1. Object oriented classification: eCognition™ software

eCognition™ has semi-automatic classification capabilities in an object-oriented environment. Where other packages classify according to pixels, eCognition™ first segments the image into polygons, or image objects, upon which classification is further conducted. Developing a model within this programme may yield an efficient means of identifying and selecting water bodies from satellite images and consequently determine water storage. Furthermore, Harayama and Jaquet (2004) claim that semi-automatic classification such as this, allows for savings of time and cost. In addition, they suggest that the accuracy object oriented classification is sufficient for most water resource management applications.

In the eCognition™ environment, the first step of image analysis is segmentation. The image is divided into homogenous segments based on colour, scale, shape, compactness and smoothness. These are all elements of visual interpretation as previously mentioned.

The segments can be merged or divided based on these parameters (Kressler *et al.* 2005). The programme sets a context for the classification of the image, in that each object 'knows' its surrounding objects (eCognition™, 2000; Herald *et al.* 2002). For example, an object at a given level is related to objects within the same level but also to objects in levels above and below it. Classification algorithms can be used with reference to this network. The classification process that will be followed in this study will only operate at one level so as to maintain a certain level of simplicity. Algorithms making use of brightness thresholds, distance relationships and the shape of features are means of classifying an image.

The University of South Carolina, NASA Affiliate Research Center (ARC) assisted DWA to identify a cost-effective methodology to accurately measure and monitor agricultural land use. The aim was to investigate the accuracy of various digital image-processing algorithms, on various remote sensing data, to inventory the type and spatial distribution of agriculture present in the study area. The research assessed the accuracy of many image classification algorithms and found the most accurate results were obtained using object oriented image segmentation techniques (eCognition^{TM}) applied to SPOT multispectral and panchromatic data.

Kressler *et al.* (2005) conducted a land cover classification study using IKONOS data. In this study, water was classified using the relative area and the brightness classification features. As previously discussed, these are criteria to consider when creating a classification rules in eCognition^{TM}.

In 2008 Lewinski and Bochenek presented a paper on the use of SPOT imagery for land cover mapping in Poland. The authors found the object-oriented approach to give the best results for land cover mapping. This is due to the use of spectral and non-spectral features in the classification process. In the study, the classification of water bodies was delineated using multi-resolution segmentation based on SPOT 3 band. This approach was viewed as adequate to identify shapes of lakes. The result was further refined using SPOT 4 bands. Other surfaces were classified using brightness thresholds and NDVI. It is also stated that in conducting an accuracy assessment, the classification for water obtained the most accurate result. The approach used by Lewinski and Bochenek (2008) was verified on two other SPOT scenes. It is noted that to achieve a high level of accuracy, thresholds had to be modified, however the principles of the process were unchanged.

Once a combination of classification criteria has been used to develop in a rule set to identify water bodies effectively, the classification of water bodies within eCognition^{TM} should allow for farm dams to be categorized into a single image objects i.e. water body polygons. The surface area of farm dams can be obtained since each image object is associated with image features; this value for surface area is a key input for the volume of water stored.

2.8. Determining dam capacity

As previously mentioned, a vast amount of remotely sensed data exists, each with subjective benefits and limitations. This thesis is concerned with determining surface area values for farm dams and subsequently quantifying the volume of water stored. It then follows that the best available spatial resolution of the imagery is essential for the study. The literature review of the *K5/1690* WRC project identified SPOT 5 data as an appropriate data source for this study, as it is *freely available* for research purposes. It is also appropriate for this study since it offers *high-resolution* data that is likely to provide the most accurate result for the purposes of the study. In addition, the *infrared band* available is very useful for identifying water bodies. For the purposes of this study, the use of eCognition™ software is the key focus in determining the surface area of water bodies i.e. farm dams, however, other software will also be considered for comparing the outputs produced.

The surface area input resulting from this object-oriented classification approach (and other methods) will be used in a volume equation to estimate the amount of water stored in farm dams.

Sharma and Sharma (1992) define a dam as "a hydraulic structure constructed across a river or stream to impound part of runoff from the catchment upstream of the dam". According to South Africa's National Water Act (Schedule 1), water use is authorised by a license and the amount of water stored in dams is registered under the Act. It becomes necessary to register water use when the dam storage volume exceeds 10 000 cubic metres or where the water area at full supply level exceeds 1 hectare in total (DWA, 2007).

Gibbings and Raine (2005) discuss ways to improve irrigation efficiency in the Australian agricultural sector. The authors state that accurate information regarding farm dam volumes in Australia is limited even though this information is an important step in optimising water use. The authors report that the most accurate measure of dam storage is obtained using traditional surveying methods and when the dam is empty, however such opportunities are limited. It is further noted that monitoring the change in water level is a simple and relatively accurate indicator of change in volume of water stored in farm dams. Other methods of obtaining depth measurements include echo sounding, sonar and laser scanning. These methods may not be suitable for farm-scale measurements due to the high costs (Gibbings and Raine, 2005).

Gibbings and Raine (2005) use a relatively cheaper methodology was used to establish the volume of water retention in farm dam. An electronic depth sounder and GPS antenna was attached to a 3m boat. Depth measurements were taken along 10 X 5m, 20 X 10m and 20 X 20m transects. The values obtained were used to develop a digital terrain model for the full storage volume. In addition, the plumb line method was used at random points to further evaluate the accuracy of the previously mentioned methods. The authors found this method to be relatively accurate, with errors being comparatively minor. In this study a similar method of ground truthing, however, an electronic depth sounder was not available for this study and a plumb line method will be used.

Gupta and Banerji (1985) proposed a method for estimating storage capacity of water bodies using Landsat MSS data. Their findings suggest that there is a strong correlation between water surface area and water volume stored. This relationship is supported by the accurate findings of Magome *et al.* (2003) where the method was applied in both Ghana and Japan.

Sharma and Sharma (1992) suggest that the determination of the capacity of dams can be established by taking contoured area at equal intervals and totaling up by the following formulae:

1. **Cone Formula**

$$V = H/3\ (A_1 + A_2 + \sqrt{A_1 A_2})$$

Where A_1 is one contour and A_2 is another contour (sq. km) and H is the contour interval (m)

2. **Simpson Formula**

(a) Volume between any odd number of contours

$$V = H/3\ [2(A_1 + A_2 + \ldots + A_n) + 4(A_2 + A_4 + \ldots + A_{n-1}) + (A_1 + A_n)]$$

=H/3 (twice the sum of the area between odd contours + 4 times the sum of areas of even contours + areas of first and last contours)

(b) Volume for even number of contours

$$V = 2H/3\ [(A_2 + A_4 + \ldots + A_m) + 2(A_1 + A_3 + \ldots + A_{m-1})]$$

The Simpson formula is one of the formulas used by DWA to quantify storage of large dams.

A paper by Finch (1997) considers three regions in Botswana reiterating the above-mentioned relationship between surface area and volume. An algorithm for maximum dam capacity was development based on the estimated surface of the dam:

$$C_f = 7.38 A_f^{1.25}$$

Following this, the volume of water stored at any other level, C_t, is a function of the Area at that time, A_t, by the following equation:

$$C_t = C_f (A_t/A_f)^{0.65}$$

Further work by Van de Giesen *et al.* (2004) supports the conclusions of the authors mentioned above. Van de Giesen *et al.* (2004) used remote sensing as a tool for calculating volumes of water in small dams in Ghana. In this study, particular attention is given to runoff in which surface area of water is converted to volumes using the following equation:

$$V = 8.52 * Area^{1.437}\ (10^{-3} m^3)$$

The authors state that according to a bathymetric survey conducted for sixty dams, 97.5 per cent of the observed variability in volume could be explained on the basis of surface area.

In addition, the Australian Department of Natural Resources published a simple method of dam capacity estimation for the purposes of water use licensing. Three different calculations for surface area are provided for triangular, rectangular and circular shaped dams. According to the Department, once surface area has been determined, the value can then be used to determine volume:

$$\boldsymbol{V = 0.4 * Area * Depth}$$

Where 0.4 is a conversion factor that takes into account the slope of the sides of the dam (NSW Government, 2006). Since the depth of all the dams in the study area is not readily available, this equation will not be used in this study.

Sawunyama *et al.* (2006) addresses a similar problem as presented in this thesis, where the author uses Landsat data extracted from images covering Zimbabwe to identify small reservoirs used for domestic purposes and farming. The authors concluded that remote sensing is a way to improve water resource management given the constraints of time and cost. The authors reviewed existing area-capacity relationships and errors of dams and deemed it feasible to develop a model equation for estimating storage capacity of small reservoirs. Given the parallels of these two studies, the capacity equation and analysis approach used by Sawunyama *et al.* (2006) will be used in the methodology of this thesis.

The data for surface area and capacity was transformed into log equations and corresponding R^2 values were calculated for each reservoir. The regression equations for log capacity area were classified into two categories, depending on the shape of the reservoir and the length of the throw back[3]. The first category represents an oval shaped reservoir with a short throwback and the second category resembles a triangular shaped reservoir with a long throw back.

An equation for category 1 was established using logarithmic principles and is given by:

$$\boldsymbol{C = 0.031 * A^{1...31}}$$

The equation established for category 2 is as follows:

$$\boldsymbol{C = 0.017 * A^{1.35}}$$

The assumed general characteristics of the reservoirs in terms of topography, geology, size and maximum depths led to one general equation to establish capacity in terms of

[3] Distance from dam wall along reservoir axis usually to the point where river enters (Sawunyama *et al.* 2006).

its relationship to surface area. This best-fit equation is for the area-capacity relationship that will be used in this thesis is given by:

$$C = 0.023 * A^{1.33} \ (R^2 = 0.95)$$

Where C is capacity in m^3 and A is area in m^2.

The relationship was validated by four independent reservoirs in the catchment. A t-test was conducted and that showed a strong correlation for surface area at 95% confidence interval.

Possible reasons for error may be as a result of the coarse resolution of imagery used in this study i.e. 30m Landsat imagery. This thesis makes use of 2.5m resolution imagery that should allow for more accurate results. The authors further note that vegetation in shallow water might account for the error, even though the error is considered minimal.

Similarly, Liebe (2002) developed a methodology that makes it possible to estimate storage volumes of reservoirs as a function of their surface area on the premise that knowledge of such a function allows calculating reservoir volumes on the basis of remotely sensed data. Liebe (2005) used 61 reservoirs that were precisely measured in the field and modeled to derive regularities and interrelations between the three variables 'area', 'depth', and 'volume'. Transferring their geometric properties into a generalized equation allowed the estimation of storage volumes based on surface areas. In combination with remotely sensed reservoir surface areas, this relation can be utilized to make reservoir volume inventories on regional or even higher level. The derived formula is given as:

$$Vol = 8.52 * Area^{1.437} \ (10^{-3} \ m^3)$$ (Van de Giesen *et al*, 2004)

Examples found in the literature provide positive responses to using remote sensing for determining dam capacity. However, challenges do exist in obtaining accurate results for identification and quantification of water bodies. Some issues to consider are reflectance, sedimentation and spatial resolution as these factors may contribute to data inaccuracies. For example, areas of high reflectance and/or sedimentation that should fall within a category classed as water may be inaccurately classified as a result of dissimilar pixel values. It is important to note, that the accuracies of water volume calculation will be dependent on the resolution of the data used in the calculations. Since this thesis is concerned with the monitoring of volume in small farm dams, issues of scale will have an influence in the results. The higher the resolution of the satellite data or aerial photography, the more accurate the surface area calculation will be and therefore render better volume calculation results. All things considered, this study attempts to obtain a relatively accurate result for water surface area and volume of water stored.

Chapter 3

Methodology

3.1. Introduction

The research design addresses the objective of delineating agricultural storage dams to determine surface area using SPOT XS data. Seven SPOT scenes, captured at various times, were classified in eCognition^{TM} to produce reasonable and comparable results for surface area. For further comparison, the scenes were classified in Bilko^{TM} using supervised and unsupervised classification methods. A ground-truthing exercise was also conducted to verify the results.

The total area (m^2) were converted into volume of water stored to address the third objective of this study by means of two equations, described by Sawunyama *et al.* (2006) and Van de Giesen (2004) respectively. These results were then compared with the ground-truth results as well as the data registered in the WARMS dataset to identify licensed and unlicensed dams.

3.2. Data

3.2.1. Background to source data

SPOT XS multispectral imagery is the primary data source used in this study because it is optimal in extracting data from surface water bodies that reflect light. The data were obtained from the Satellite Applications Centre and distributed in a GeoTIFF format. All imagery was processed to level 1A, meaning that it entails no geometric corrections or resampling, and some systematic sensor related radiometric artifact removal. This ensures that the data are distributed to the user in its raw form, and therefore enable the user to conduct further processing according to individual needs. Only imagery with less than 10 % cloud cover was accepted as reliable.

3.2.2. Orthorectfication procedures

The ortho-rectified panchromatic imagery was used to rectify the multi-spectral imagery by automatic selection of ground control points. The level 3 ortho-rectified images consist of the 10m multispectral (J), the 2.5 m panchromatic (T) and the 2.5m pan-sharpened (JT) product. Universal Transverse Mercator (UTM) based on the WGS84 datum was the map projection chosen for the research. Scenes that were explored are listed in the Table 3.

Table 2: Satellite imagery obtained from SAC

Scene ID	5 118-416	5 117-416	5 118-416	5 117-416	5 118-416	5 118-416	5 117-416
Acquisition date	12/03/2007	20/01/2009	12/03/2007	20/01/2009	12/11/2006	17/07/2008	13/01/2007
Instrument	HRG 1	HRG 2	HRG 1	HRG 2	HRG 1	HRG 2	HRG 1
Spectral mode	A	A	J	J	J	A	J
Number of bands	1	1	4	4	4	1	4
Subset number*	364	829	498	453	956	518	161

*The subset number will be used to identify the scenes used in this methodology.

3.3. Ground truthing

Three farm dams were surveyed in the study area (refer to Figure 1) to obtain bathymetric measurements that were used for validating the classification of the remotely sensed data. The dams that were surveyed on the farms of Langeberg, Bugler's Post and Mouton's Valley, largely because they offered relatively easy access and also had some form of craft available on site for use during field measurements. In each case, a small boat was used to traverse each dam. Measurements of the depth were recorded at approximately 10m intervals along a predetermined transect. The co-ordinates at each measured point were recorded using a hand held Garmin GPS.

The recorded point data was uploaded to ArcMap™ to display the results on the SPOT XS image for the study area. Polygons were created from onscreen digitizing to represent the dams so that values for the surface area of the respective dams could be calculated. Thereafter, triangulated irregular networks (TINs) were created for each dam to interpolate the bathymetry of the dams for a volume estimate. The results are displayed in Chapter four.

3.4. Object-oriented classification

Surface water bodies were classified to prepare for the calculation of the surface area. This was achieved by:

- Applying a segmentation algorithm;
- Developing a classification model using eCognition™ to identify farm dams based on various feature characteristics; and
- Obtaining the surface area of feature objects.

3.4.1. Segmentation

The classification process in eCognition™ begins with segmentation where the image is divided into image objects. Image segmentation is the crucial process whereby homogenous areas are grouped by polygons or segments. The multi-resolution segmentation algorithm was chosen for all image segmentation since it groups areas of similar pixel values into image objects. This algorithm starts by selecting a single pixel in the image and compares it with its neighbours, clustering them pair-wise in a way that minimises heterogeneity. Clusters are then compared with their neighbours to form larger segments until the threshold scale parameter has been reached. This results in segments of varying size where larger segments are in homogeneous areas while smaller segments are in areas of high variability. The segmentation is operated by the scale parameter but there is no definite rule in assigning the parameter. The appropriate value to use for a specific image is determined by trial and error (eCognition™, 2005).

Appendix C illustrates how different scale parameters influence the segmentation of an image.

3.4.2. Classification

eCognition^{TM} calculates a variety of image object features were calculated per segment which provided the basis for classification. These variables include (but are not limited to):

- Layer values - mean, standard deviation, ratio between mean and general brightness;
- Polygon shape features - area, length, width, border length, length width ratio, shape index, density, main direction, asymmetry; and
- Line features – length, width, curvature, standard deviation.

Scale parameters were set and the image subsets were explored in terms of customized algorithms, mean values for the image layers and geometry. These values are displayed in the image object information window that is visible in all the screenshots provided. To keep this section concise, the full Process Tree will only be shown for image subset 161 as this image was used for the ground truthing exercise.

Refer to Appendix C for further examples regarding classification.

3.4.3 Object-oriented classification for the study area, using image subset 161.

The classification rules developed within eCognition^{TM} are displayed as a 'process tree' in Figure 2. These steps were central to the development of the process.

The first step towards object-oriented classification is segmentation. Through trial and error, it was found that a scale parameter of 10 was best suited to the image subset. Since the ratio *r+b/r-b* previously provided an indication of water bodies, the same ratio was explored for the classification of image 161. The feature information showed that, using this ratio, the value for the known water bodies, such as Mouton's Valley, was largely negative. Therefore a threshold of "0" was applied and the result was assigned to a Water class. The result was not without errors; thus, other band ratios set to particular thresholds were also explored to classify variations of surface water for the interim classification. It was found that *b+r/b-r>5* provided a reasonable result for water bodies and the result was assigned to a Possible Water class. For this particular example the ratio *b+g/b-g* was also explored. The object feature information indicated that a threshold of "-11" was appropriate for this algorithm. The result was assigned to a Water Body class. After having identified water bodies to a reasonable extent, the classes required further refinement to, as far as possible, exclude misclassifications.

The ratios used in defining the Possible Water and Water Body classes were useful in identifying water bodies; however, in some areas roads were also included in the classification. In this example the error was not easily corrected by simply changing the thresholds hence other feature objects were considered. Since roads are linear objects, the Asymmetry properties were used to correct the classification. The rule Asymmetry > 0.91 was applied to both the Possible Water and the Water Body class. The result was assigned to a Road class. When using certain algorithms, the shadow on the mountain slopes often displayed similar feature information as water. Here the Mean Brightness of image objects was used to assign misclassified shadow to a

High Slope class or back to "unclassified". The High Slope class is illustrated in yellow in Figure 2. Any of the varying water classes that were not captured by the Mean Brightness thresholds were accounted for using distance relational features. Water classes that had a Possible Distance of "0" to High Slopes were assigned to the High Slope class. Once a satisfactory result for surface water bodies was obtained, the varying water classes were merged to create single image objects. These image objects could then be exported to ArcGIS™ as a polygon shape file with associated area values.

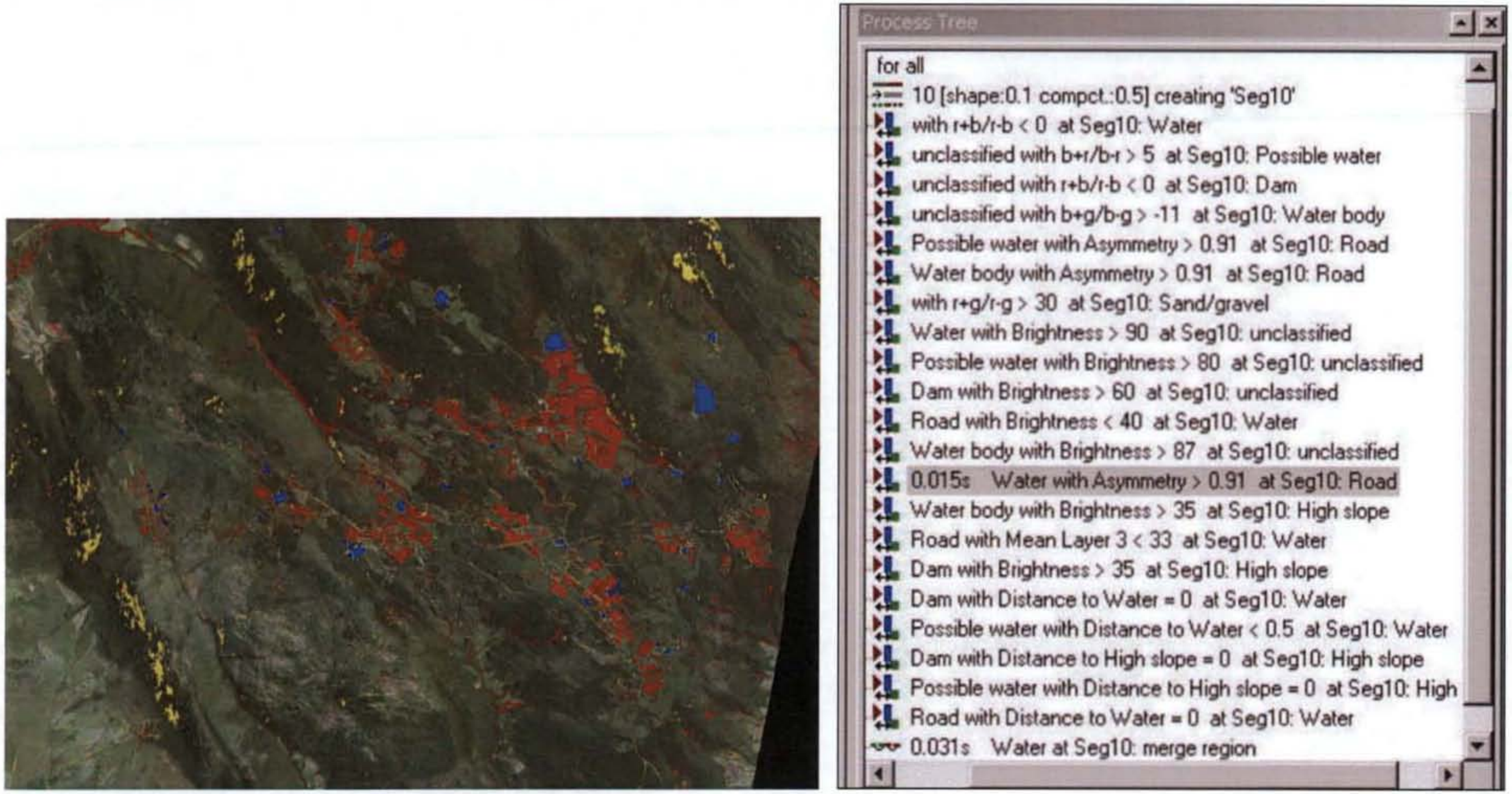

Figure 2: Process tree and map for the classification of surface water bodies

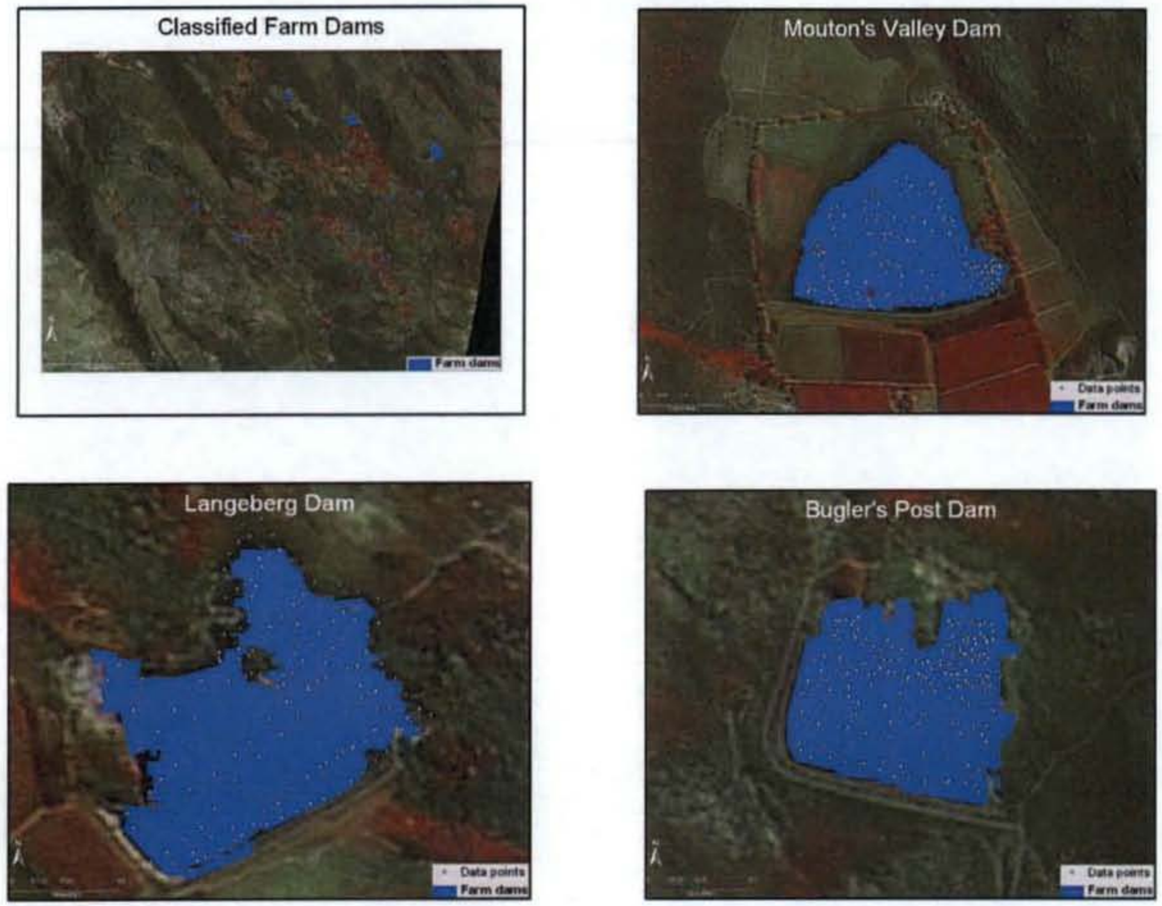

Figure 3: Object-orientation results for the surveyed dams

The results of the object-oriented classification of farm dams in image 161 were uploaded to ArcGIS™, as can be seen in Figure 3.The result shows many small dams within the study area; however, in terms of the National Water Act, only dams with storage volume of greater than 10 000m^3 need to be registered in WARMS so that many of the smaller dams were excluded from the analysis. Three relatively larger farm dams were explored for fieldwork component of the study.

Figure 3 illustrates the object-oriented classification results for the respective fieldwork sites. The full extent of the water body was not included in the classification since some fieldwork data points along the dam wall fall outside of the polygon.

The location of the data points for the Langeberg dam shows that the object-oriented classification did not classify the full extent of the dam. The classification also incorrectly included a section of the dam wall in the water class. The object-oriented segmentation and subsequently the classification correctly excluded the rocky outcrops and vegetation within the dam boundaries. The classification for the Bugler's Post dam encompasses all the fieldwork data points. There appears to be a possibility that water to the north-north-west of the dam was not included in the classification. Despite these obvious limitations, the object-oriented classification produced the following results for surface area.

Table 3: Surface area result calculated using eCognition™

Farm Dam	Subset 161 Surface Area (m^2)	Subset 364 Surface Area (m^2)	Subset 829 Surface Area (m^2)	Subset 498 Surface Area (m^2)	Subset 453 Surface Area (m^2)	Subset 956 Surface Area (m^2)
Langeberg	45040	48210	45960	39950	56750	58420
Mouton's Valley	124200	155860	143970	100120	148210	132550
Bugler's Post	33310	46110	33540	28470	44900	41430

As previously noted, it may be useful to compare the object oriented classification results with other means of classification, despite this not being an objective of this study. The method used for supervised classification in Bilko™ is discussed in the section that follows.

3.5. Supervised classification

The first step in Bilko™ is connecting the different bands to make image composites as the composites are easier to interpret than the individual greyscale bands. Composites are very helpful in interpreting vegetation and other features in images and in guiding supervised classification; however, only water bodies will be classified here.

Supervised classification makes use of training samples as the user is trying to "train" Bilko™ to recognize different land use classes. In this study, typical examples of water bodies were manually selected which Bilko™ uses to work out their spectral signatures. The selection is linked to a training sample table where the land use class is defined. The training sample (TS) table links to the stack of images and allows you to define training sample areas of known water bodies. It has the following columns:

1) **Description:** in which the number of each training sample area is listed (e.g., TS #003)

2) The UTM or Lat/Long coordinates of the **Upper Left** of the rectangular area chosen for the training sample (e.g., (506056.0E, 0214860.0N)).

3) The **Size** of the training sample measured in number of pixels across (W–E) by number of pixels down (N–S) (e.g., (0011, 0009)).

4) The number of **Pixels** included in the training sample (e.g., 324).

5) The habitat **Class** e.g. water

6) The **Mean TD,** which is the mean (average) Transformed Divergence between the spectral signature for that training sample and the other training samples for that class. The mean TD values provide some guidance as to whether training samples are unusual or atypical (Bilko™, 2000).

Refer to Appendix D for the supervised classification process used in this study.

3.6. Unsupervised classification

Unsupervised classifiers do not use training samples as the basis for classification; rather algorithms cluster pixels in a data set based on statistical relationships. These algorithms examine the pixels in an image and assign them to a class, based on the natural grouping or clustering of the digital number values. The basic premise is that values within a given cover type should be close together in measurement space, whereas data in different classes should be well separated (Mather, 1999).

In Bilko™, the unsupervised classification generates a Classifying table and a Classifying image in a similar way to the supervised classification. Bilko™ uses a *k-means clustering* procedure as described in Mather (1999). This can be useful in identifying locations of spectrally similar areas on images and planning ground-truthing surveys based on these.

Refer to Appendix E for the unsupervised classification used in this study.

Summary

The methodology presented here takes into account ground truth data as well as object-oriented classification. The ground truth data was conducted to verify the classification to a certain extent. It requires the use of onscreen digitizing to obtain surface area values. Creating polygons in this manner has to be done on a case-by-case basis. This is suitable when only a few polygons are required but is not appropriate when attempting to quantify numerous dams across the study area.

The object-oriented approach addresses this challenge, as the classification is semi-automatic. Although this sort of classification allows for the exclusion of rock outcrops, other misclassifications may occur.

The object oriented classification begins with image segmentation. Image segmentation is the crucial process whereby homogenous areas are grouped by polygons or segments; resulting in segments of varying size where larger segments are in homogeneous areas while smaller segments are in areas of high variability. Image classification strongly depends on the quality of segmentation. Thereafter, various ratios and image object information was explored for classifying each image subset. The algorithm b+g/b-g and mean brightness was found to be most useful in classifying multi-spectral imagery.

For comparison, supervised and unsupervised classification was also run on the SPOT scenes. In general, the examples of maximum likelihood classification display a better representation of water bodies in the area. Since fieldwork was conducted for this study, supervised classification is more appropriate than unsupervised classification. Subtle differences between the crop types are not revealed by unsupervised classification, in general distinct habitats such as water and built-up areas form identifiable clusters.

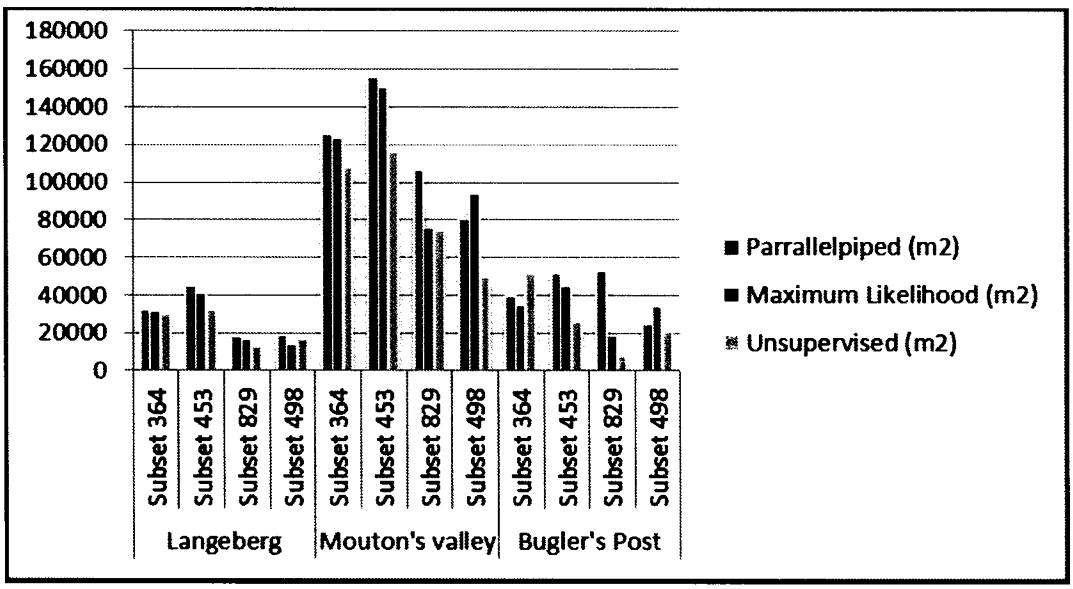

Figure 4: Surface area results for supervised and unsupervised classification

Table 4: Comparison of surface area using Supervised and Unsupervised Classification

		Parallelpiped (m^2)	Maximum Likelihood (m^2)	Unsupervised (m^2)
Langeberg	Subset 364	32210	31530	30420
	Subset 453	45200	40830	32540
	Subset 829	18220	17120	12860
	Subset 498	18950	14110	17130
Mouton's valley	Subset 364	125630	123320	108100
	Subset 453	156100	150320	115910
	Subset 829	106930	76110	74871
	Subset 498	80551	94220	49530
Bugler's Post	Subset 364	39640	34860	51743
	Subset 453	51850	44972	26210
	Subset 829	53210	18740	7964
	Subset 498	24874	34010	20645

In Figure 4 and Table 4 we can see that the values for supervised classification are closer aligned than the values for unsupervised classification, particularly with image subsets 364 and 453. In general, unsupervised underestimates the value for surface area, with a few exceptions. It is also noted that the values for Bugler's Post show the most variation across the image subsets. The results for image subset 498 are consistently lower in comparison. This may be due to the image being captured in later summer.

The results for surface area and volume that were obtained from these classifications are presented in the next chapter.

Chapter 4

Results and Analysis

4.1 Introduction

This section begins with an analysis of the relationship between the fieldwork data and the results obtained from object-oriented classification, referred to as the satellite data in section 4.2.1, to determine whether there is a good linear fit between the two data sets.

All the results for 'volume per image' subset across the different classification methods are provided. Using correlation statistics, general observations were made for these results and the analysis proceeds together with a discussion on the differences between the various findings for each dam.

As highlighted in Chapter 3, a limitation of object oriented classification is that the results for surface area will be strongly influenced by segmentation. Similarly, Bilko™ classification may be influenced by the manual selection of training samples that introduces a possibility of human error.

4.2 Determining storage volume

The 3-D Analyst feature in ArcGIS™ uses interpolation to estimate the surface area and volume (Table 4 in Chapter 3). This was achieved by substituting the surface area value, as discussed in Chapter 3, into the selected equation, where $\boldsymbol{C = 0.023 * A^{1.33}}$ (Sawunyama *et al.* 2006) and $\mathbf{V = 8.52 * Area^{1.437}}$ (10^{-3} m^3) (Van de Giesen *et al*, 2004) to determine the volume of water stored in farm dams.

Sawunyama *et al.* (2006) assume general characteristics of the farm dam in terms of topography, geology, size and maximum depths led to one general equation to establish capacity in terms of its relationship to surface area. Van de Giesen *et al*, (2004) uses generral the equation constants based on gradient of the farm dam. These characteristics all have bearing on possible errors implicit in the final equation.

The relationship between the fieldwork data and the object oriented image classification data was considered, before the volumes across all image subsets for each dam was calculated,

4.2.1. The relationship between fieldwork and image classification results

The recorded point data was uploaded to ArcMap™ to display the results on the SPOT XS image for the study area. Polygons were created from onscreen digitizing to represent the dams so that values for the surface area of the respective dams could be calculated. Thereafter, triangulated irregular networks (TINs) were created for each dam to interpolate the bathymetry of the dams for a volume estimate (refer to the Figures that follow).

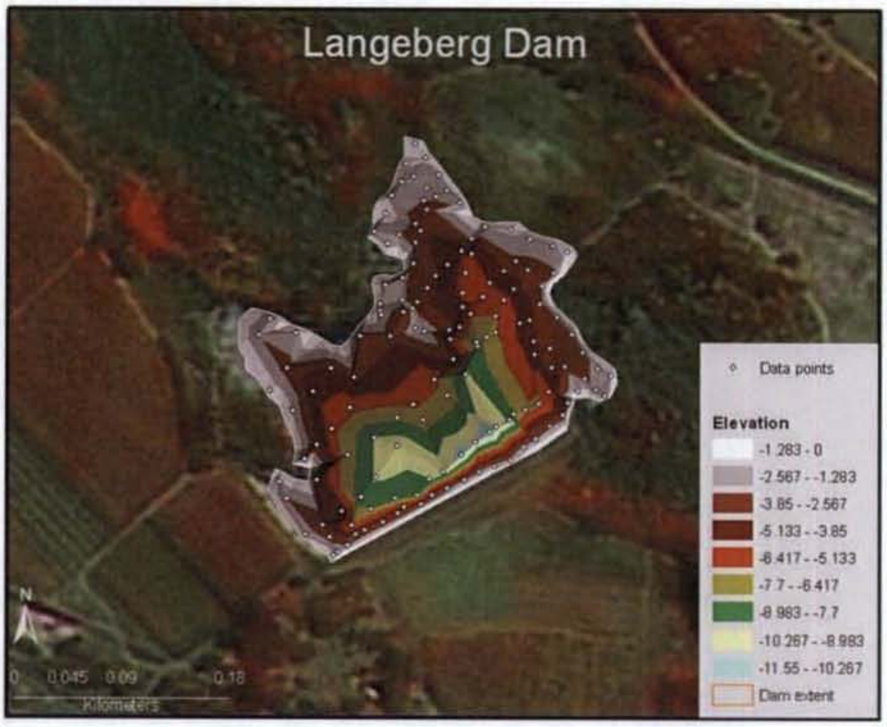

Figure 5: Polygon and TIN for Langeberg dam

The digitized polygon of the water body surface layer and the TIN that was derived from the bathymetric interpolation layer, were used to establish the area of the surface and volume of water in each dam in ArcMap™ 3-D Analyst feature. These calculated values are listed in Table 5.

Table 5: Surveyed dams with their calculated surface areas and volume determined by TIN

Farm Dam	**Date of Survey**	**No. of Records**	**Surface Area (m^2) ArcMap™**	**Volume (m^3) from TIN**
Langeberg	20-11-07	151	54 970	239 166
Bugler's Post	02-04-08	183	31 520	96 594
Mouton's Valley	11-04-08	155	129 420	316 749

There are two limitations in the development of these polygons in ArcGIS™:

- The polygons do not account for any rock outcrops or vegetation that may be present within the boundaries of the polygon i.e. dam; and
- Onscreen digitising can be a subjective approach to the estimation of area because the user decides which pixels to include in the creation of polygons, for example, dense vegetation could be misinterpreted as water and vice versa. Nevertheless, the ground truth data provides a useful estimate for surface area and volume of water stored.

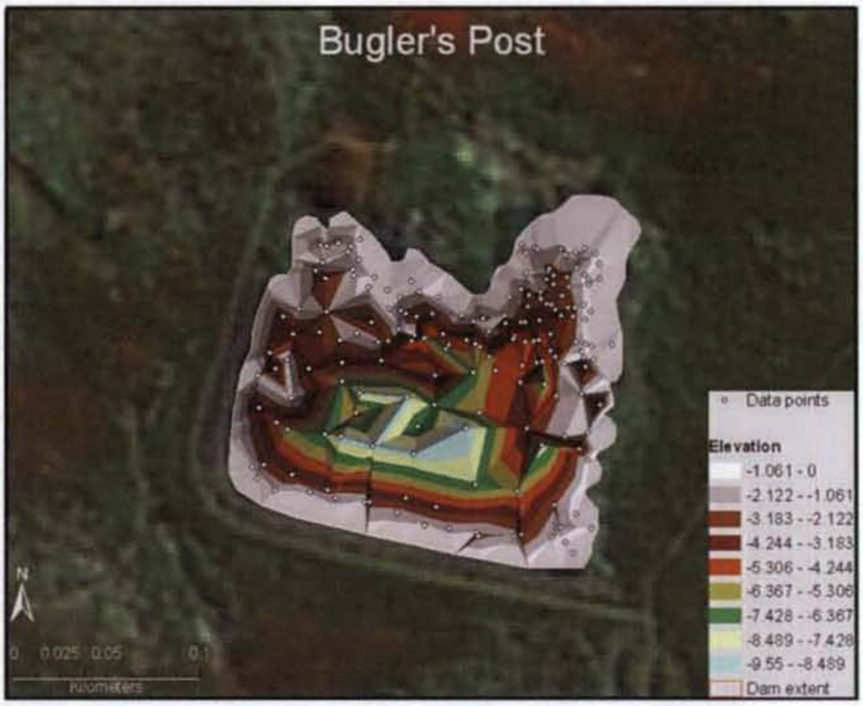

Figure 6: Polygon and TIN for Bugler's Post dam

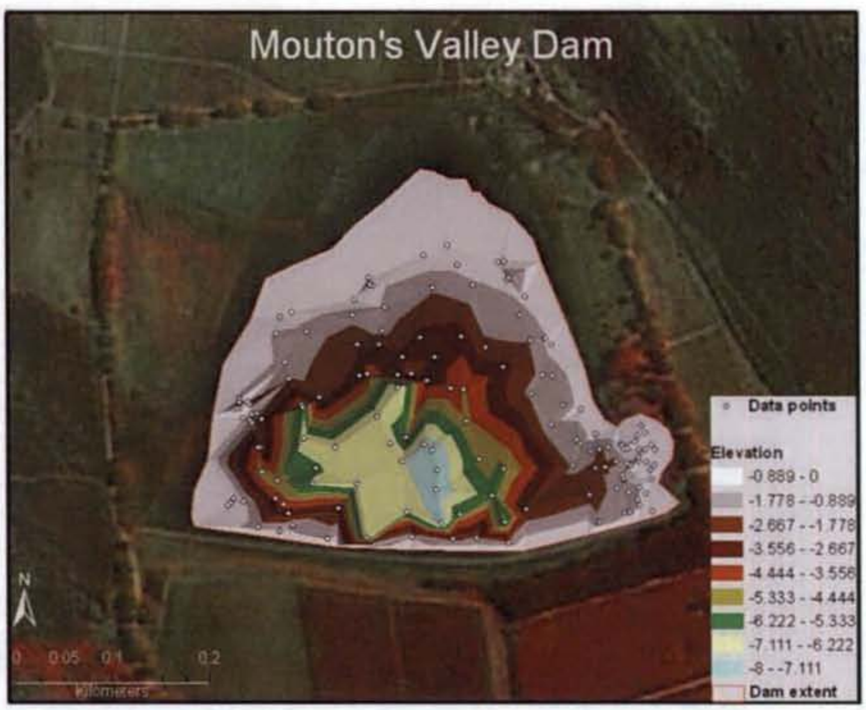

Figure 7: Polygon and TIN for Mouton's Valley dam

Some minor problems were encountered in the ground truth exercise. The classification did not completely match the fieldwork results as illustrated in Figures 5 to 7. However, the classification process produced a satisfactory result in that it identified water bodies in the study area and provided a relatively good indication of surface area. Since the SPOT image used for the pilot study area was captured in January 2005 and fieldwork conducted between November 2007 and April 2008, a variations are to be expected; probably due to annual precipitation and vegetation growth. An improvement in the accuracy could be achieved if the fieldwork was conducted at the same time of year that the image was captured.

In Figures 2 and 5, the fieldwork exercise for the Langeberg dam accounts for a larger surface area than the object-oriented classified. Differences in volume may also be related to natural variations in inflow and seepage (Van de Giessen, 2004). Another anomaly in the classification was observed in the case of the Langeberg dam where part of the dam wall was classified as water.

The Normalized Difference Area index (NDAI) adapted from Liebe (2002) and the Deviation Area Index (DAI) adapted from Sawunyama *et al.* (2005) were used to compare the surface area measured by satellite and in the field.

NDAI and DAI are defined as follows:

$$\mathrm{NDAI} = \frac{(\mathrm{Area}_{\mathrm{field}} - \mathrm{Area}_{\mathrm{sat}})}{(\mathrm{Area}_{\mathrm{field}} + \mathrm{Area}_{\mathrm{sat}})}$$

$$\mathrm{DAI} = \frac{(\mathrm{Area}_{\mathrm{field}} - \mathrm{Area}_{\mathrm{sat}})}{\mathrm{Area}_{\mathrm{field}}}$$

The NDAI value lies between -1 and 1 where values close to zero give the best linear fit between the surface areas obtained from field work and the image classification. A negative value implies that $\mathrm{Area}_{\mathrm{field}} < \mathrm{Area}_{\mathrm{sat}}$ and vice versa.

The DAI values also lie between -1 and 1, with values close to 0 giving the best linear fit between the field work and the image classification. A negative value implies that $\mathrm{Area}_{\mathrm{field}} < \mathrm{Area}_{\mathrm{sat}}$ and vice versa. These values are included in Table 6 below.

Table 6: Fieldwork and object oriented image classification

	Langeberg	Mouton's Valley	Bugler's Post
eCognition Area (m^2)	45040	124200	33310
ArcGIS Area (m^2)	54970	129420	31520
NDAI	0.09929	0.020581973	-0.027610674
DAI	0.180644	0.040333797	-0.05678934
Std. Dev. for surface area	0.702157	0.36911	0.126572

The results obtained from the NDAI and DAI show that there is a good linear fit between the two data sets. This relationship is confirmed by the correlation coefficient (0.9937) for surface area for the three dams. The negative NDAI and DAI values for Bugler's Post implies that the $Area_{field}$ < $Area_{sat.}$ A possible reason for the under estimation of the fieldwork data may be due to the time of year that the fieldwork being conducted in summer which coincides with high evaporation rates and maximum irrigation.

A regression analysis was conducted for the respective surface area values obtained in ArcMap™ and eCognition™. Table 6 shows that the values are not significantly different. All the standard deviations were low and fall within one standard deviation of the mean. This means that there is significance between the values for surface area using eCognition™ compared to the value obtained by the fieldwork exercise.

4.2.2 Comparison of results for volume of water stored

The values for volume stored obtained from the objected-oriented classification was then applied to the other image subsets and compared to the results obtained from the Bilko™ classification.

A summary of all the results is provided in Table 7.

Table 7: Summary of image subsets across all the dams

Image Subset	Equation/Classification Type	Langeberg	Mouton's Valley	Bugler's Post
364	Sawunyama eCognition	38931	185380	36692
	Van de Giessen eCognition	45720	246831	42886
	Sawunyama parallelpiped	22770	139162	30009
	Van de Giessen parallelpiped	25611	181066	34511
	Sawunyama maximum likelihood	22133	135770	25294
	Van de Giessen maximum likelihood	24837	176301	28692
	Sawunyama unclassified	21102	113950	42771
	Van de Giessen unclassified	23591	145897	50611
829	Sawunyama eCognition	36534	166813	24029
	Van de Giessen eCognition	42685	220230	27144
	Sawunyama parallelpiped	10673	112313	44391
	Van de Giessen parallelpiped	11294	143633	52686
	Sawunyama maximum likelihood	9824	71457	11079
	Van de Giessen maximum likelihood	10327	88119	11760
	Sawunyama unclassified	6715	69914	3550
	Van de Giessen unclassified	6846	86065	3438
453	Sawunyama eCognition	48362	173378	35417
	Van de Giessen eCognition	57795	229610	41278
	Sawunyama parallelpiped	35732	185760	42889
	Van de Giessen parallelpiped	41675	247378	50761
	Sawunyama maximum likelihood	31213	176669	35493
	Van de Giessen maximum likelihood	36009	234322	41373
	Sawunyama unclassified	23080	125028	17310
	Van de Giessen unclassified	25989	161280	19045
498	Sawunyama eCognition	30321	102901	19322
	Van de Giessen eCognition	34900	130673	21448
	Sawunyama parallelpiped	11245	77055	16146
	Van de Giessen parallelpiped	11959	95601	17666
	Sawunyama maximum likelihood	7596	94916	24477
	Van de Giessen maximum likelihood	7822	119750	27692
	Sawunyama unclassified	9832	40355	12602
	Van de Giessen unclassified	10336	47530	13515

A few general observations of Table 7 include, but are not limited to:

- eCognition™ estimates the largest value for surface area across all farm dams and subsequently estimates the largest volumes of water stored;
- Van de Giesen *et al.* (2004) equation renders higher estimates for volume of water stored than the Sawunyama (2006) equation (refer to Figures 8-10);
- Image subsets 829 and 364 yield results closer to the ground truth exercise than the other classification methods;
- Parallelpiped classification renders slightly higher results than maximum likelihood; however, the estimates given under the two supervised classifications show no significant difference;

• Unsupervised classification produced relatively low estimates for surface area across all three dams. The surface areas to volume conversions are therefore relatively low;
• The results for image subset 498 are all lower than the fieldwork estimates.

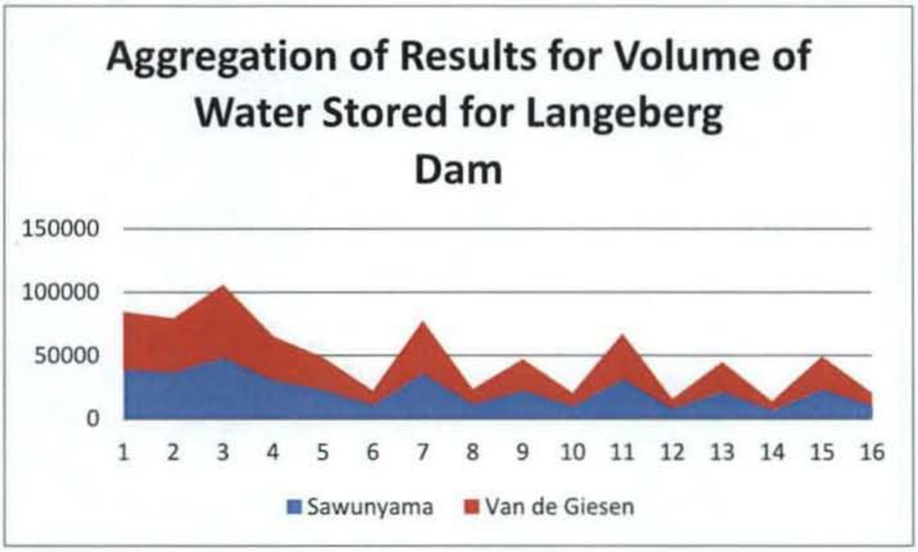

Figure 8: Aggregation of results for volume of water stored for Langeberg dam

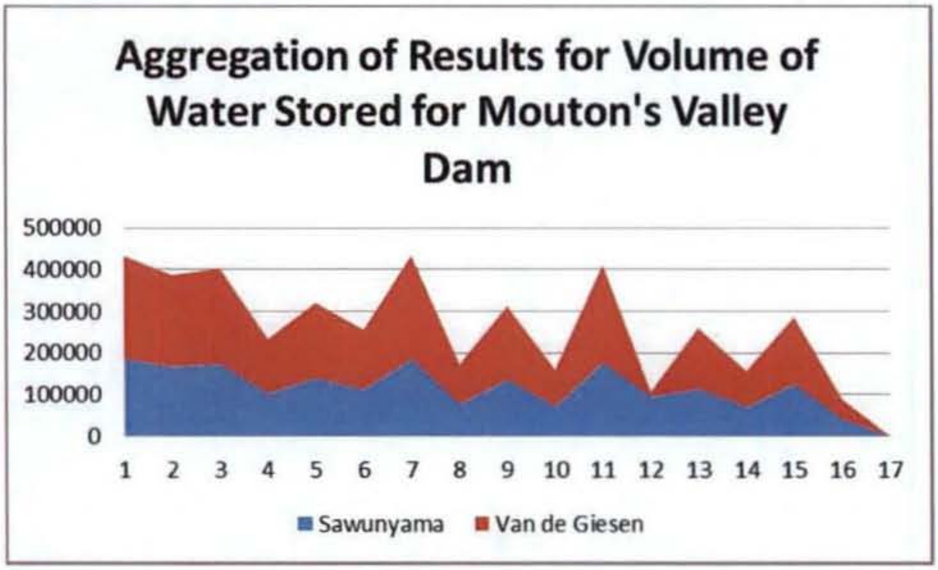

Figure 9: Aggregation of results for volume of water stored for Mouton's Valley dam

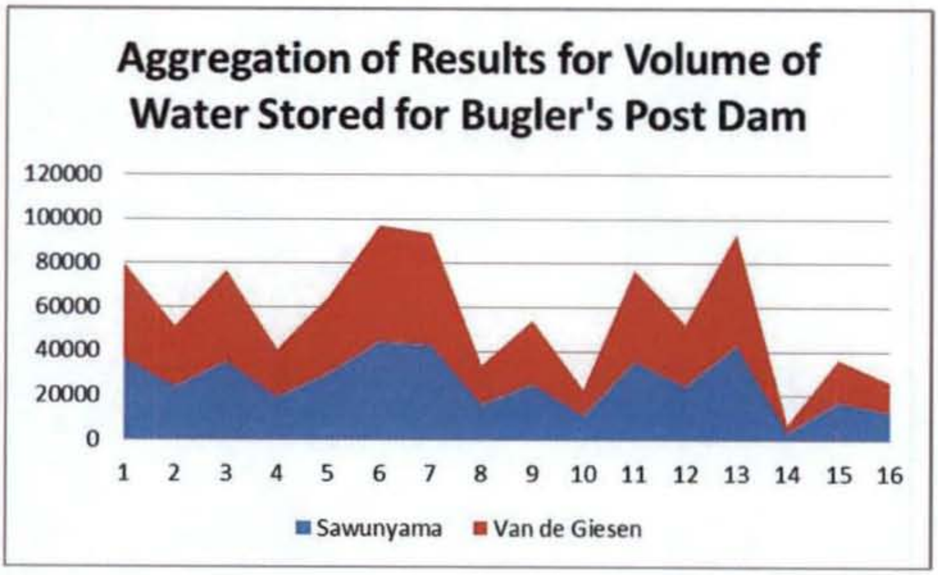

Figure 10: Aggregation of results for volume of water stored for Bugler's Post dam

For all the image subsets, the Van de Giesen *et al.* (2004) equation results in a larger volume estimate compared to the Sawunyama *et al.* (2006) equation. According to Smith *et al.* (2002), landscape characteristics that have been hypothesized to contribute to pixel misclassification include high land cover heterogeneity, small patch size and convoluted shapes. Relief plays an important role regarding possible dam construction. On the one hand, dam construction necessitates a certain landscape roughness, whilst homogeneous relief properties are of great importance to the feasibility and success of a surface area to volume relationship. However, as long as the surface roughness is approximately constant, the presence of area volume relations is expected. If Liebe (2005) is considered, applying one formulae across a catchment as diverse as in this study (G10K) then inaccuracies are expected. If the topography of the study area used by Liebe (2002) (which was used to develop the Van de Giesen *et al.* (2004) formula) is compared with the G10K catchment, the dissimilarity is very apparent. The differences in topography are given in the Table 8 below.

Table 8: Differences in topography between G10K catchment and the Ghanaian study area

	G10K	Liebe (2002) study area
Minimum elevation (m)	17	122
Maximum elevation (m)	1132	455
Mean elevation (m)	174	197
Standard deviation (m)	207	35.33
Average slope angle (°)	5.45	0.49
Total area (km²)	1260	8689

Source (Liebe, 2002)

If an accurate estimation of dam volume is required, it is therefore necessary to work only within topographically homogenous areas, conduct extensive field surveys to establish the relationship (and therefore a formula) between surface area and volume and apply the formula to remaining dams in the area. It is possible that formulae may be used between regions that are homogeneously similar however; this would need to be tested.

These general observations are noted nevertheless the analysis proceeds by discussing the differences between the various findings for each dam. There appears to be a strong positive correlation between object-oriented classification and unsupervised classification for Tables 9-14. Therefore, the results will not be discussed further here. The discussion that follows will be a comparison of object-oriented classification and supervised classification.

Table 9: Pearson Correlation of different classification methods for Langeberg dam (Sawunyama (2006) method)

Classification Type	Parallelpiped	Maximum Likelihood	Unsupervised
eCognition	0.9279	0.9398	0.7723

Table 10: Pearson Correlation of different classification methods for Langeberg dam (Van de Giesen *et al.* 2004 method

Classification Type	Parallelpiped	Maximum Likelihood	Unsupervised
eCognition	0.9307	0.9413	0.7773

In Table 9 and 10, there is a very strong positive association between object-oriented classification and the supervised classification methods.

Table 11: Pearson Correlation of different classification methods for Mouton's Valley dam (Sawunyama, 2006 method)

Classification Type	Parallelpiped	Maximum Likelihood	Unsupervised
eCognition	0.7607	0.4391	0.8586

The associations provided in Table 11 are not as strong as in the Table 9 and 10. There are outliers for the supervised classification that may have attributed to these correlation statistics (refer to Table 7). For the parallelpiped classification, these values are 77 055m^3 and 112 313m^3, obtained from image subsets 498 and 829 respectively. For the maximum likelihood classification, the values are 94 916m^3 and 71 457m^3, obtained from image subsets 498 and 829 respectively. The correlation between object oriented classification and unsupervised classification are stronger here.

Table 12: Pearson Correlation of different classification methods for Mouton's Valley dam (Van de Giesen *et al.* 2004 method)

Classification Type	Parallelpiped	Maximum Likelihood	Unsupervised
eCognition	0.7632	0.8303	0.8540

The correlation coefficients in Table 12 show strong positive associations. As can be seen in Table 7, possible outliers for parallelpiped classification may be 247 378m^3 and 95 601m^3, obtained from image subsets 453 and 498 respectively.

A possible outlier for maximum likelihood classification may be 88 119m^3, obtained from image subset 829.

Table 13: Pearson Correlation of different classification methods for Bugler's Post, using Sawunyama (2006) equation to determine volume

Classification Type	Parallelpiped	Maximum Likelihood	Unsupervised
eCognition	0.4363	0.5589	0.7219

Table 14: Pearson Correlation of different classification methods for Bugler's Post (Van de Giesen et al. 2004 method)

Classification Type	Parallelpiped	Maximum Likelihood	Unsupervised
eCognition	0.4242	0.5642	0.7223

The correlation coefficients for supervised classification in Table 13 and 14 show little or no association. Possible outliers for parallelpiped classification may be 52 686m^3, 50 761m^3, 16 146m^3 and 17 666m^3. These values were obtained from image subsets 823, 453 and 498 respectively. Possible outliers for maximum likelihood classification may be 11 760 and 11 709m^3, obtained from image subset 829. (Refer to Table 7).

4.3 Comment on segmentation

Segmentation is the first step towards object oriented classification. It was shown that scale parameters for segmentation cannot be generalised for all imagery. Each image must be segmented into image objects with scale parameters that work best for the respective image as classification strongly depends on the quality of segmentation. Despite this being a trial and error process, segmentation is not excessively time-consuming. The selection of training samples for the Bilko™ classification is arguably more laborious since the training samples have to be manually selected. eCognition™ intelligently segments the image subsets to a level that is usable for the purposes of classifying water bodies; however, should image objects overlap with other land cover types there is an option of changing the scale parameter to yield relatively smaller image objects. Once the water bodies have been successfully classified, the image objects can be merged so that farm dams are exported as single image objects, with their associated surface area values.

4.4 Comment of classification

The band ratio b+g/b-g and mean brightness were found to be most suitable in classifying multi-spectral imagery. Depending on the image properties, classification could be further refined using various object feature information provided in eCognition™.

Land cover heterogeneity contributes to misclassification of pixels because classification requires fine spatial resolution imagery. Despite the resolution of the SPOT XS imagery, the development of the classification process revealed that that there is always a certain level of error particularly with "mixed pixels" near the edges of the water bodies, for example, the partial misclassification of the Langeberg dam wall or shadows on the high mountain slopes. Areas of error that may exist, but are of no significant consequence, can be manually deleted from the result at the discretion of the user. It is noted that compensating for one misclassification may often lead to a misclassification of a different image object. The classification was kept accepted, given the results of standard deviation.

Object-oriented classification produced results for surface area and volume estimates that were closest to the fieldwork results. This may be due to how the eCognition™ segments the imagery into image objects, implying that the method deals with heterogeneity relatively effectively.

Provided that the fieldwork is a sound representation of reality, supervised classification underestimates the surface area of water bodies and thus yields a result for the volume of water stored that is not representative of reality.

Subtle differences between the crop types are not revealed by unsupervised classification. In general distinct habitats such as water and built-up areas form identifiable clusters and in most cases Mouton's Valley is easily identified.

The conversion for image subsets 453 and 498 largely underestimated the surface area of water bodies, subsequently affecting the estimate for volume estimates. A possible reason for the differences is in the seasonality as found in image subsets 364, 829 and 161 which were captured in the month of January (of different years). Image subset 498 was captured in March when the dams might be drier towards the end of summer. Sedimentation is another factor that the method does not take into account. The level of sedimentation is likely to influence the volume of water stored, which may differ from the volume at full capacity as required by the WARMS database.

4.5 WARMS database

The results of the various volume estimations (from field work using a TIN and formulae from the literature) are compared with the WARMS registered volumes for the selected dams and shown in Figure 11.

be used between regions that are homogeneously similar however; this would need to be tested.

These general observations are noted nevertheless the analysis proceeds by discussing the differences between the various findings for each dam. There appears to be a strong positive correlation between object-oriented classification and unsupervised classification for Tables 9-14. Therefore, the results will not be discussed further here. The discussion that follows will be a comparison of object-oriented classification and supervised classification.

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Provided that the fieldwork is a sound representation of reality, supervised classification underestimates the surface area of water bodies and thus yields a result for the volume of water stored that is not representative of reality.

Subtle differences between the crop types are not revealed by unsupervised classification. In general distinct habitats such as water and built-up areas form identifiable clusters and in most cases Mouton's Valley is easily identified.

The conversion for image subsets 453 and 498 largely underestimated the surface area of water bodies, subsequently affecting the estimate for volume estimates. A possible reason for the differences is in the seasonality as found in image subsets 364, 829 and 161 which were captured in the month of January (of different years). Image subset 498 was captured in March when the dams might be drier towards the end of summer. Sedimentation is another factor that the method does not take into account. The level of sedimentation is likely to influence the volume of water stored, which may differ from the volume at full capacity as required by the WARMS database.

4.5 WARMS database

The results of the various volume estimations (from field work using a TIN and formulae from the literature) are compared with the WARMS registered volumes for the selected dams and shown in Figure 11.

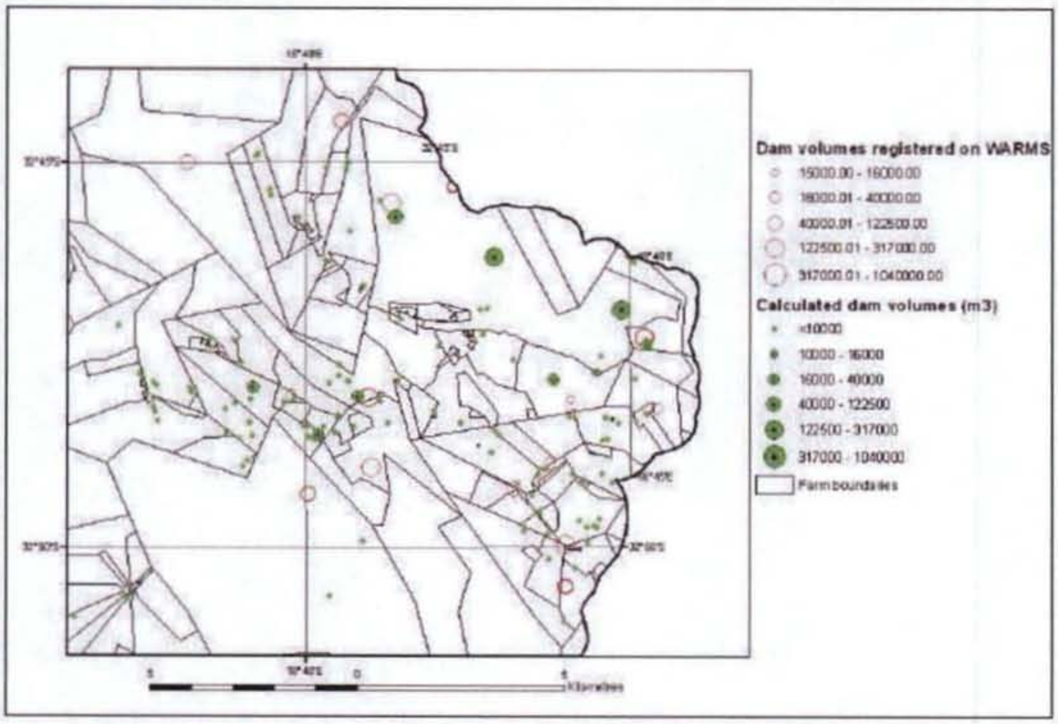

Figure 11: WARMS registration vs. calculated dam volumes

There is a similarity between the WARMS registered value and the volumes calculated from the surface area to volume formulae, than between the WARMS registered value and the TIN calculated from field work. This is explained by:

1. The volume obtained from the TIN is the closest to reality and the volumes registered in WARMS are too low and either (a) WARMS volumes are coincidentally closer to the volumes calculated using the formula or (b) the farmers have used a surface area to volume formula to calculate dam capacity for WARMS registration. This is unlikely because farmers know the capacity of their dams.

2. The WARMS registered values are correct as they may have been obtained from engineers when the dam was constructed, and (a) the surface area to volume formulae (Van de Giesen *et al*, 2004) has given an accurate value for volume and (b) there were inexplicable errors in the field survey data.

Chapter 5

Conclusion

Remote sensing and GIS can overcome the difficulty in the collection, transfer and sharing of data. The use of these technologies will enhance the efficiency of water resource management. This study found remote sensing to be a rapid and cost-effective way of obtaining information at relatively low temporal and high spatial resolutions. However, remote sensing incurs high start-up costs in terms of training in remote sensing application software, computer hardware requirements and the acquisition of satellite images.

Remote sensing and object-oriented classification was found to be a reasonably effective tool in identifying agricultural dams. Relatively simple classification processes were developed for multiple image subsets to identify farm dams and obtain an estimate for surface area, a key input for volume. Data used for this study included high-resolution satellite imagery to generate a satisfactory result for the heterogeneity of the study area. This is important in the context of this study as change in surface area has a direct effect on volume of water stored and consequently the legal status of water stored. The object-oriented approach allows for contextual information to be taken into account to improve the quality of classification. The results showed that there is a similarity between the fieldwork and object-oriented classification data for surface area.

Two equations applied to determining the capacity of dams were used to convert surface area to volume. The equations make use of surface area and a constant as inputs so implicit assumptions and errors may exist. For all the image subsets, the Van de Giesen *et al.* (2004) equation results in a higher volume estimate compared to the Sawunyama *et al.* (2006) equation. If an accurate estimation of dam volume is required, it is therefore necessary to work only within topographically homogenous areas, conduct extensive field surveys to establish the relationship (and therefore a formula) between surface area and volume and apply the formula to remaining dams in the area.

Overall, there appears to be a strong positive correlation between object-oriented classification and unsupervised classification. On the other hand, the correlation between object-oriented classification and supervised classification ranged from strong positive association to little or no association.

This study concludes that in the context of illegal water use, remote sensing is a useful tool in identifying water bodies and generating an estimate of volume stored. It was found that the model works well for the general identification of surface water bodies. However, it is necessary to modify the rule set as the areas of study differ. This is particularly necessary when dealing with a surface area (which affects volume) application as minor discrepancies can result in a significant difference in the value obtained for surface area. There remain some uncertainties as to the assessment of the surface to volume conversions and further research is recommended.

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Appendix A

Background to SPOT satellite system

In 1978 the French Centre National d'Etudes Spatiales (CNES), in partnership with Sweden and Belgium, set up the Satellites Pour l'Observation de la Terre (SPOT) or Earth Satellites remote sensing programme (CNES, 2002; Lillesand *et al.* 2004). The system comprises of a series of spacecrafts and ground receiving stations for satellite control and programming, image production and distribution (CNES, 2002). The SPOT V ground receiving station in South Africa is based at Hartebeeshoek.

The unique features of the SPOT system include high resolution; revisit capability and stereo imaging. These features enable it to acquire data for areas of interest to serve specific applications such as land use change, agriculture, cartography and forestry. The revisit capability is of particular importance as it increases the potential frequency of covering areas where cloud cover may be a problem (CNES, 2002).

The SPOT orbit is circular, polar[4] and sun-synchronous[5] and has the following characteristics:

- **Altitude:** 822 km
- **Inclination:** 98.7 degrees (i.e. near-polar orbit)
- **Revolutions per day:** 14 + 5/26
- **Period:** 101 minutes
- **Westward drift between successive ground tracks:** 2823 km
- **Cycle duration:** 26 days
- **Swath width:** 60 km
- **Orbital revolutions per cycle:** 369 (CNES, 2002)

Furthermore, the SPOT V satellite carries two High-Resolution Geometric (HRG) instruments; a High-Resolution Stereoscopic (HRS) instrument and Vegetation instrument (Lillesand et al. 2004).

The HRG systems provide high spatial resolution:

- 2.5-5m resolution in panchromatic imagery
- 10m resolution in multi-spectral imagery
- 20m resolution in the mid-IR band

[4] Polar Orbit: A satellite orbit in which the satellite passes over the North and South poles on each orbit, and eventually passes over all points on the earth. The angle of inclination between the equator and a polar orbit is 90 degrees.

[5] Sun-synchronous orbit: An orbit in which the satellite's orbital plane is at a fixed orientation to the sun, i.e., the orbit moves about the earth at the same rate that the earth orbits the sun. It has the characteristics of maintaining similar sun angles along its ground trace for all orbits, and typically has an inclination from 96 to 98 degrees, depending on the orbit altitude and orbit shape (eccentricity).

The HRG panchromatic band has two linear arrays with spatial resolution of 5m that can be combined to produce an image with a 2.5m resolution (Lillesand et al. 2004). For the purposes of this study, pan-sharpened multispectral imagery will be used. This ensures the benefit of high spatial resolution along with the spectral benefits of near-infrared characteristics.

The HRS sensors facilitate the production of digital elevation models at a resolution of 10m and allows for off-nadir viewing capabilities (Lillesand et al. 2004).

For the past 20 years, the SPOT system has played a key role in contributing to earth observation data. Satellites can cover vast areas at high resolution and with regular repeatability. Therefore, satellite data can be utilised in applications of cartography, forestry, agriculture, urban planning and natural hazard mapping (CNES, 2002). In agriculture, satellite data can assist in building an inventory of agricultural surfaces. Because of the repeatability of data, harvest forecasts can be estimated. This in turn may have implications for food security in certain areas.

Appendix B

Schedule 1: PERMISSIBLE USE OF WATER (National Water Act of 1998)

(1) A person may, subject to this Act
(a) take water for reasonable domestic use in that person's household, directly from any water resource to which that person has lawful access;
(b) take water for use on land owned or occupied by that person, for -
(i) reasonable domestic use;
(ii) small gardening not for commercial purposes; and
(iii) the watering of animals (excluding feedlots) which graze on that land within the grazing capacity of that land, from any water resource which is situated on or forms a boundary of that land, if the use is not excessive in relation to the capacity of the water resource and the needs of other users;
(c) store and use run-off water from a roof;
(d) in emergency situations, take water from any water resource for human consumption or firefighting;
(e) for recreational purposes
(i) use the water or the water surface of a water resource to which that person has lawful access; or
(ii) portage any boat or canoe on any land adjacent to a watercourse in order to continue boating on that watercourse; and
(f) discharge
(i) waste or water containing waste; or
(ii) run-off water, including stormwater from any residential, recreational, commercial or industrial site, into a canal, sea outfall or other conduit controlled by another person authorised to undertake the purification, treatment or disposal of waste or water containing waste, subject to the approval of the person controlling the canal, sea outfall or other conduit.
(2) An entitlement under this Schedule does not override any other law, ordinance, bylaw or regulation, and is subject to any limitation or prohibition there under.

Appendix C
Investigating segmentation

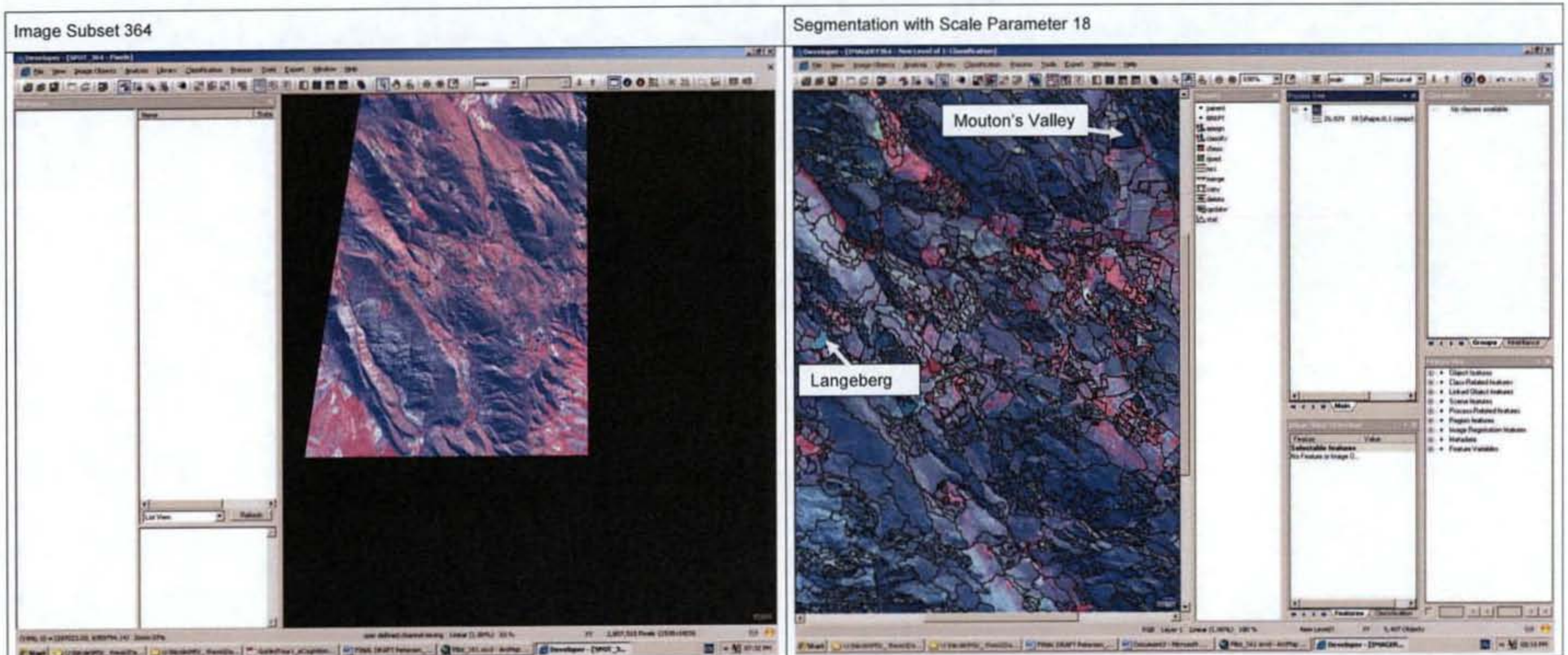


Figure 12: Segmentation of subset 364

For image subset 364, in Figure 12, the scale parameter was set to 18 and was found to be an appropriate value to use. This scale parameter segmented the image to a level where most water bodies were delineated as image objects. The area of these image objects were exported without merging image objects.

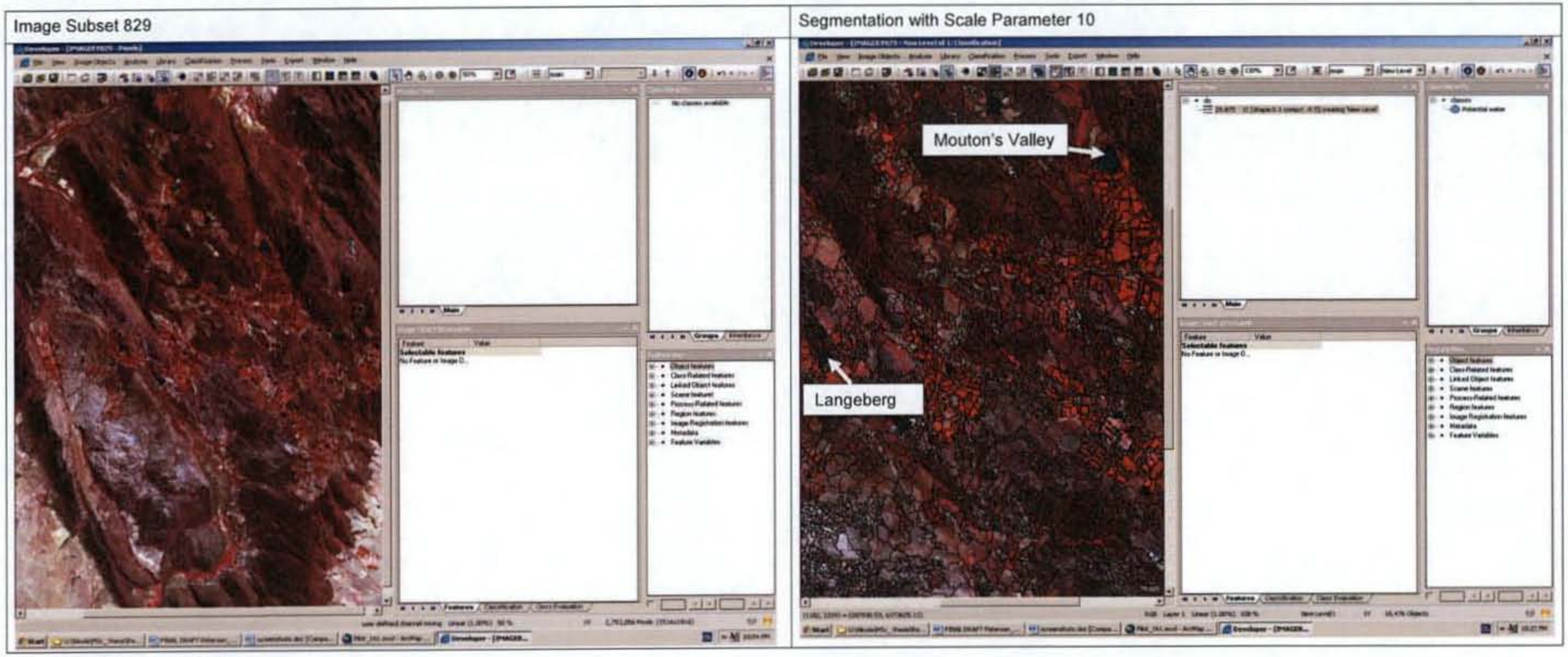


Figure 13: Segmentation of subset 829

In Figure 13, a scale parameter of 18 was found to be too large for image subset 829. Instead, the scale parameter of 10 was more appropriate. Even though the full extent of water bodies were not segmented as image objects, what is important is that the smaller image objects within the boundaries of the water bodies did not overlap with other land use covers. The image objects were classified separately and later merged to form water bodies.

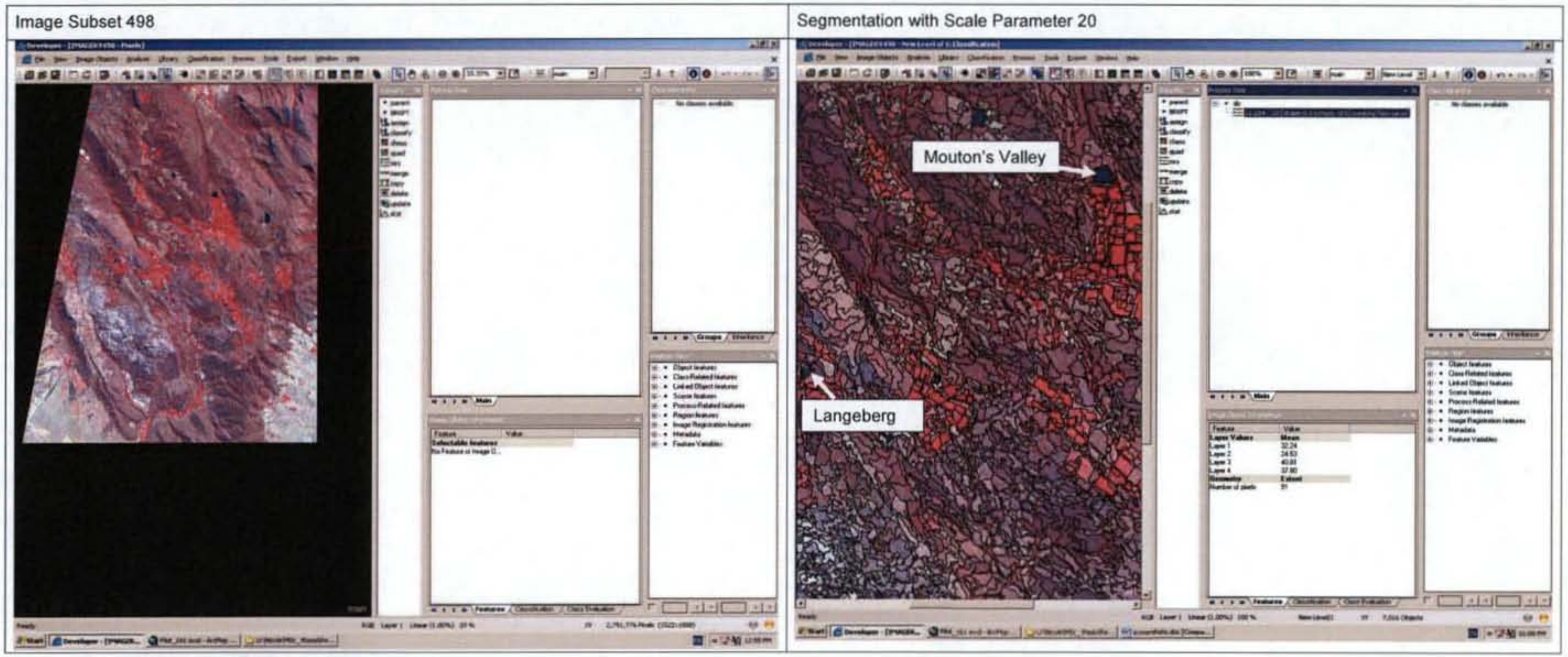


Figure 14: Segmentation of image subset 498 using scale parameter 20

Figure 14 above shows that the other water body bodies are appropriately segmented as single image objects.

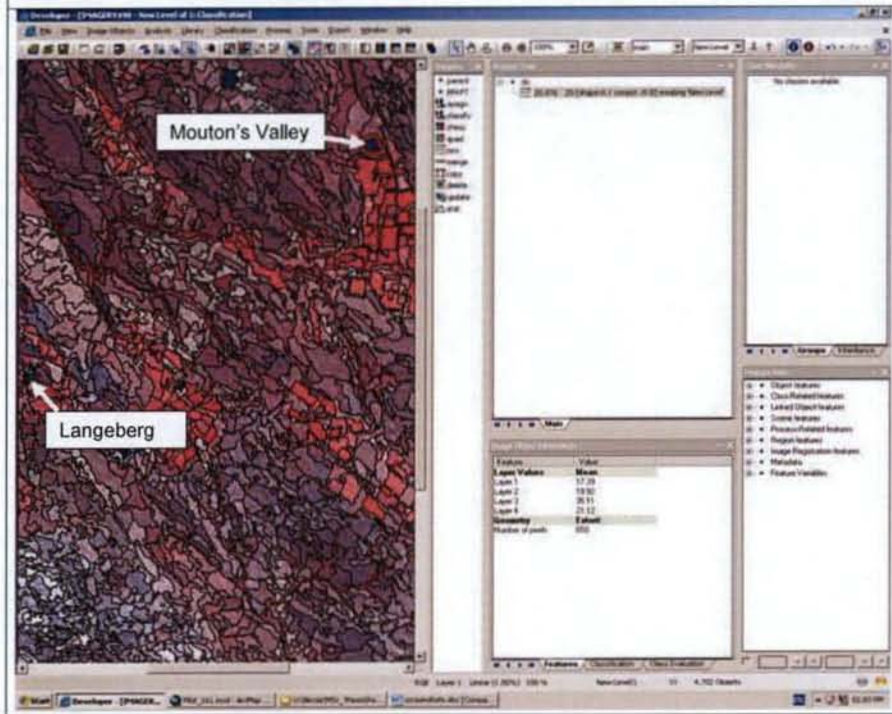
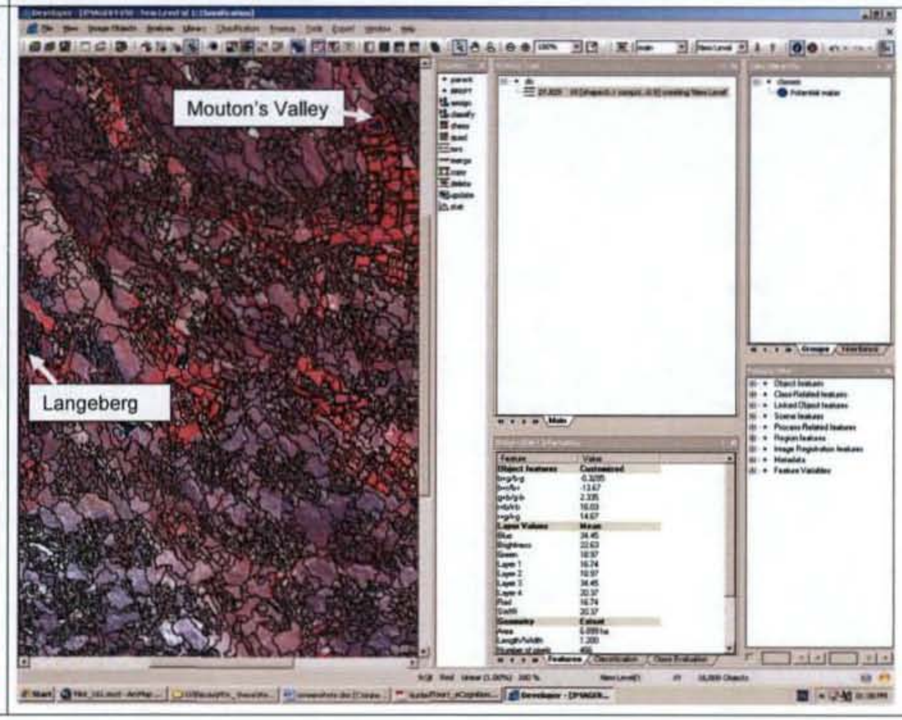
Segmentation with Scale Parameter 25	Segmentation with Scale Parameter 10
	

Figure 15: Segmentation of subset 498 using scale parameter 10

Figure 15 shows how the image is influenced by a scale parameter of 25 versus a scale parameter of10.

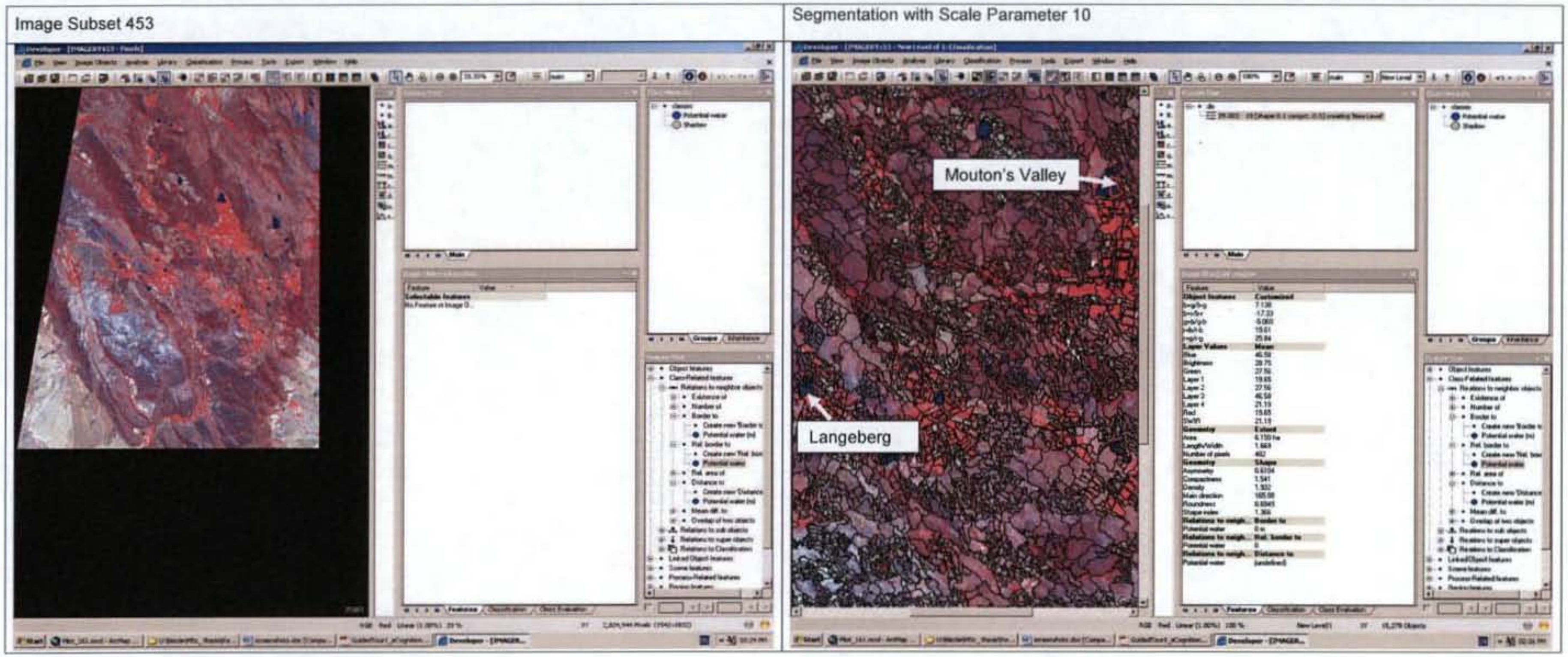


Figure 16: Segmentation of subset 453

In Figure 16 scale parameter 10 creates relatively small image objects. Even though Mouton's Valley dam is segmented into more than one image object which can later be merged, it can be seen that the other water body bodies are appropriately segmented as single image objects.

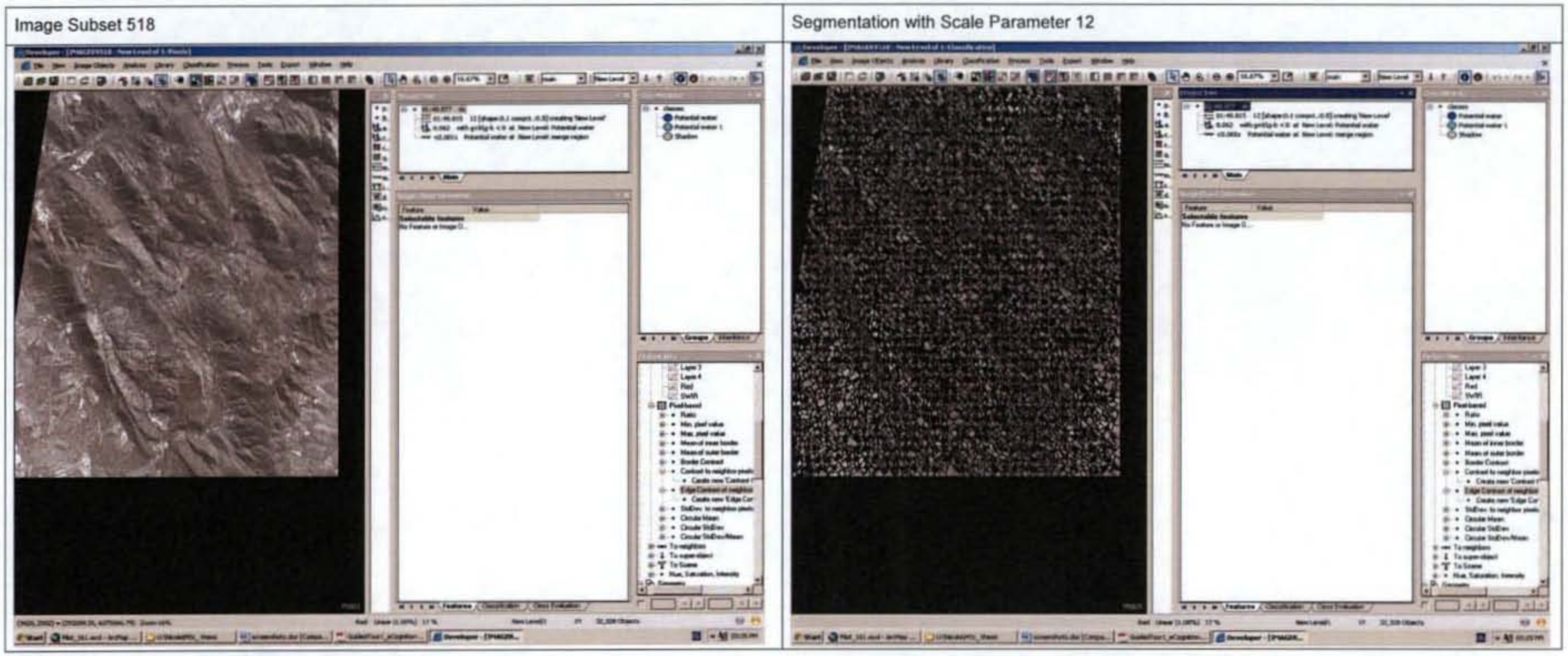


Figure 17: Segmentation of image subset 518 using scale parameter 12

Figure 17 and 18 shows the difference between using a scale parameter of 12 and 15 respectively. It can also be seen that panchromatic images do not distinctly display water bodies from other land covers at this scale in the segmentation process as well as multispectral imagery do.

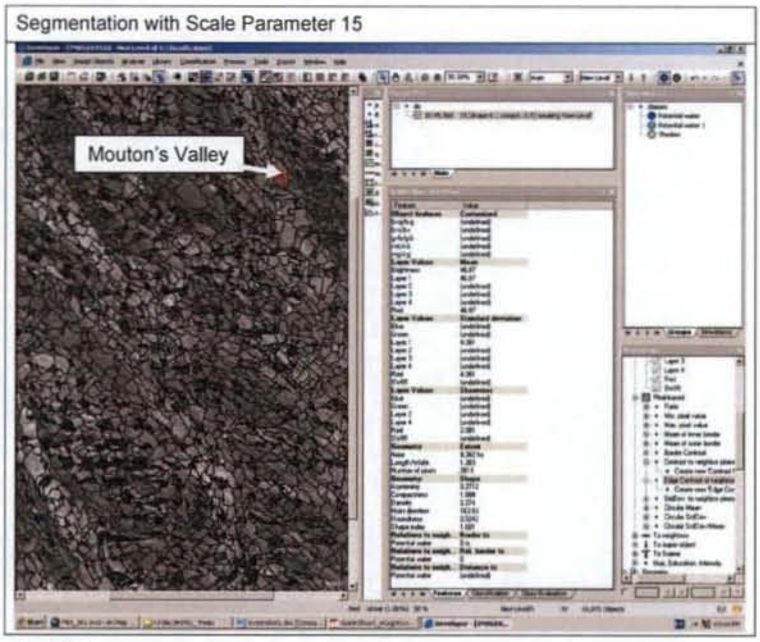


Figure 18: Segmentation of subset 518

Segmentation is the first step towards object oriented classification. It was shown that scale parameters for segmentation cannot be generalised for all imagery. Each image must be segmented into image objects with scale parameters that work best for the respective image as classification strongly depends on the quality of segmentation.

Appendix D
Investigating classification

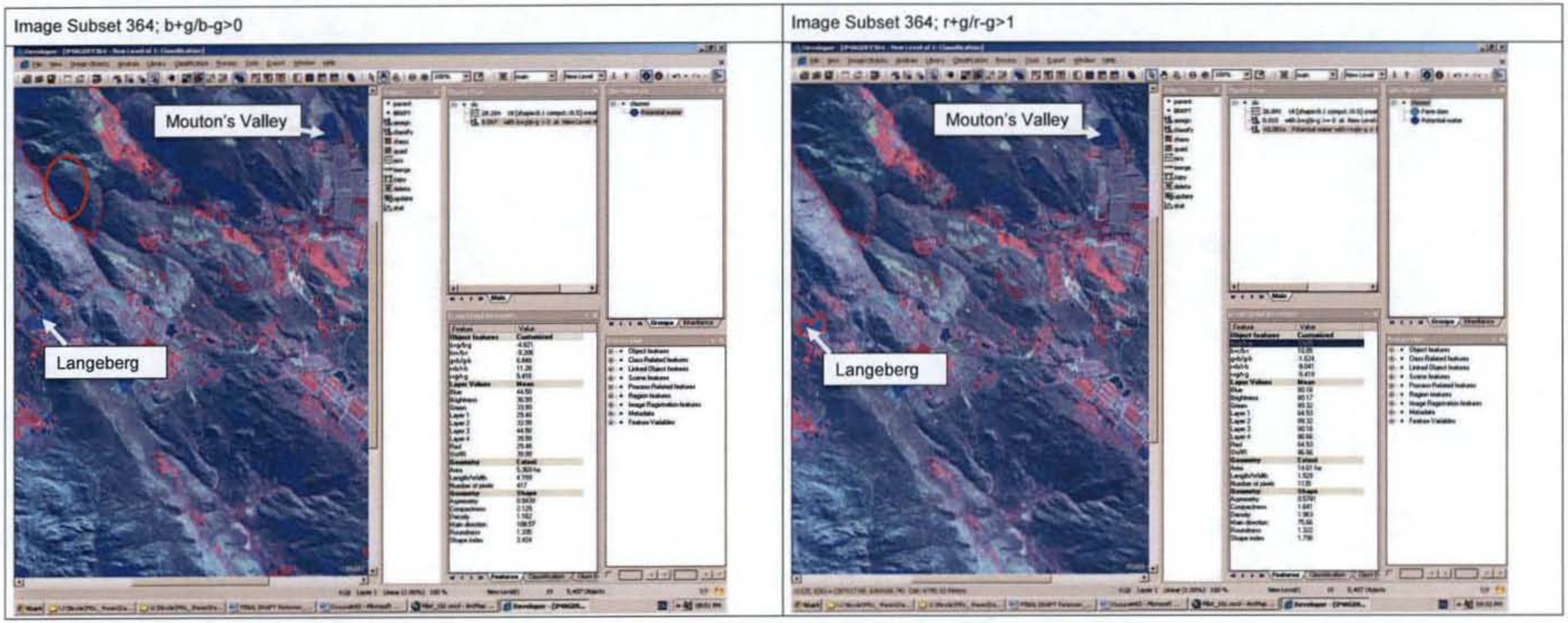


Figure 19: Classification of image subset 364 using ratios and thresholds

The object features were explored for image subset 364. Figure 19 above shows that a useful feature was a ratio of the blue and green bands i.e. b+g/b-g. Using this ratio, a positive value was obtained for most water bodies. A rule was executed where a 'Potential Water' class was assigned to image objects with b+g/b-g > 0. It can be seen that this rule misclassifies shadows on the mountain slopes as Potential Water. In an attempt to rectify the misclassification, other image features were explored. The ratio r+g/r-g>1 maintains the initial water body classification and eliminates a lot of the shadow. The results were exported at this stage and the minor misclassifications on the high slopes were manually removed.

Image Subset 829 b+g/b-g>0

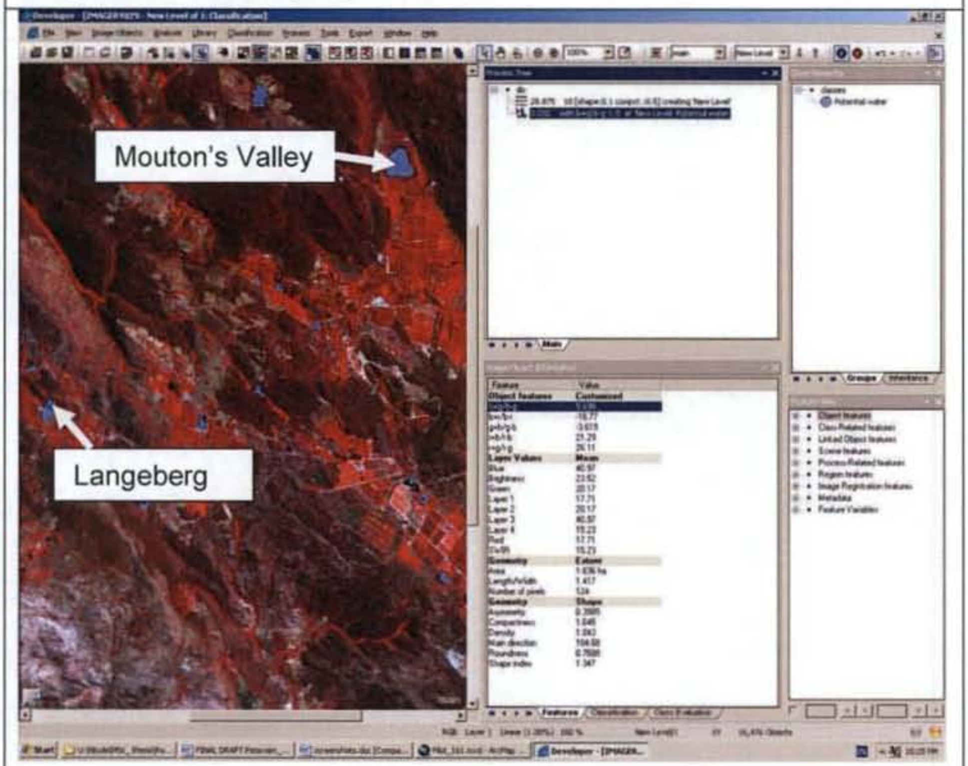


Figure 20: Classification of image subset 829

From the previous example, the ratio b+g/b-g > 0 provided a good starting point for classifying water bodies. Given the similar image object information for this ratio, the ratio was used for image subset 829 and yielded a favourable result, as shown in Figure 20 above. In this case shadows on the steep gradients were classified as Potential Water. The area of the classified image objects was then exported.

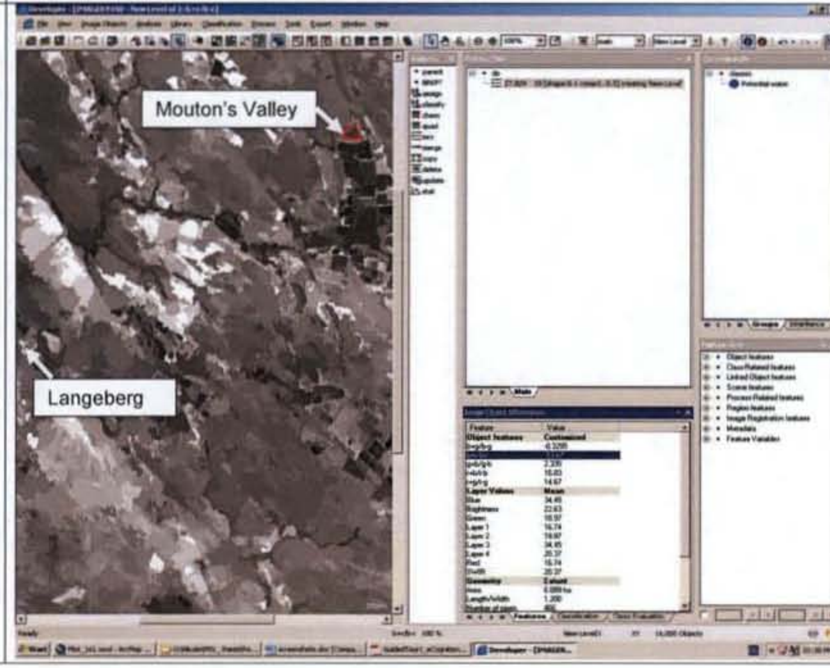
Image Subset 498; b+g/b-g	Image Subset 498;b+r/b-r
	

Figure 21: Classification of image subset 498 using band ratios

In Figure 21, the b+g/b-g ratio proves once again useful as it highlights water bodies as white i.e a low negative feature value. Here Mouton's Valley and Langeberg were easily identified. The ratio b+r/b-r does not display water bodies as clearly. The values for water bodies do not correspond as closely as the previous example. The values for water are not easily identified from other land covers.

Image Subset 498; g+b/g-b

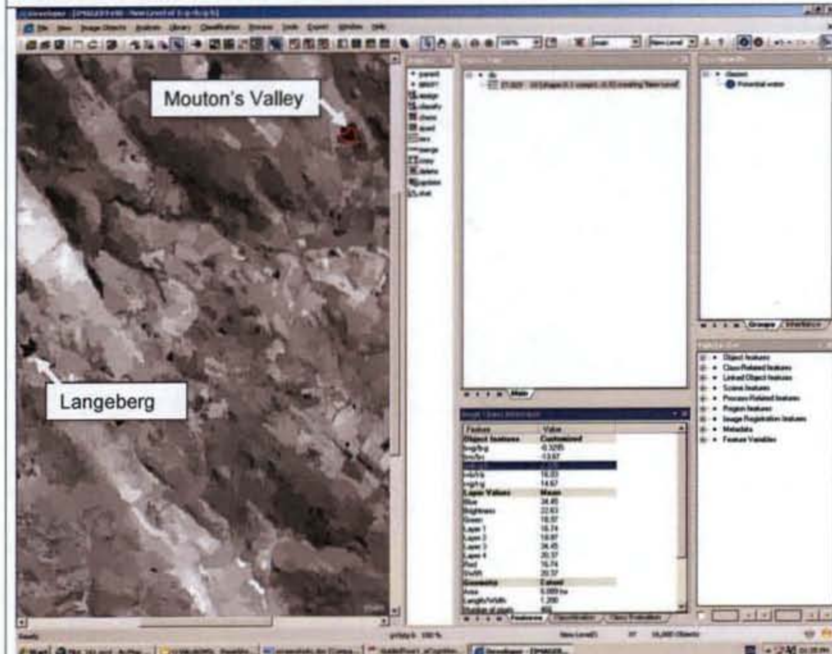


Image Subset 498; r+b/r-b

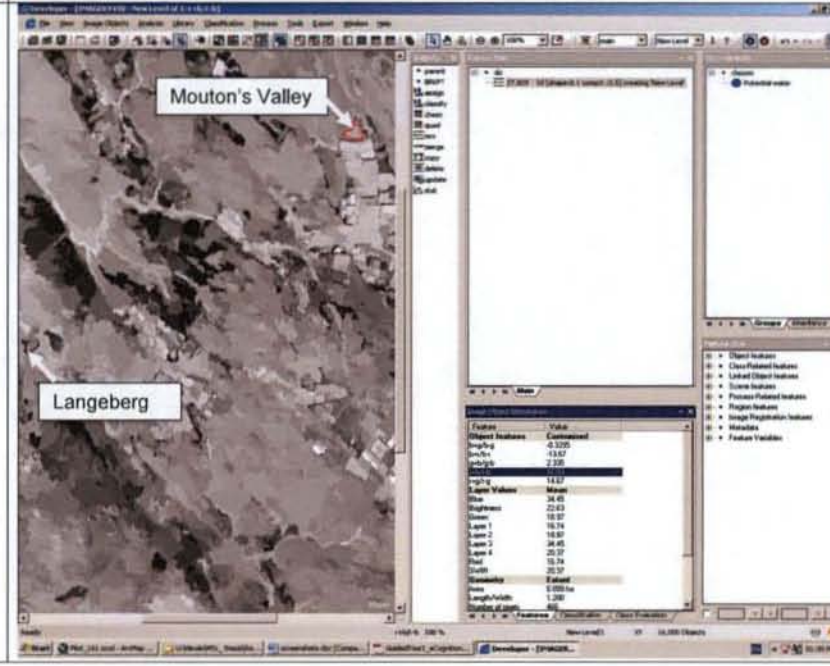


Figure 22: Comparison of band ratios for subset 498

For image subset 498, in Figure 22, the ratios that use the blue and green layers enhance water identification. The ratio of red and blue layer ratio did not result in a distinct identification.

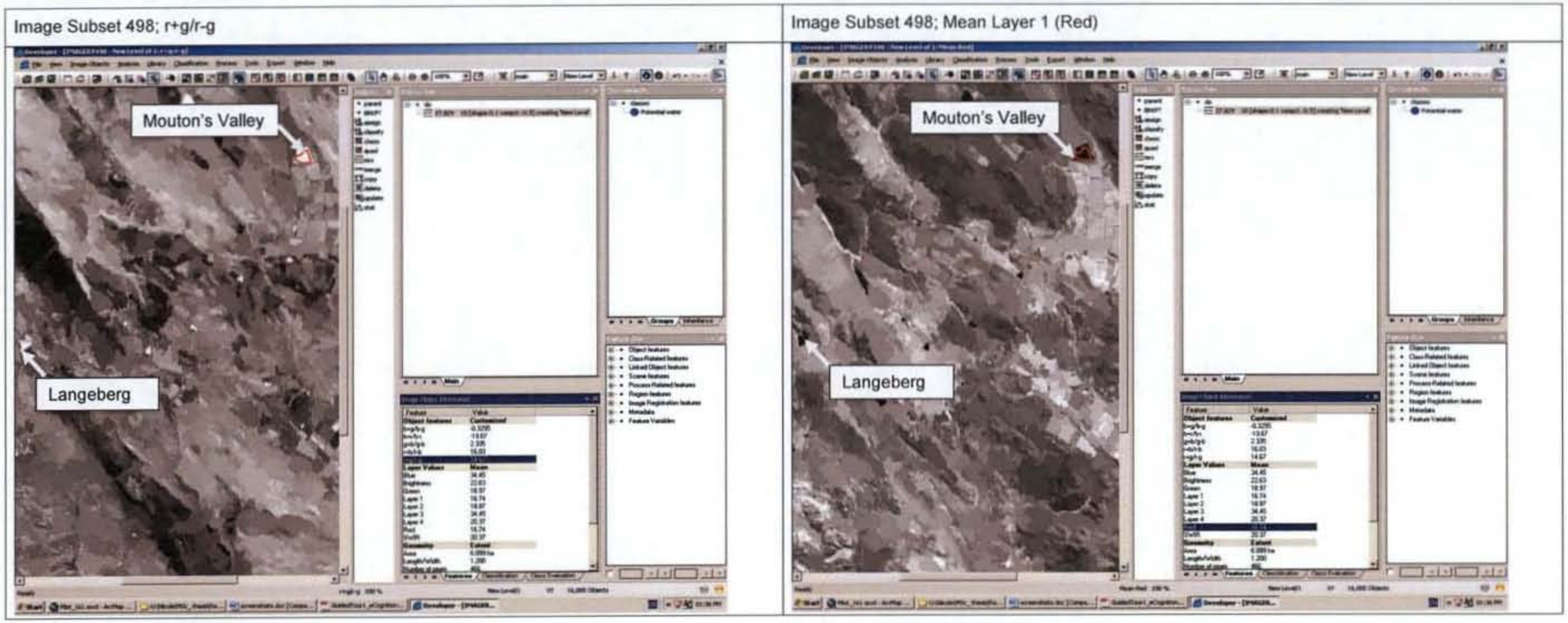


Figure 23: Classification of image subset 498 using band ratio and mean

Figure 23 clearly identifies the various water bodies. The values are shown in the image object information window i.e. Mouton's Valley is 14.67 and 16.74 respectively. These values were assigned to a class of Potential Water. Using the mean of the red layer also shows the water bodies in black. By comparison, the layer mean identifies water bodies more distinctly than the red/green ratio.

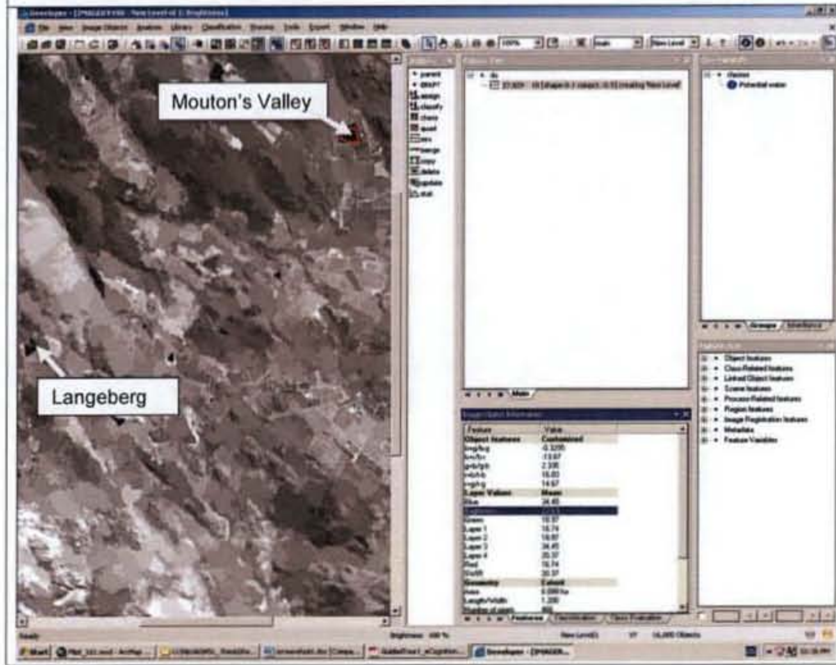
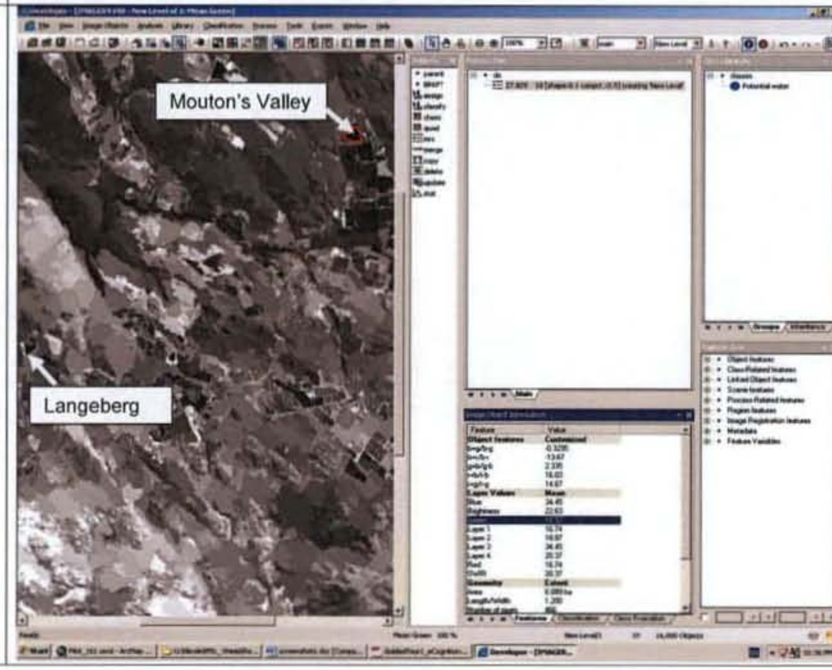
Image Subset 498; Mean Brightness	Image Subset 498; Mean Layer 2 (Green)
	

Figure 24: Classification of image subset 498 using features about the mean

In Figure 24, when using the mean brightness, water bodies are displayed in black given its positive feature value. Similarly, using the mean for the green layer (layer 2), water bodies are also shown as black; however this is not as distinct as the result for brightness as some cultivated land and shadow is also displayed in black. So for this particular image mean brightness is the more useful object feature.

Image Subset 498; Mean Layer 3 (Blue)

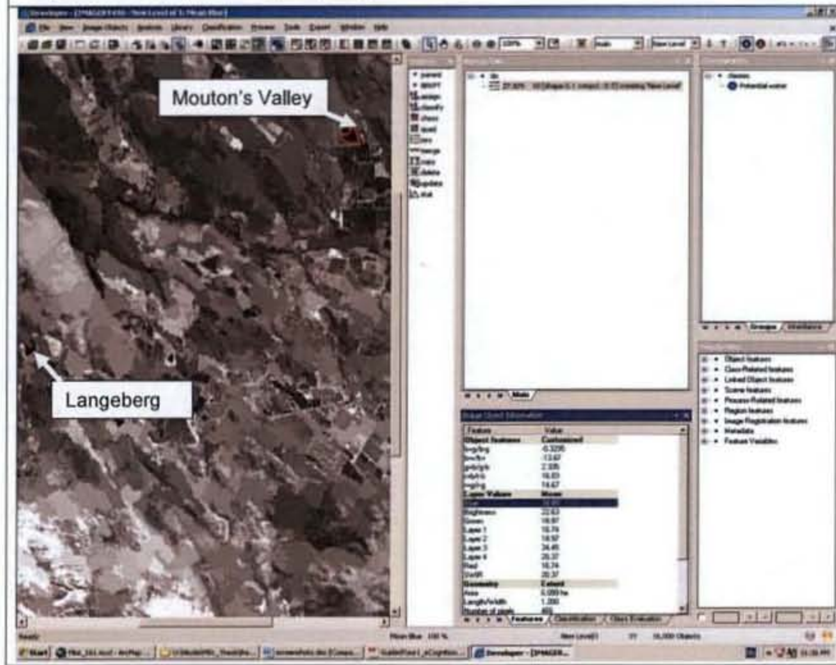


Image Subset 498; Mean SWIR (Layer 4)

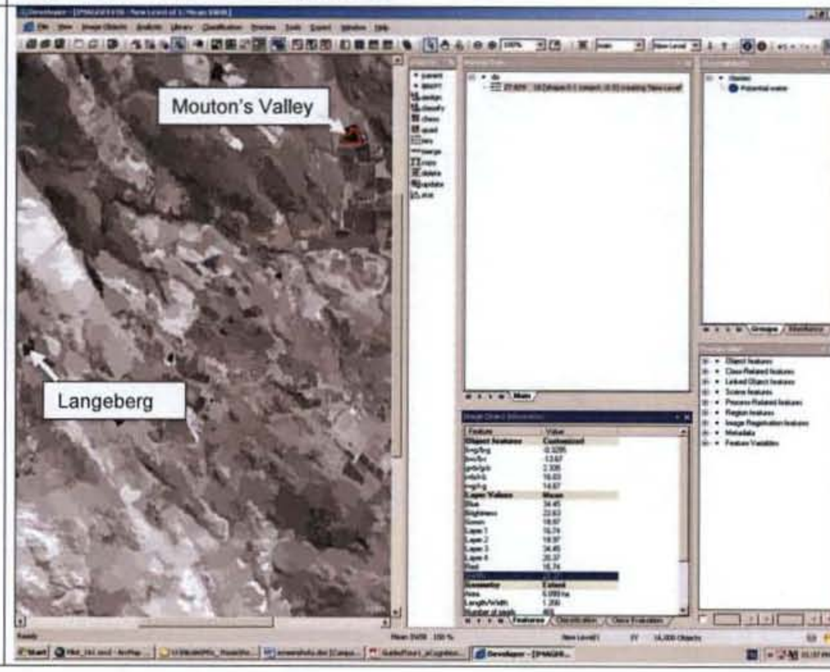


Figure 25: Comparison of band means for subset 498

Figure 25 identifies water bodies from the mean of blue layer (layer 3). Although many water bodies are shown in black, it is not the most distinct result as some cultivated land and shadow is also displayed in black. By comparison, the mean of the SWIR layer (layer 4) provides a more useful result.

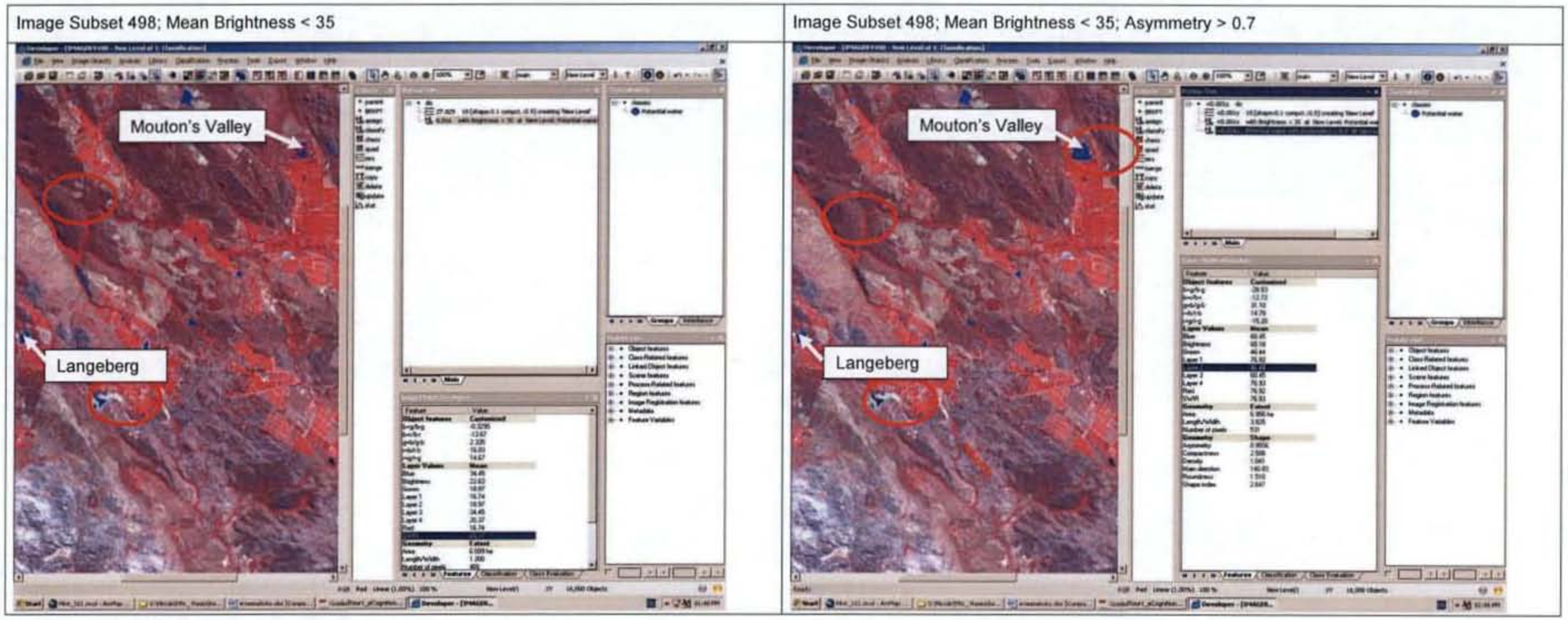


Figure 26: Refining the classification of image subset 498 using mean brightness thresholds and asymmetry

Mean brightness was previously shown as a useful indicator of water bodies. In Figure 26, Mouton's Valley was selected and is shown in the image object information window; mean brightness for the selection is 22.63. After comparing the mean brightness values of other land covers in the scene, a rule was defined using this information where Mean Brightness < 35 was assigned to the Potential Water class. This rule produced a relatively good result for classifying water bodies, although shadow on the mountain slope were also included in the classification. Other object feature information needed to be considered to address misclassification.

Given that the shape of most of the water bodies are not elongated compared to the misclassified shadow areas, the geometry of the image objects was used for further classification. The asymmetry values for the water bodies versus the shadows were considered and a rule was defined and applied to the Potential Water class. Where the Potential Water class had an Asymmetry > 0.7 it was classified back to the default 'Unclassified'. This rule assisted in eliminating the shadows but also excluded a small portion of Mouton's Valley and completely unclassified a dam further south as indicated in the Figure 26 above. The threshold for asymmetry needed further consideration to produce a more accurate result.

Image Subset 498; Mean Brightness < 35; Asymmetry > 0.8

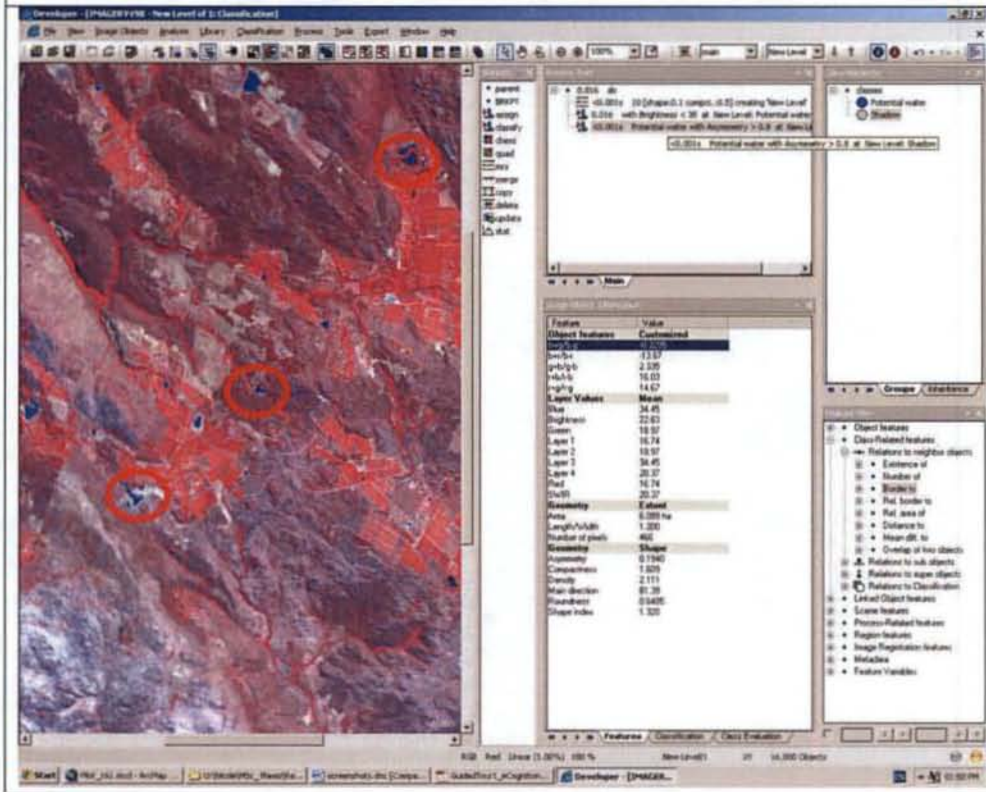


Figure 27: Comparison of mean brightness and use of asymmetry for subset 498

A satisfactory result was obtained for this image subset by re-classifying Potential Water that has an asymmetry > 0.8 to a Shadow class. As indicated in the Figure 27 above, there are some areas adjacent to the water bodies that have been assigned to the Shadow class.

Image Subset 498; Border to Potential Water (Pxl)	Image Subset 498; Shadow with Border to Potential Water > 0

Figure 28: Using distance relationships for image 498

In Figure 28, a Class Related Feature was used to correct for the shadow that was classified as water, where the relationship to neighbour objects was considered. Shadow with a Border to Potential Water > 0 was assigned to the Potential Water class, as shown in the Figure above.

The area values of the image objects classified as water could now be exported for further analysis.

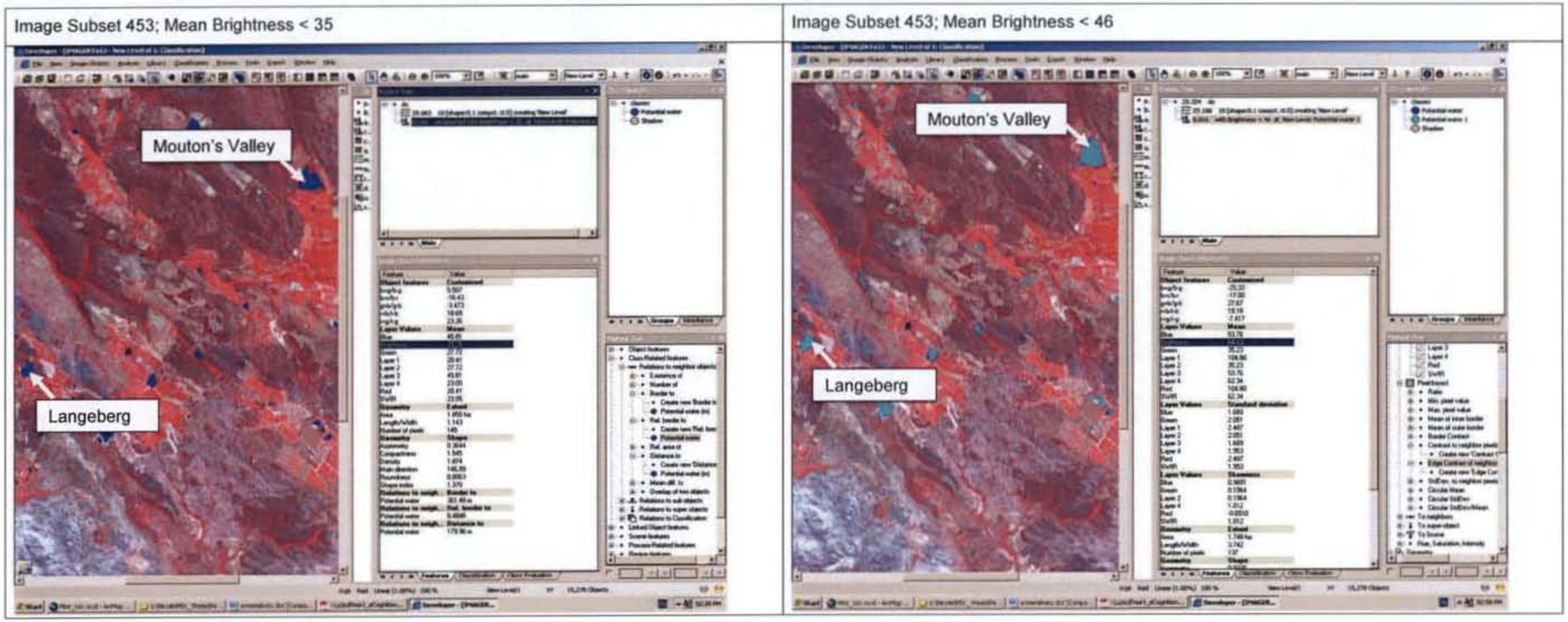


Figure 29: Comparison of mean brightness thresholds

In Figure 29, Mean Brightness was used for classification since previously deemed a useful feature for the initial identification of water bodies. The result obtained for Mean Brightness < 35 was good; however, it appears that the full extent of the water bodies was not included. The threshold value was not appropriate for this image subset and was increased to 46, producing a more satisfactory result as shown above.

Image Subset 956; g+b/g-b

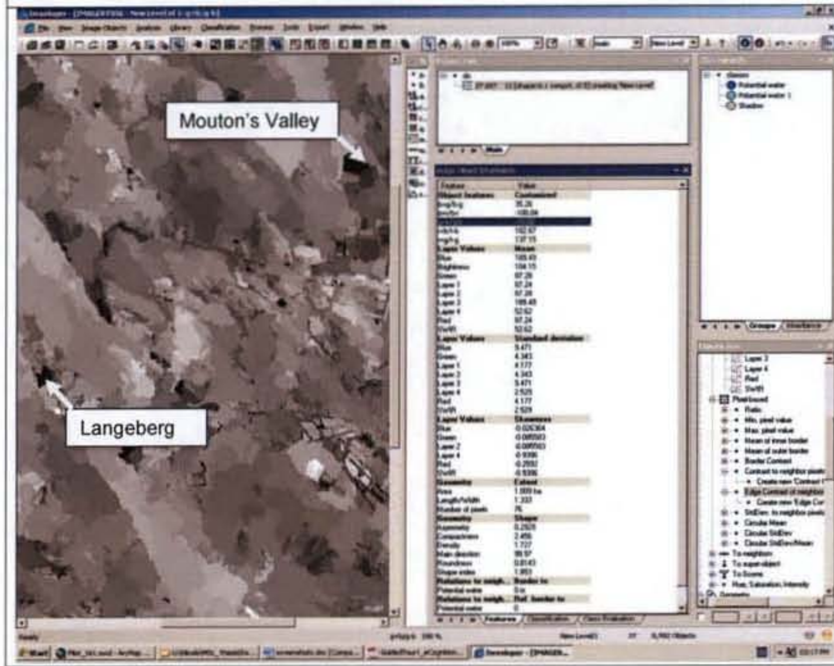


Image Subset 956; g+b/g-b < 0

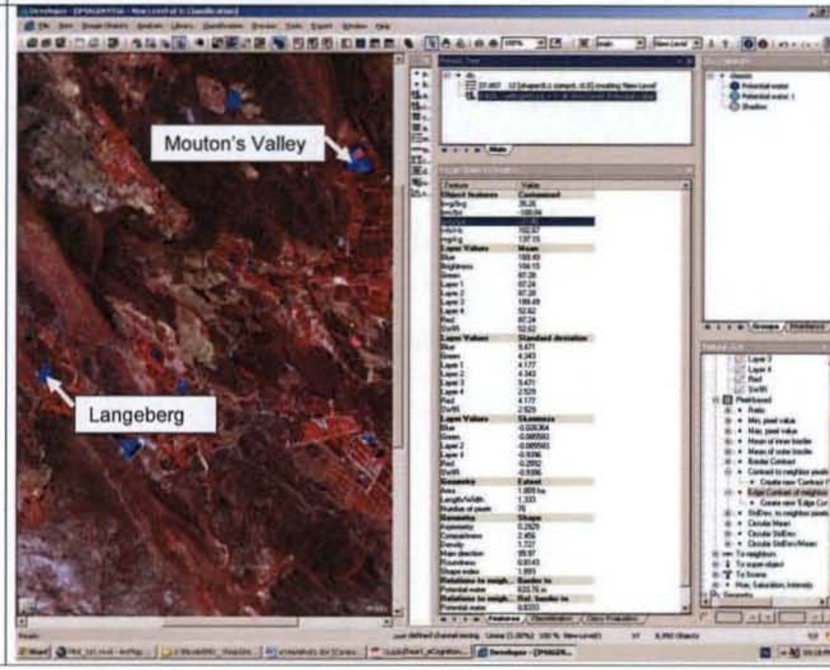


Figure 30: Using band ratio thresholds for subset 956

The various image object features were explored for image subset 956, as shown in Figure 30 above. The ratio g+b/g-b rather clearly displayed water bodies as black. The object feature values for the black image objects were explored, most of which had negative values in terms of this ratio. A rule was defined where g+b/g-b < 0 is classified as Potential Water. The result obtained is fair although the unclassified edges of the water bodies were noted.

Image Subset 956; Segmentation challenge

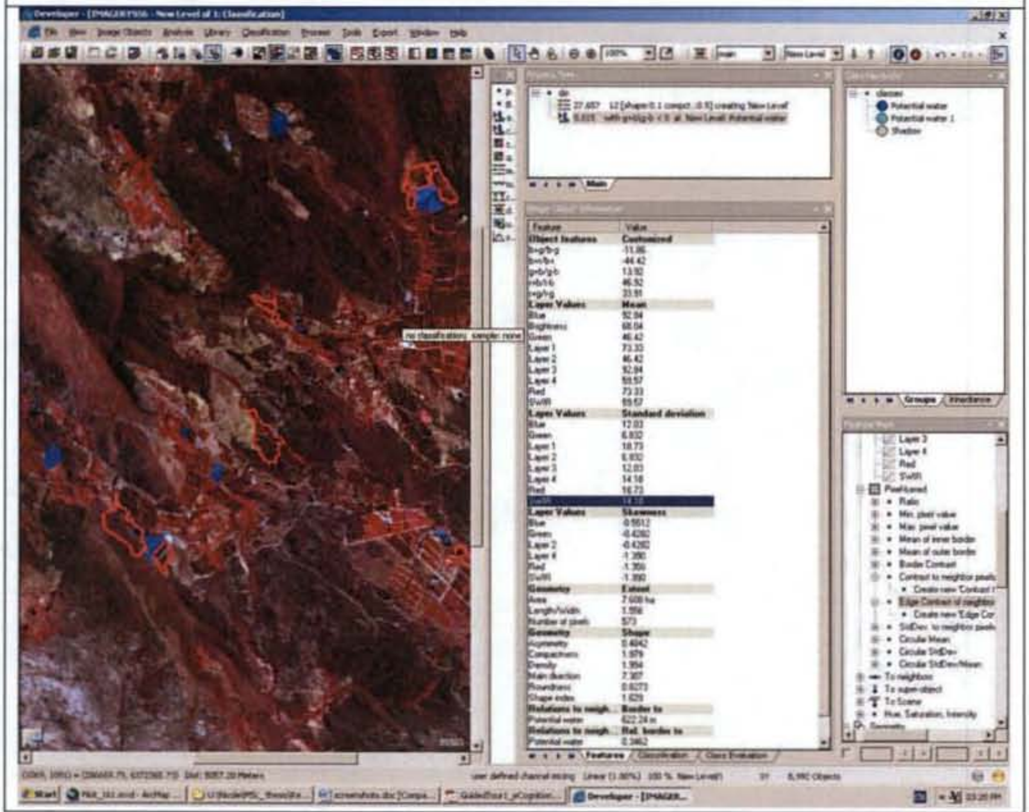


Figure 31: Illustrating the segmentation challenge

In Figure 31, the chosen segmentation scale parameter of 12 affected further classification. By adjusting thresholds or defining a rule in terms of relation to neighbours would probably not work in this case since the image objects are relatively large and overlap with other land covers. Smaller image objects might resolve the overlap problem.

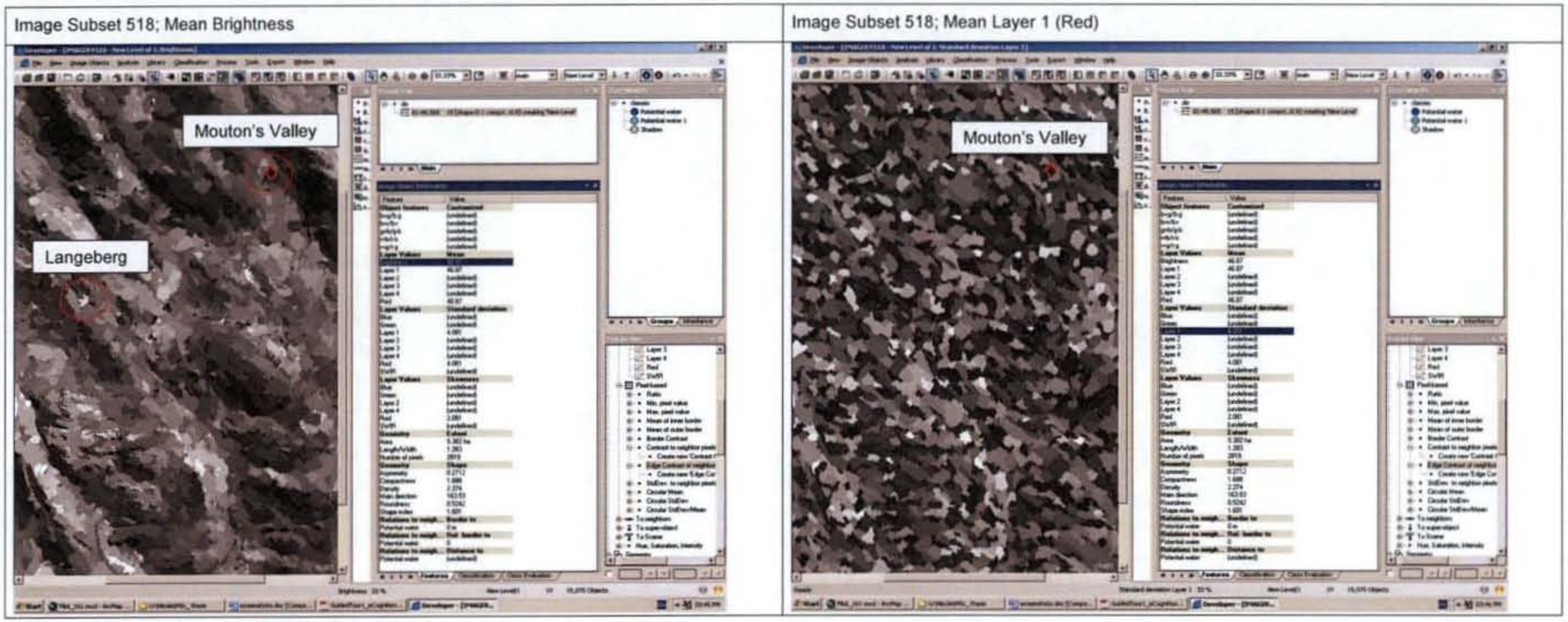


Figure 32: Using band means and mean brightness for classification of subset 518

Figure 32 shows that the Mean Brightness of a panchromatic image is not as useful as previously demonstrated in multispectral imagery as it does not give a clear indication for water bodies. In this example, Mouton's Valley is depicted in black whereas Langeberg is shown as white, implying that the mean brightness values are dissimilar. The Mean of Layer 1 provides a heterogeneous result and the water bodies are not clearly shown.

Image Subset 518; Layer 1 (Red) Skewness

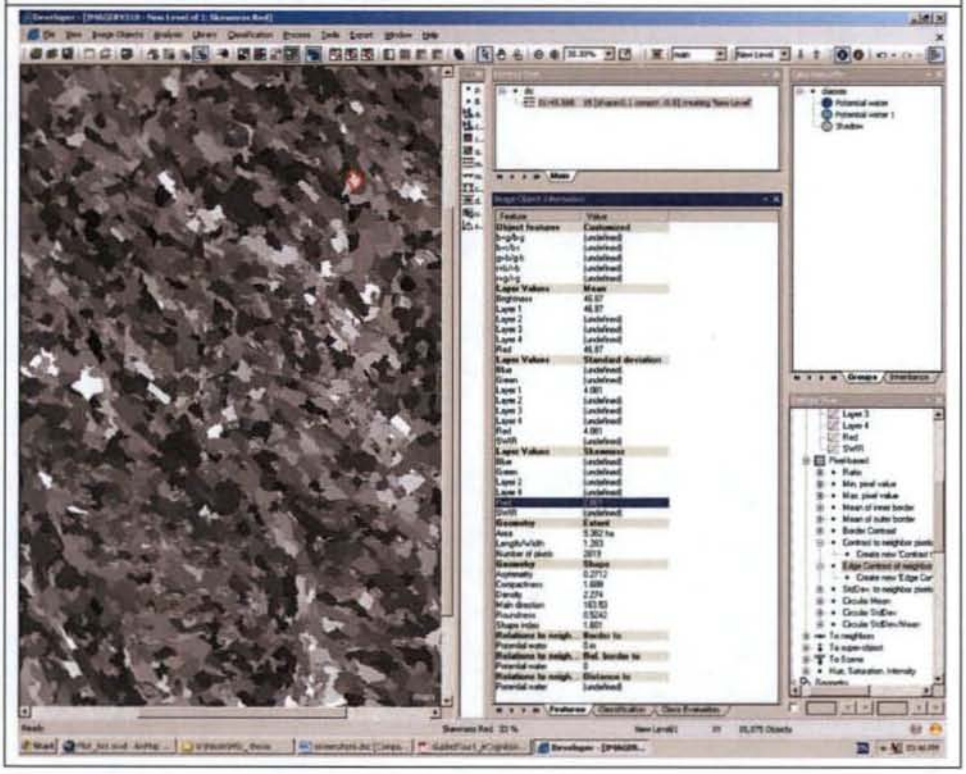


Figure 33: Using skewness characteristics to assist in classification of subset 518

Other features such as Mean Skewness for Layer 1 were also explored, as shown in Figure 33 but could not provide a useful visual representation for the purposes of this study. Multi-spectral imagery is shown to be more useful in segmenting imagery and identifying water bodies.

The presentation of these Figures was used to provide a sequence of object features to support the identification of water bodies which is one of the challenges in this study. It has been shown that the segmentation scale parameters and classification algorithms differ across the imagery but the most useful ratio for initial water body identification was b+g/b-g.

Appendix E

Investigating supervised classification

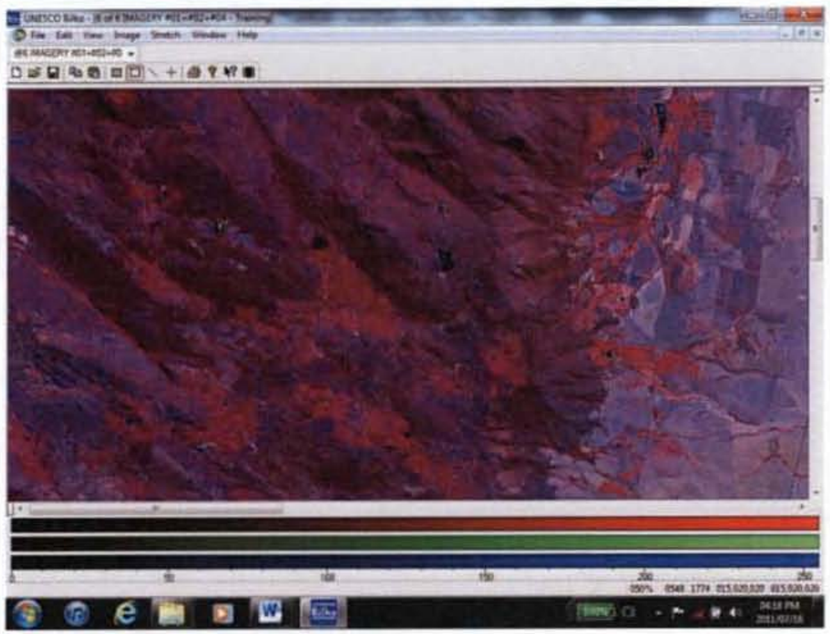
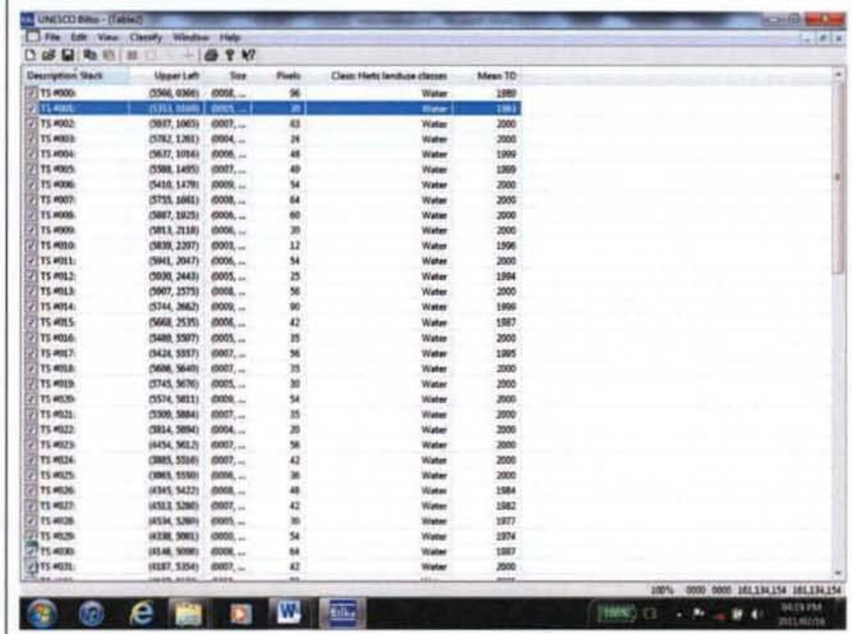
Image subset 453; band selection 4,2,1	Training Sample Table
	

Figure 34: Example of image composite and training sample table

Figure 34 illustrates an example of an image composite and a training sample table. Composites were created for each image subset and training samples for typical water bodies were selected respectively. Both parallelepiped and Maximum Likelihood classification types were run on the image subsets for further comparison.

In the parallelepiped parameters, class limits were set to mean and probability as it provides more control of the training sample. The probability option allows the user to decide how close to the mean value in band the pixel needs to be to be classified as water. For all examples, the probability was set to 90 i.e. 90% chance of being in the water class. The overlap rule was set to maximum likelihood, meaning that the pixel is assigned to the class that it is most likely to belong to, based on the statistics of the classes involved. This option is likely to give the best results (Bilko™, 2000). Similarly, the probability of 90 was also used for the maximum likelihood classification. There is no overlap rule for the maximum likelihood classification. For image subset 364, a composite of bands 4, 1 and 3 was created as it effectively displays water bodies in black and vegetation in green and red. The mountainous areas are also displayed in red tones. This is useful for distinguishing between water bodies and shadows in the high mountain slopes. The training samples are shown in Figure 35 below.

Image subset 364; bands 4,1,3

Figure 35: Training samples for image subset 364

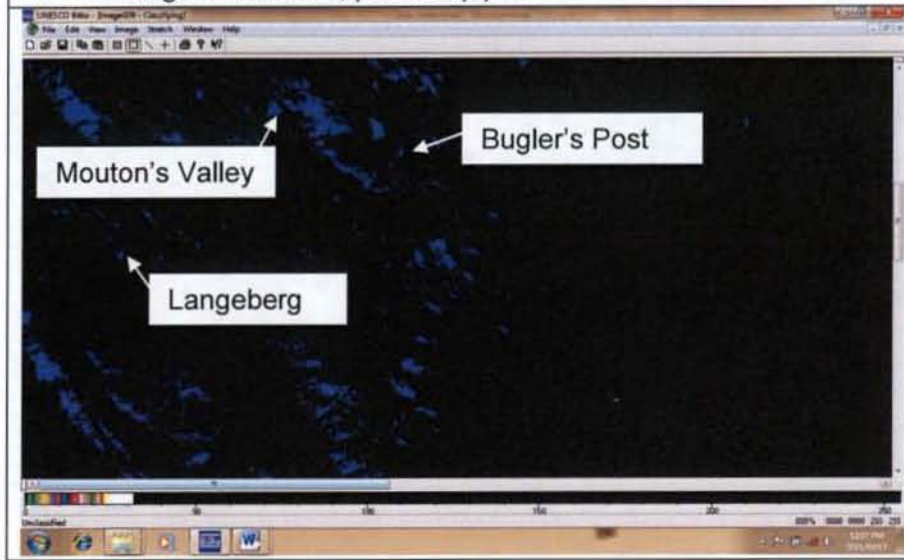
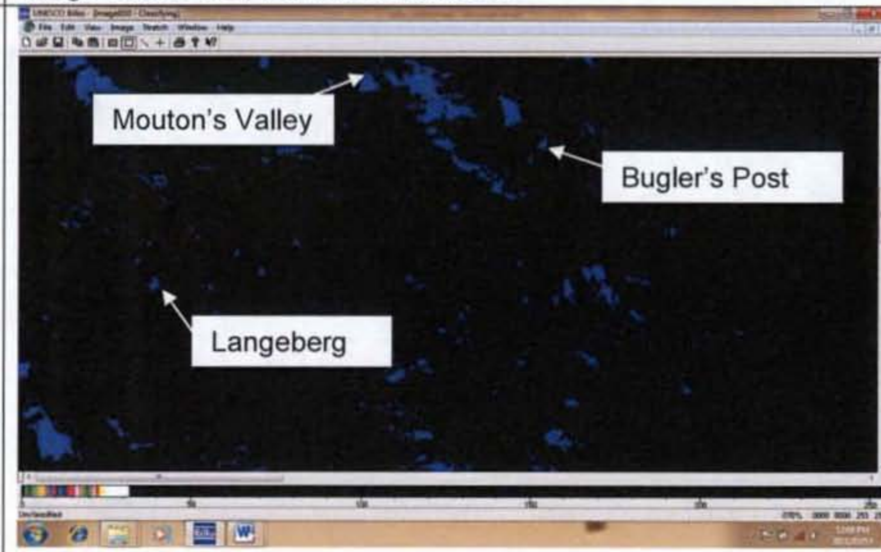
Image subset 364; parallelepiped	Image subset 364; maximum likelihood
	

Figure 36: Classification of image subset 364

Figure 36 illustrates the classifications for subset 364. The result appears to be relatively similar; however, Bilko™ assigns 97% and 87.7% accuracy to relative classifications. The higher accuracy of the parallelepiped classification may be due to the options of using the mean and probability to set the boundaries and maximum likelihood to deal with overlap between classes.

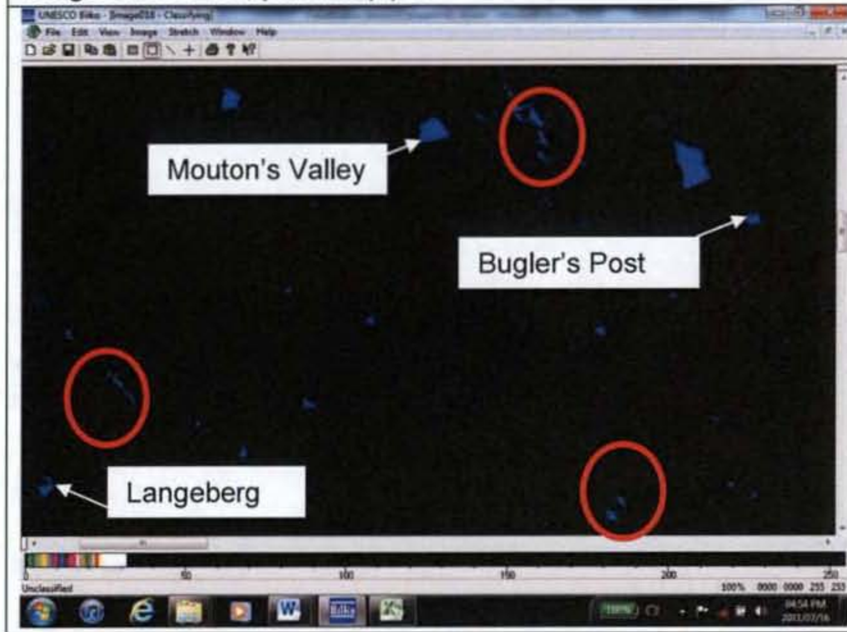
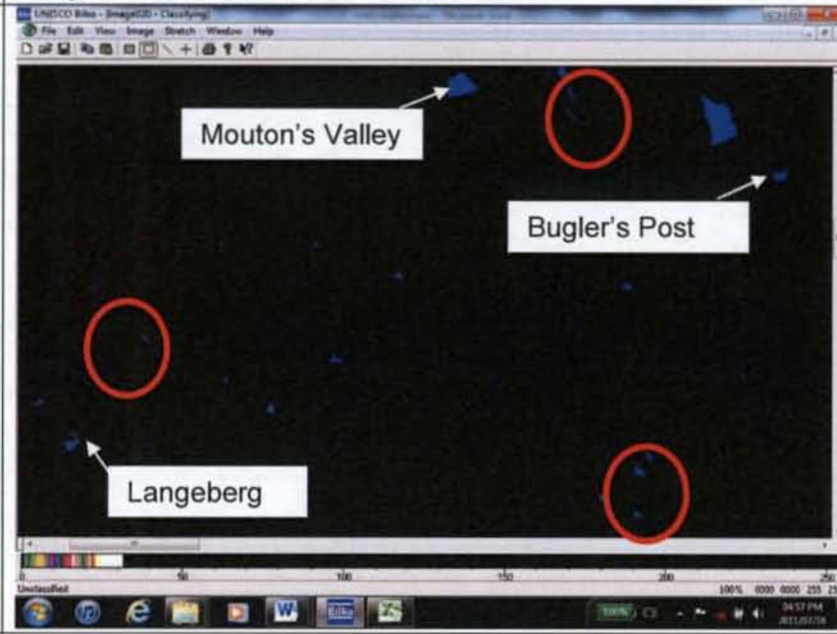
Image subset 453; parallelepiped	Image subset 453; maximum likelihood
	

Figure 37: Classification for subset 453

Figure 37 illustrates the classifications for subset 453. The parallelepiped classification appears to display a higher percentage of the image classified as water than the result for maximum likelihood classification. The most noticeable differences are highlighted in red. Bilko^{TM} assigns 94% and 85.6% accuracy to relative classifications. The higher accuracy of the parallelepiped classification is most likely due to the options of using the mean and probability to set the boundaries and maximum likelihood to deal with overlap between classes.

A composite of bands 4, 1 and 3 for image subset 829 is shown below. This band combination effectively displays water bodies in black and vegetation in green. This is useful for distinguishing between water bodies and shadows in the high mountain slopes. The training samples are also shown in Figure 38 below.

Image subset 829; bands 4,1,3

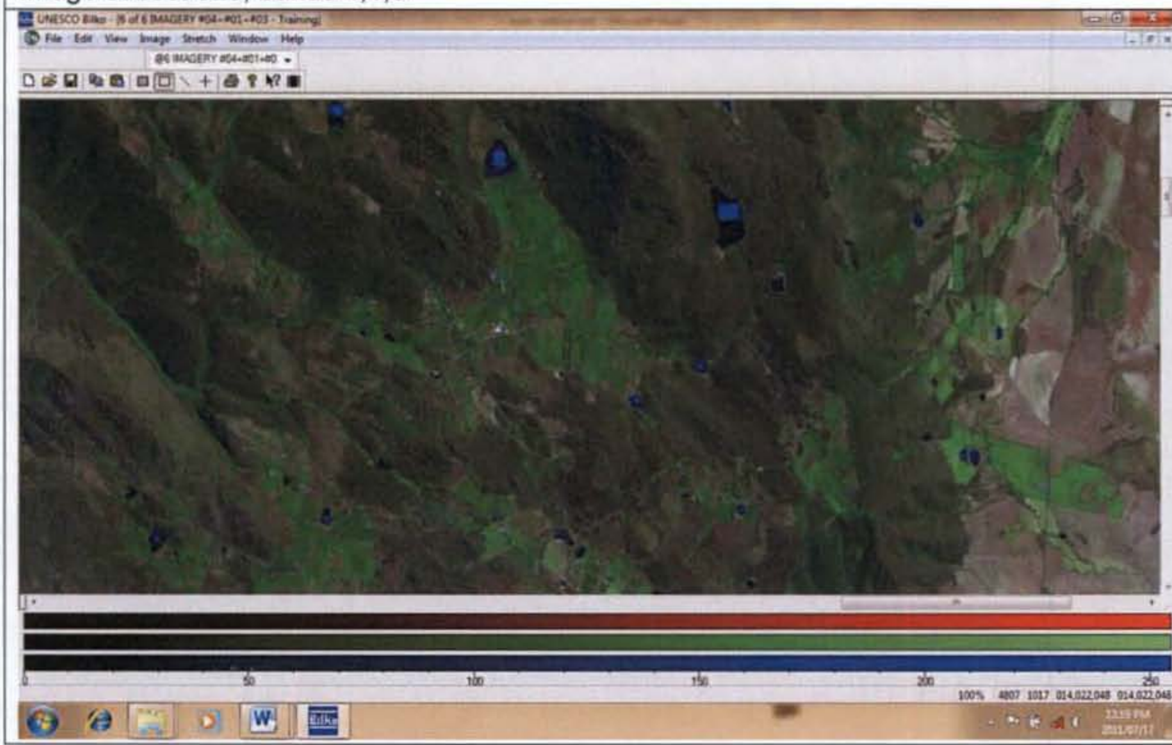


Figure 38: Training samples for image subset 829

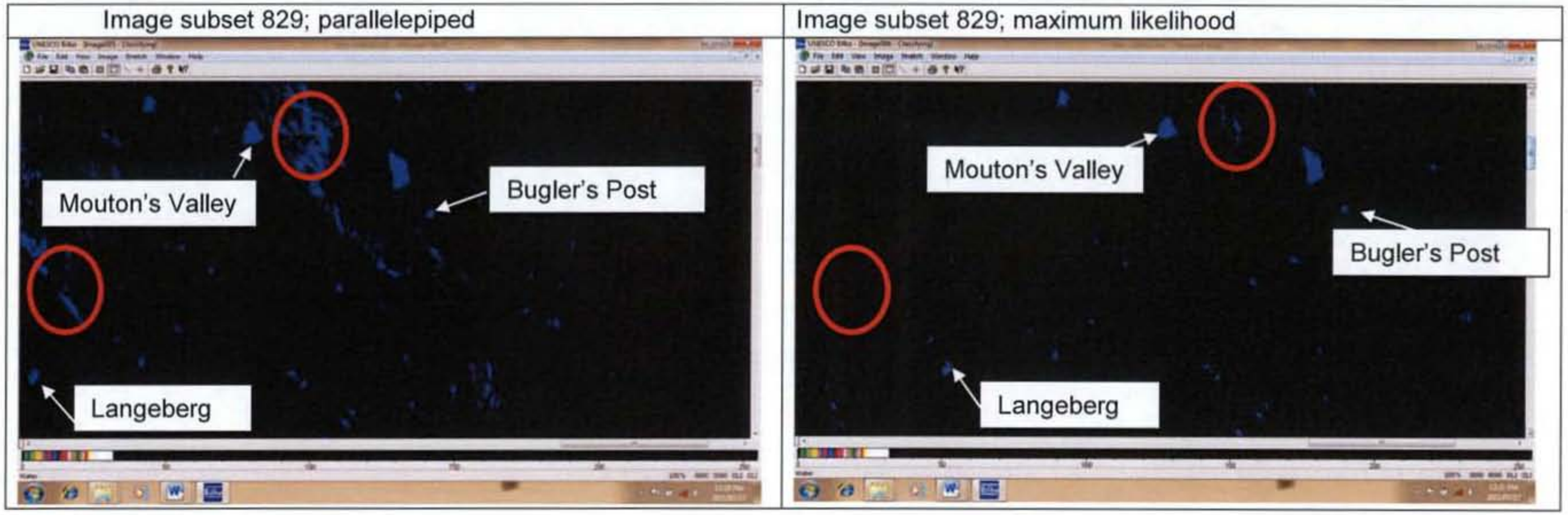


Figure 39: Classification for image subset 829

Figure 39 above illustrates the classifications for subset 829. Once again, the parallelepiped classification appears to display a higher percentage of the image classified as water than the result for maximum likelihood classification. Bilko™ assigns 98.2% and 91.1% accuracy to relative classifications. Despite the higher accuracy of the parallelepiped classification, the parallelepiped classification appears to have classified shadows on the mountain slopes as water. The most noticeable differences are highlighted in red.

A composite of bands 4, 1 and 3 for image subset 829 is shown below. This band combination effectively displays water bodies in black and vegetation in shades of green and pink. The training samples shown in Figure 40 below should produce a favourable result for classifying water bodies.

Image subset 498; bands 4,1,3

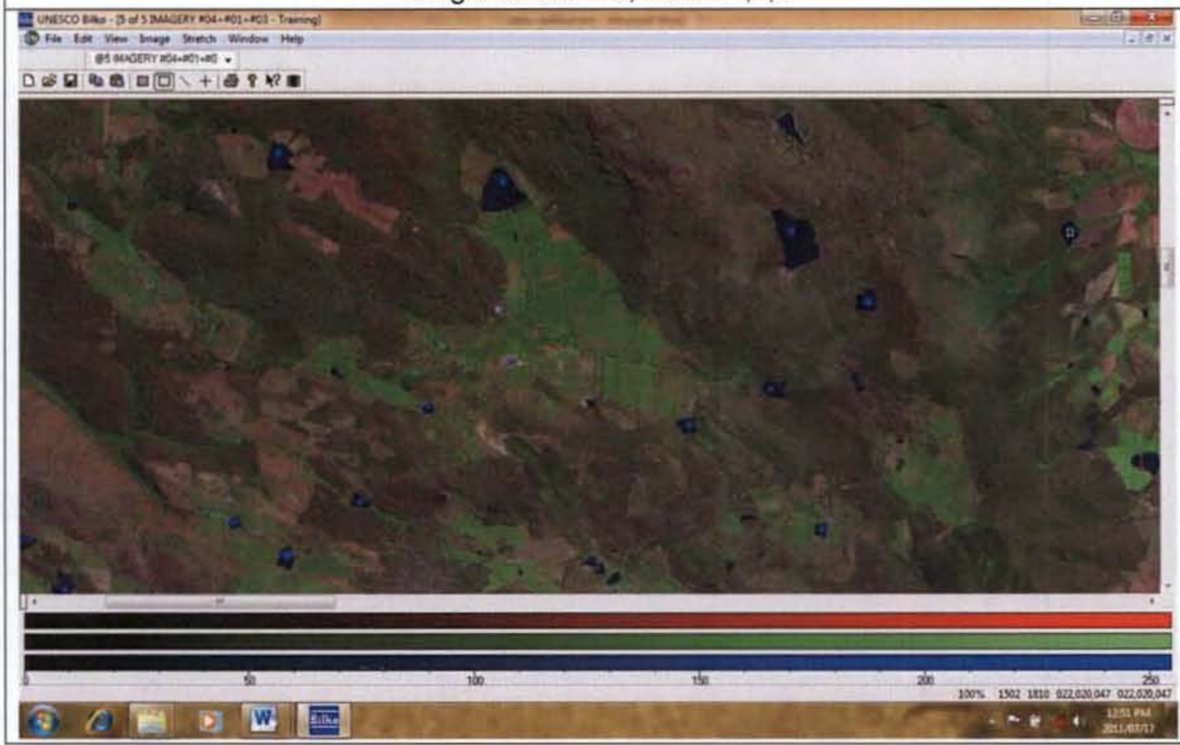


Figure 40: Training samples for image subset 498

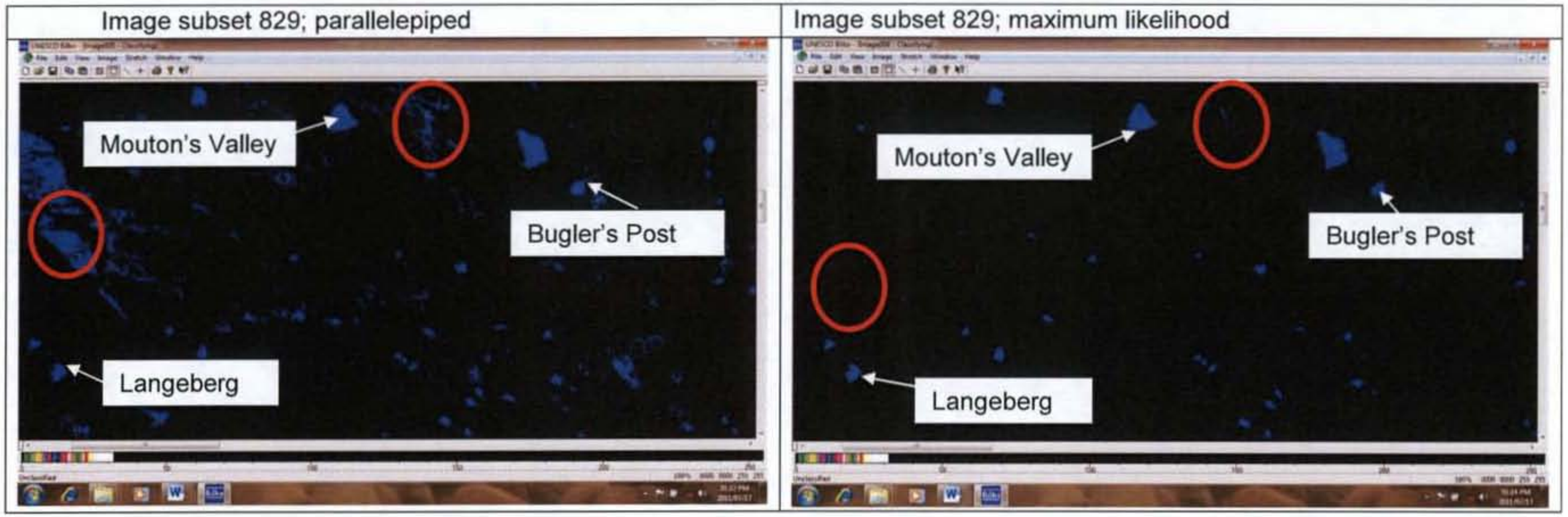


Figure 41: Classification for image subset 829

Figure 41 illustrates that the parallelepiped classification display a higher percentage of the image classified as water than the result for maximum likelihood classification. Bilko^{TM} assigns 93.7% and 88.2% accuracy to relative classifications. As highlighted in red above, the parallelepiped classification classified shadows on the mountain slopes as water.

In general, the examples of maximum likelihood classification above display a better representation of water bodies in the area. Less misclassification of shadow on is prevalent.

Since fieldwork was conducted for this study, supervised classification is more appropriate than unsupervised classification; however, unsupervised classifications are included in Appendix F for further comparison.

Appendix F

Investigating unsupervised classification

Unsupervised classifications were run on the image subsets and the results are displayed in Figures 42-35 below.

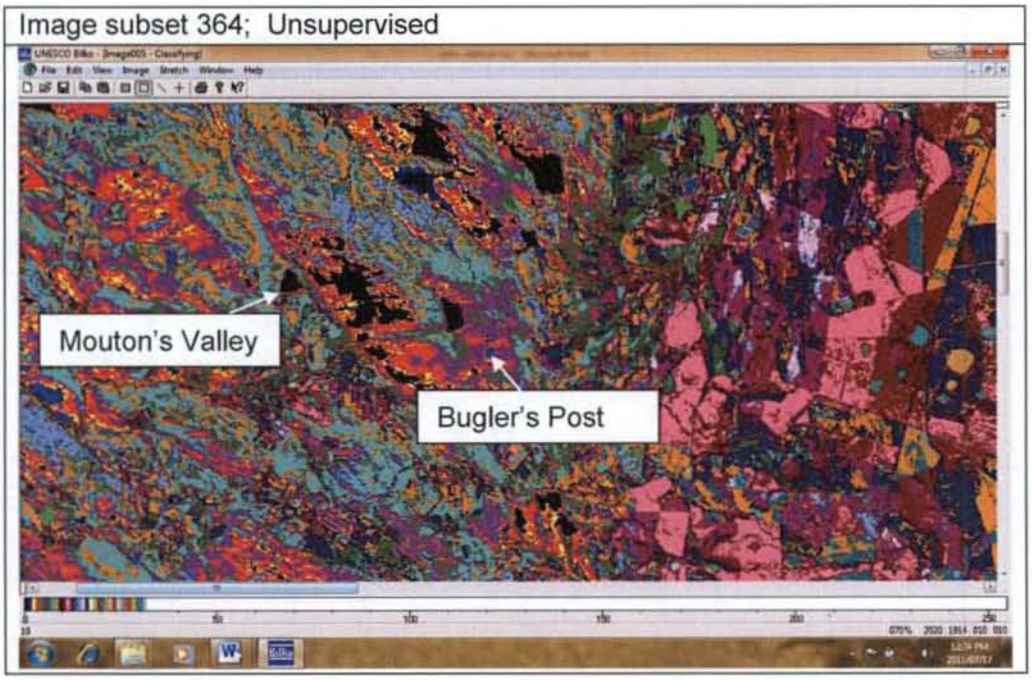


Figure 42: Unsupervised classification of image subset 364

Image subset 453;

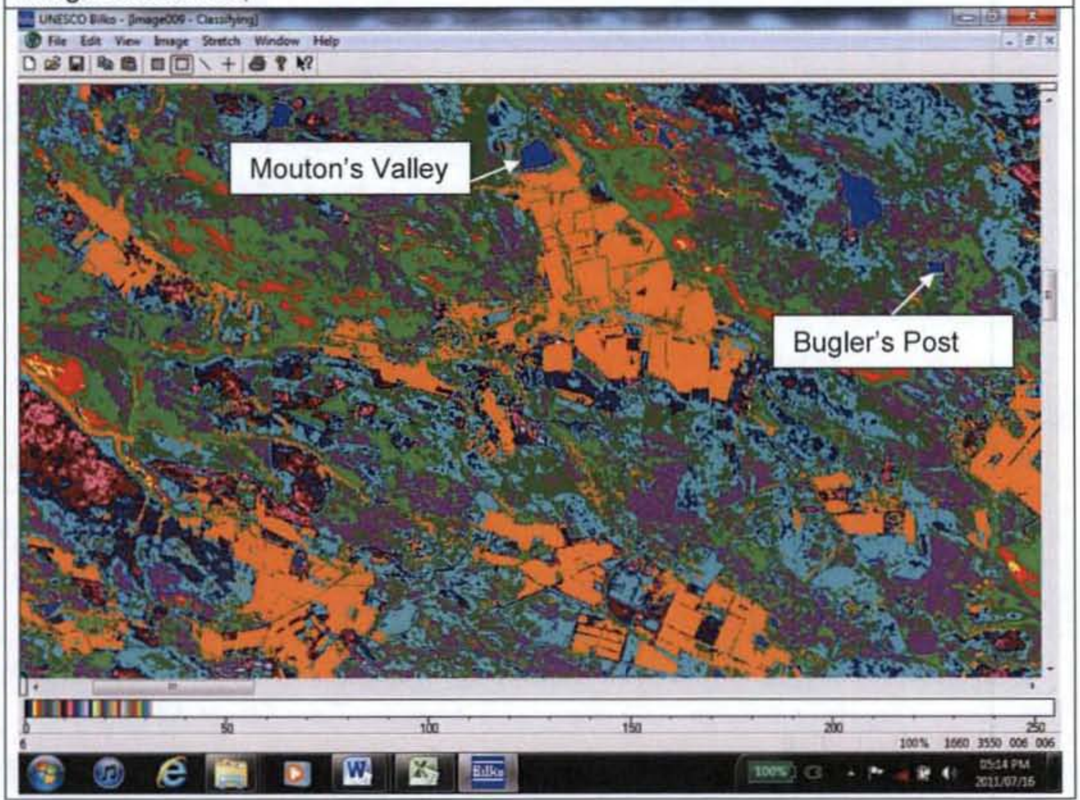


Figure 43: Unsupervised classification of image subset 453

Image subset 829

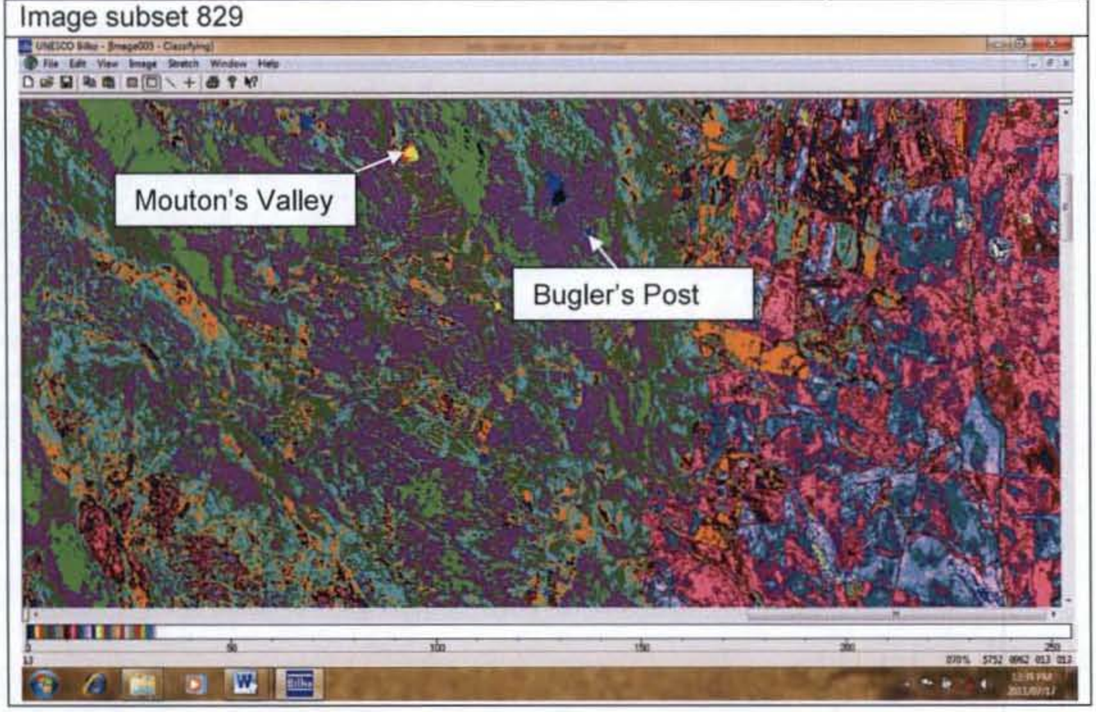


Figure 44: Unsupervised classification of image subset 829

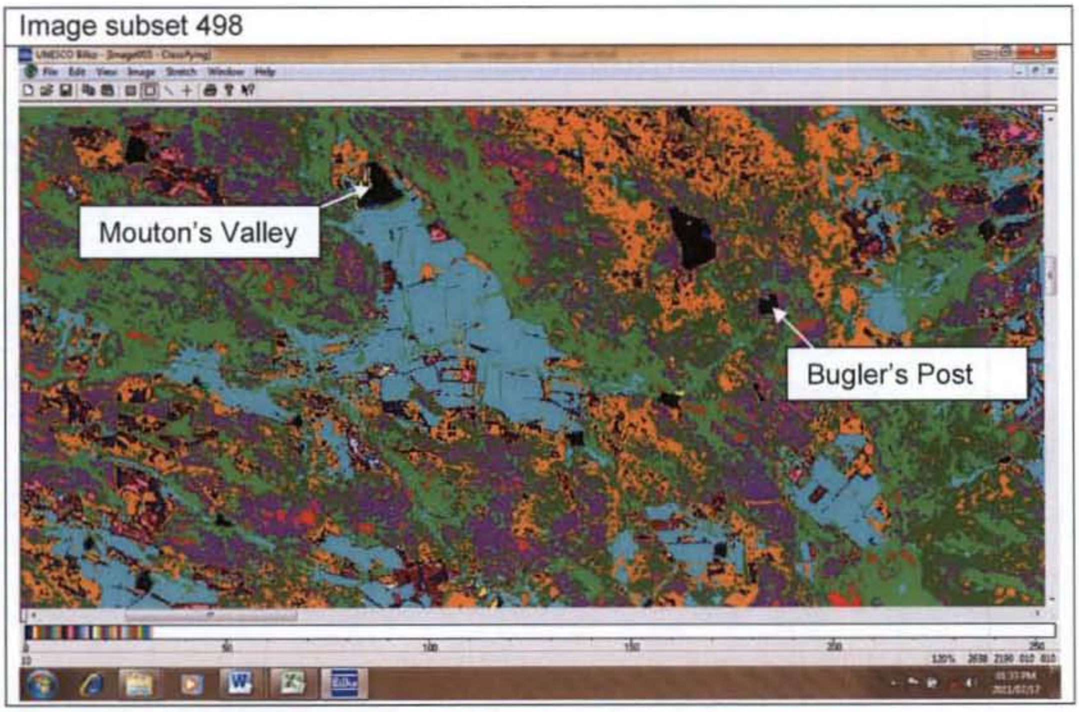


Figure 45: Unsupervised classification of image subset 498

Subtle differences between the crop types are not revealed by unsupervised classification, in general distinct habitats such as water and built-up areas form identifiable clusters. Mouton's Valley is easily identified in most examples given above.

Using the classified images, it was necessary to obtain the areas for water bodies, specifically the farm dams that were surveyed in the groundtruthing exercise. The classified images were exported to ArcGIS™ as .tiff files and converted to shape files using the "Raster to Polygon" tool. An area field was added to the attribute table and the "Calculate Geometry" tool in ArcGIS™ was used to calculate area. The three farms that were surveyed in the groundtruthing were selected and their attribute data was exported as a .csv file to be used in MS Excel. The results are shown in Table 7.

The different classifications that were presented here effectively identified water bodies that could be exported as polygons with an associated value for surface area. These values are key inputs for determining the volume of water stored. The results are shown in Figure 4.