AN EARTH OBSERVATION APPROACH TOWARDS MAPPING IRRIGATED AREAS AND QUANTIFYING WATER USE BY IRRIGATED CROPS IN SOUTH AFRICA

Report to the

WATER RESEARCH COMMISSION

AND

DEPARTMENT OF AGRICULTURE, FORESTRY AND FISHERIES

Report by

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BACKGROUND

South Africa (SA) is classified as a water scarce country (DWAF 2004; Reinders 2010) and has an estimated average annual rainfall ranging between 451 (FAO 1995) and 495 mm (Annandale et al. 2011), depending on the source quoted. Only 3% of SA's land surface is considered moderate to high-potential arable land (World Wide Fund for Nature 2018) and the FAO estimates the area with irrigation potential to be 1.5 million ha (FAO 1995). This is similar to the 1996 National Department of Agriculture's (NDA) estimation of potential irrigable land (1.58 million ha) (Backeberg 2003; DWAF 2004).

The estimations of the area of irrigated crops are outdated and vary greatly. A number of assessments since 1990 documented either the actual area under irrigated crops or the registered area under irrigation, using various approaches to derive the estimates. According to these estimates, the area under irrigation ranged between 1.21 and 1.58 million ha and the area registered for irrigation use between 1.44 and 1.68 million ha. Given the uncertainty about the area currently irrigated, the estimated amount of water used by irrigated agriculture is also unclear. It has been estimated that irrigated agriculture uses between 51% (Backeberg et al. 1996) and 63% (Water Accounts for South Africa 2000, in Reinders (2010) of SA's water resources. According to DWAF (2004) and Statistics South Africa (2010), 62% of water is being used by irrigation, 23% for meeting urban requirements and the remaining 15% is shared by other users (rural users, mining and bulk industrial, power generation and afforestation). The water use by irrigated agriculture is affected by assurance of supply, varies regionally across SA and the source of water (surface or groundwater) differs.

In view of a clear need for irrigated agriculture to support crop production, food security and economic growth, it is alarming to note that in the year 2000, 12 out of the 19 water management areas (WMAs) in SA already faced a water deficit (Reinders 2010; Statistics South Africa 2010). There consequently seems to be little room for increased surface water extraction or abstraction. The WWF estimated that 98% of the available water resources are already allocated (World Wide Fund for Nature 2018). In addition, SA has few exploitable aquifers, and groundwater currently only contributes to a small portion of the total water supply (13%) (World Wide Fund for Nature 2018). New groundwater contributions will be limited, since the overexploitation of groundwater and substantial drops in water tables have already been reported in a number of areas (Burger 2008). Irrigation in some areas is made possible – and will remain possible – only through significant water transfer between the various WMAs (Statistics South Africa 2010). With the added pressures of climate change, population growth and decline in water quality due to salinisation, the need for improved assessments of the current water resources and land uses is critical. Actions related to improved water use efficiency (WUE) and irrigation expansion, or water reallocation, can only follow once this information is available. With irrigated agriculture being labelled the largest water user, it is important to obtain recent and accurate data on water used by different irrigated crops over time (i.e. throughout the growing season) and space (i.e. in different geographical areas). Combining these data sets into a WA framework will improve our understanding of the true pressures on SA's water resources and will better inform the expansion of irrigated agriculture.

RATIONALE

Remotely sensed Earth observation (EO) data are regularly captured from a wide variety of aerial and satellite platforms. The wide coverage and cost-effective nature of EO images are not only ideal for determining the area under irrigated agriculture, but have, for many years, been employed in energy balance modelling to provide up-to-date estimates of actual evapotranspiration (ET) and the total amount of water utilised by irrigated agriculture (Bastiaanssen & Harshadeep 2005; Jarmain et al. 2014). The consumptive water use by various land uses need to be understood before new water allocations can be granted. Over the past two decades, various international initiatives have been developing WA frameworks to support water managers and decision makers. Using remotely sensed data within a WA framework will be invaluable for water resources management, by providing a comprehensive overview of water resource use for a given area. The efficacy of such a framework is illustrated in this project. The overarching aim of this research was to update the existing estimations of the amount of water used by irrigated agriculture in SA.

The specific objectives to achieve the overarching aim were to:

1. Update the total area used for irrigated agriculture in SA;
2. Update the estimated total amount of water used by irrigated agriculture in SA;
3. Quantify the water used by selected irrigated crops in selected areas;
4. Demonstrate how water accounting (WA) can be employed to determine water use and water availability over large catchments;
5. Develop capacity in EO and other geospatial techniques, specifically those relating to water use estimations, land cover and crop type mapping, and WA; and
6. Engage with industry to stimulate participation, increase awareness of crop water use and availability and encourage adoption of new technologies and datasets.

METHODOLOGY

One of the main reasons for the uncertainty about how much of SA’s land and water resources are used by irrigated crops is that traditional methods for mapping irrigated areas and for quantifying crop water use are too laborious and costly to be applied over large areas. Most of the existing estimates at national level are thus based on qualitative methods and secondary data sources. A literature review of existing methods revealed that EO is the only viable approach to use for national assessments. This research consequently employed various EO and geographical information systems (GIS) techniques, including the mapping of irrigated agriculture and the modelling of actual ET. Monthly datasets of ET for a 12-month period were generated for the entire SA. The ET datasets describe the water consumption and land productivity between 1 August 2014 and 31 July 2015 and thus capture the phenology of natural vegetation, crop production cycles and associated water consumption in SA. The production of the irrigated area map and the calculation of the total water use by irrigated crops were informed by these datasets. The mapping of irrigated areas included all agriculture that was actively irrigated, and thus excluded areas that are usually irrigated but that lied fallow over the study period. A geodatabase of agricultural fields was generated by collating a series of land cover, land use and field boundary data. One recognised method for differentiating between irrigated and rainfed fields involves comparing the accumulated (annual) rainfall and evapotranspiration (i.e. $ET_{yr} – P_{yr}$). Theoretically, where ET_{yr} exceeds P_{yr} for a given agricultural area, crop are typically irrigated. This assumption was investigated by comparing the $ET_{yr} – P_{yr}$ of both known irrigated and rainfed fields for 2014/15, with the results suggesting a difference threshold value of 300 mm/yr. Applying this threshold was found to be effective in the drier areas of SA, but performed poorly in regions with higher rainfall (e.g. Limpopo, Mpumalanga and KwaZulu-Natal (KZN)). This was attributed to the large variation in rainfall throughout SA (necessitating the use of multiple or region specific $ET_{yr} – P_{yr}$ thresholds) and the poor spatial accuracy of rainfall data. The difference between $ET_{yr} – P_{yr}$ was generally lower and more variable in wetter regions. The ET and P data used in the classification were consequently supplemented with high spatial resolution (30 m), multi-temporal Landsat 8 imagery to better differentiate between irrigated and rainfed fields. A range of spectral indices were generated from the Landsat 8 images and incorporated into the geodatabase, where each field contained multi-temporal ET, P and spectral index values. To account for the climatic variability of SA, the country was subdivided into nine rainfall regions. Examples (samples) of fields that were known to be irrigated or rainfed were identified within each region and used to train a machine learning classification algorithm (CART). The output of this exercise was a highly accurate (>95%) irrigated area classification for each rainfall region. These regional classifications were merged into a single irrigated area map (IAM) for SA, which was then assessed through manual inspection by the project team and industry stakeholders. The resulting map was essential for quantifying the water used by irrigated crops at national, provincial and regional (catchment) scales. This was done by aggregating the cumulative ET measurements (as modelled by ETLook and recorded in the geodatabase) of all actively irrigated fields. The Water Accounting Plus (WA+) framework was subsequently applied to seven secondary catchments throughout SA (selected based on characteristics such as population size, agricultural activities and proportion of irrigation) to demonstrate how it can be applied to determine whether water resources are available for the extension of irrigated agriculture.

MAIN FINDINGS

Irrigated area (ha)

The ETLook model used to produce the monthly ET dataset proved robust despite some challenges with available and accurate (spatial) rainfall data. The IAM generated using the ET dataset – along with other remotely sensed data – was judged highly accurate by participating stakeholders. Minor errors were identified during a validation and correction process carried out by the project team. Most of the identified errors were related to inaccuracies in the field boundary delineations or where only parts of fields were utilised. All known misclassifications were manually corrected to produce the final, validated version of the map (Version 3). The map showed that **1 334 562 ha** (1.1%) of SA's land surface was actively irrigated during 2014/15. This constituted 10% of the total area under cultivation (including fallow areas) of the area used for agriculture in 2014/15. It was found that the Western Cape contributes the most (269 476 ha), with Limpopo having the second largest area under irrigation (218 302 ha). Given that it is the first of its kind, it was not possible to compare the IAM spatially with earlier datasets.

The IAM in itself is invaluable for establishing a record of irrigation activities at national level and forms a benchmark against which future assessments can be done. The map was essential for quantifying the water used by irrigated crops at national, provincial and regional (catchment) scales. This was done by aggregating the cumulative ET estimates (as modelled by ETLook and recorded in the geodatabase) of all actively irrigated fields. Although this was a relatively simple procedure, a sensitivity analysis was carried out to better understand the influence of using the relatively low (250 m) resolution ET datasets for quantifications at field level. A number of cases of ET under- and overestimation was noted, mainly due to pixel mixing caused by non-agricultural land cover directly adjacent to fields. For instance, land cover types with high ET (e.g. water and plantations) neighbouring agricultural fields caused an overestimation of crop water use, while land cover types with low ET (e.g. bare soil) caused underestimations. However, the sensitivity analysis (Section 5.3) revealed that the effect of these over- and underestimations are insignificant at regional scales, as they tend to offset (cancel out) one another.

Water use (ET)

The outcome of the sensitivity analysis was supported by an assessment of the ET frequency distributions per selected crop types. Although some outliers and variation within particular crop types were noted, all of the ET distributions (histograms) of crop types (for which a sufficient number of fields were available) were unimodal and had acceptable standard deviations (less than 40% of median values). This suggested that the adjacent land covers had a marginal effect on ET and that the median ET values are reliable representations of the water used per crop type. Apart from the validating role that the crop-specific ET analyses played, it also provided a better understanding of how ET varied among crop types and between climatic regions. For instance, citrus recorded the highest median ET values (of the crops assessed), with 911 mm/yr and 678 mm/yr in the summer and winter rainfall region respectively. Wine grapes generally used less water, with rainfed vineyards in the winter rainfall region producing the lowest median ET values (500 mm/yr). The crop-specific analyses of ET also revealed that the ET of irrigated crops are not disproportionate to those of rainfed crops. For instance, the ET of irrigated wheat in the summer rainfall region was 737 mm/yr, while the ET of rainfed wheat in the same region was 611 mm/yr, a difference of only 20%. The frequency of irrigation applications would have had a substantial impact on this figure. The increase in the consumptive water use of irrigated maize, compared to rainfed maize, should be considered within the large increase in yields when maize fields are irrigated.

The national aggregation of ET for all irrigated areas in 2014/15 showed that the total consumptive water use from irrigated agriculture in SA was **10 221 million** m^3/yr. This compares well with previous estimates such as the 1996 Overview of Water Resource Availability and Utilisation in South Africa, which estimated the water use by irrigated agriculture to be 10 740 million m^3/yr and 7 836 million m^3/yr in 2000 (as part of the National Water Resources Strategy (NWRS)), with the latter based on a 98% assurance of supply (Backeberg 2003; DWAF 2004). The water use estimate for irrigated agriculture in 2014/15 was marginally lower than this estimate, despite the 44 430 ha increase under irrigation, implying either improved water use efficiencies or production of crops with lower water use requirements. However, differences in accuracies and methods between the 1996 estimations and the current study may also account for these dissimilarities.

Water accounting (WA)

Although the mapping of irrigated areas and the quantification of consumptive water use provides a sound foundation for understanding the *status quo* of irrigation in SA, it does not answer the question of whether water resources are available for extending irrigated agriculture. WA frameworks (comprising quantitative information on water use and water availability) have been developed to simplify and communicate information to policy makers. The process is analogous to financial accounting and provides inter alia information on the water resource base, consumption, productivity and withdrawal within a particular catchment. For this study, the WA+ framework, developed by eLEAF with inputs from International Water Management Institute (IWMI), FAO and the Technical University of Delft, was used to determine whether water resources are available for the extension of irrigated agriculture. This framework, currently being further developed by Wateraccounting.org, was applied to seven secondary catchments throughout SA, selected on the basis of characteristics such as population size, agricultural activities and proportion of irrigation. The results showed that in Mzimvubu, Kowie and the Breede River catchments the water resources were likely sufficient to allow for additional storage and productive use of (surface) water. This additional water could potentially be used by existing water users to meet their crop demand in summer or store additional water in wetter years as insurance for drier years. Additionally, or alternatively, this water could possibly be used to support the expansion of the area under irrigation in the respective regions. In Mzimvubu in particular, a substantial amount of surface water available for productive use. However, since these findings represent conditions in 2014/15 only, it should be interpreted with caution as it does do not necessarily represent the long-term conditions. The availability of water is highly dependent on various dynamic factors and more work is needed to monitor changes over multiple seasons, specifically during periods of drought. An ongoing challenge for applying the WA+ framework is the unavailability of high-quality spatial rainfall data; accurate information on rainfall in mountainous areas is particularly absent. WA+ should consequently be applied retrospectively (at least from 2015 onwards) and on an ongoing basis, preferably at national scale, to gain a better understanding of the fluctuations in water availability.

SA has a limited availability of suitable land and adequate water resources for irrigated crop production. With the added pressures of climate change, population growth and decline in water quality due to salinisation, the need for improved assessments of the current water resources and land uses is critical. Actions related to improved WUE and irrigation expansion, or water reallocation, can only follow once this information is available. With irrigated agriculture being labelled the largest water user, it is important to obtain recent and accurate data on water used by different irrigated crops over time (i.e. throughout the growing season) and space (i.e. in different geographical areas). Combining these datasets into a WA framework will improve our understanding of the true pressures on SA's water resources and will better inform the expansion of irrigated agriculture.

RECOMMENDATIONS

During the course of the study, several avenues for future research have been identified. This includes the development of EO methods for automated land cover mapping, field boundary delineation, crop type differentiation, and cost-effective ET modelling at high resolution. The incorporation of remotely sensed data into climate surface interpolations was also highlighted as a research priority.

This project provides a good indication of the *status quo* of irrigated agriculture water use for the period of 1 August 2014 to 31 July 2015. The study established a methodology that can be replicated for other periods. Given that it is unlikely that the IAM and water use quantifications produced in this project are representative of the long-term situation, the application of the methodology to other periods is essential in aiding sound water management practices and supporting decisions about additional allocations. The FAO recently released an Africa-wide, freely available, monthly open access of remotely sensed derived data (WaPOR) ET dataset at 250 m resolution (also generated using ETLook and thus very similar to the ET dataset used in this project) for the period 2009–2019 (see Section 2.3.6), which will considerably reduce the cost of future implementations in SA. Coupled with the recently released and freely available Sentinel 2 imagery, the FAO ET datasets will allow for the production of seasonal (even monthly) IAMs and water use quantifications up to 2019. If the irrigated area mapping process is automated, the latency (period required for production) can be reduced to a few weeks, which will substantially increase the reliability of the water use estimations, as it will allow for *in situ* validation to be carried out. Consequently, based on the findings of this research, it is recommended that:

1. the IAM is compared to soil suitability maps;
2. water application in relation to ET crop water requirements is investigated;
3. techniques are developed whereby irrigation type (permanent, supplementary or occasional) and methods (surface, sprinkler or micro/drip) can be determined;
4. actual irrigation is compared to lawful water use;
5. the IAM be used to assess the scale of irrigation schemes (small, medium, large) in South Africa;
6. the WaPOR ET dataset is recalibrated using local climatic and land use data;
7. the irrigated area mapping procedure is fully automated;
8. the IAM is continuously (i.e. on a seasonal or monthly basis) updated;
9. *in situ* observations are used to validate (ground truth) the IAM;
10. consumptive water use of irrigated crops is revised on a continuous (seasonal or monthly) basis at national scale; and
11. the WA+ framework is applied on primary catchment level, preferably to all catchments in SA.

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LIST OF ACRONYMS

ACRU	Agricultural Catchments Research Unit
AI	Artificial intelligence
ALEXI	Atmosphere-Land Exchange Inverse
ARC	Agricultural Research Council
CART	Classification and regression tree
CGA	Centre for Geographical Analysis
CPP	Cloud physical properties
CPWF	Challenge Program on Water and Food
DAFF	Department of Agriculture, Forestry and Fisheries
DEA	Department of Environmental Affairs
DEM	Digital elevation model
DT	Decision tree
DWA	Department of Water Affairs
DWS	Department of Water Affairs and Sanitation
EO	Earth observation
ETM	Enhanced Thematic Mapper
FAO	Food and Agricultural Organization
FSC	Full storage capacity
GDP	Gross domestic product
GEOBIA	Geographical object-based image analysis
GIS	Geographical information systems
GPM	Global Precipitation Measurement Microwave
GPW	Gridded Population of the World
GSMaP	Global Satellite Mapping of Precipitation
GSOD	Global summary of the day
HESS	Hydrology and Earth System Sciences
HTML	Hypertext markup language
IAHS	International Association of Hydrological Sciences
IAM	Irrigated area map
KNMI	Koninklijk Nederlands Meteorologisch Instituut
LAI	Leaf area index
LDCM	Landsat Data Continuity Mission
LST	Land surface temperature
MLC	Maximum likelihood classification
MMU	Minimum mapping unit
MODIS	MODerate-resolution Imaging Spectroradiometer
MSG	Meteosat Second Generation
MWU	Managed water use
NDA	National Department of Agriculture
NDMI	Normalised difference moisture index
NDVI	Normalised difference vegetation index
NGI	National Geospatial Information

NN	Nearest neighbour
NOAA	National Oceanic and Atmospheric Administration
NRI	Natural Resource Inventories
NWA	National Water Act
NWRS	National Water Resources Strategy
OBIA	Object-based image analysis
OLI	Operational Land Imager
PBIA	Pixel-based image analysis
PICES	Producer Independent Crop Estimate System
PM	Penman-Monteith
SA	South Africa
SANCID	South African National Committee on Irrigation and Drainage
SAR	Synthetic aperture radar
SASRI	South African Sugarcane Research Institute
SEBAL	Surface Energy Balance Algorithm for Land
SEBS	Surface Energy Balance System
SEVIRI	Spinning Enhanced Visible and Infrared Imager
SVM	Support vector machines
SWB	Soil water balance
TIRS	Thermal Infrared Sensor
TM	Thematic Mapper
TSEB	Two Source Energy Balance
VHR	Very high resolution
VITT	Vegetation Index/Temperature Trapezoid
WA	Water accounting
WA+	Water accounting plus
WBMP	Waterbody mixed pixels
WCPDA	Western Cape Provincial Department of Agriculture
WMA	Water management areas
WRC	Water Research Commission
WUE	Water use efficiency
WWF	World Wildlife Fund for Nature

1 INTRODUCTION AND OBJECTIVES

1.1 Introduction

South Africa (SA) is classified as a water scarce country (DWAF 2004; Reinders 2010) and has an estimated average annual rainfall ranging between 451 (FAO 1995) and 495 mm (Annandale et al. 2011), depending on the source quoted. An estimated 21% of SA is considered arid, receiving less than 200 mm/yr rainfall, while 44% is regarded as semi-arid as it receives between 200 and 500 mm/yr (Annandale et al. 2011). The Food and Agricultural Organisation (FAO) estimated that 65% of SA does not receive enough rain to support successful dryland agriculture (FAO 1995; World Wide Fund for Nature 2018). In addition, most (~80%) rainfall occurs within a five-month period of the year (Reinders 2010). Hence, only a fraction of the surface area of SA is suitable for crop production. An estimated 12 to 13% (approximately 14 million ha) of soils are fertile and can support dryland crop production (Annandale et al. 2011; World Wide Fund for Nature 2018); however, most of this area is considered marginal. Only 3% of SA's land surface is considered moderate to high-potential land (World Wide Fund for Nature 2018) and the FAO estimates the area with irrigation potential to be 1.5 million ha (FAO 1995). This is similar to the 1996 National Department of Agriculture's (NDA) estimation of potential irrigable land (1.58 million ha) (Backeberg 2003; DWAF 2004).

The estimations of the area of irrigated crops are outdated and vary greatly. A number of assessments since 1990 documented either the actual area under irrigated crops or the registered area under irrigation, using various approaches to derive the estimates. According to these estimates, the area under irrigation ranged between 1.21 and 1.58 million ha and the area registered for irrigation use between 1.44 and 1.68 million ha. Given the uncertainty about the area currently irrigated, the estimated amount of water used by irrigated agriculture is also unclear. It has been estimated that irrigated agriculture uses between 51% (Backeberg et al. 1996) and 63% (Water Accounts for South Africa 2000, in Reinders (2010) of SA's water resources. According to DWAF (2004) and Statistics South Africa (2010), 62% of water is being used by irrigation, 23% for meeting urban requirements and the remaining 15% is shared by other users (rural users, mining and bulk industrial, power generation and afforestation). The water use by irrigated agriculture is affected by assurance of supply, varies regionally across SA and the source of water (surface or groundwater) differs.

Despite irrigated agriculture's use of a large proportion of available water resources, the importance of this sector for the economy and food security is undisputed. Irrigation supports approximately 25 to 30% of national agricultural production; it is estimated that up to 90% of irrigated areas are planted with high-value crops (e.g. potatoes, vegetables, grapes and other fruit and tobacco), of which 25 to 40% are industrial crops such as sugarcane and cotton (Backeberg 2005).

Overall, the direct contribution of agriculture to SA's gross domestic product (GDP) is relatively low, estimated to be between 4 and 5.3% (Backeberg et al. 1996; NDA 1996). A more recent estimate for 2008 indicates a contribution of 2.5% (World Wide Fund for Nature 2018). However, it is estimated that the indirect contribution of agriculture to the GDP is much higher at between 14% (World Wide Fund for

Nature 2018) and 20-30% (Fenyes & Meyer (2003) in Backeberg (2005).

In view of a clear need for irrigated agriculture to support crop production, food security and economic growth, it is alarming to note that in the year 2000, 12 out of the 19 WMAs[1] in SA already faced a water deficit (Reinders 2010; Statistics South Africa 2010). There consequently seems to be little room for increased surface water extraction or abstraction. The WWF estimated that 98% of the available water resources are already allocated (World Wide Fund for Nature 2018). In addition, SA has few exploitable aquifers, and groundwater currently only contributes to a small portion of the total water supply (13%) (World Wide Fund for Nature 2018). New groundwater contributions will be limited, since the overexploitation of groundwater and substantial drops in water tables have already been reported in a number of areas (Burger 2008). Irrigation in some areas is made possible – and will remain possible – only through significant water transfer between the various WMAs (Statistics South Africa 2010). With the added pressures of climate change, population growth and decline in water quality due to salinisation, the need for improved assessments of the current water resources and land uses is critical. Actions related to improved WUE and irrigation expansion, or water reallocation, can only follow once this information is available. With irrigated agriculture being labelled the largest water user, it is important to obtain recent and accurate data on water used by different irrigated crops over time (i.e. throughout the growing season) and space (i.e. in different geographical areas). Combining these data sets into a WA framework will improve our understanding of the true pressures on SA's water resources and will better inform the expansion of irrigated agriculture.

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The consumptive water use by various land uses need to be understood before new water allocations can be granted. Over the past two decades, various international initiatives have been developing WA frameworks to support water managers and decision makers. Using remotely sensed data within a WA framework will be invaluable for water resources management, by providing a comprehensive overview of water resource use for a given area. The efficacy of such a framework is illustrated in this project.

1.2 Aim and objectives

The overarching aim of this research was to update the existing estimations of the amount of water used by irrigated agriculture in SA. This was be done by employing various EO and geographical information systems (GIS) techniques, including the mapping of irrigated agriculture and the modelling of actual ET at national scale. The study focussed on estimating consumptive water use as represented by actual ET and did thus not estimate irrigation applied. Crop mapping was undertaken in selected

[1] The 19 WMAs were since amalgamated into 9 WMAs (South Africa 2016).

areas and the water use of specific crops was quantified. In addition, the project demonstrated how combining these different spatial datasets can be used to determine how much water (*if any*) is available for new allocations.

The specific objectives to achieve the overarching aim were to:

1. Update the total area used for irrigated agriculture in SA;
2. Update the estimated total amount of water used by irrigated agriculture in SA;
3. Quantify the water used by selected irrigated crops in selected areas;
4. Demonstrate how water accounting (WA) can be employed to determine water use and water availability over large catchments;
5. Develop capacity in EO and other geospatial techniques, specifically those relating to water use estimations, land cover and crop type mapping, and WA; and
6. Engage with industry to stimulate participation, increase awareness of crop water use and availability and encourage adoption of new technologies and datasets.

Important definitions

Irrigated area: In this study, irrigated land included all agricultural areas actively irrigated during the period 1 August 2014 to 31 July 2015, whether for the full 12-month period, or a part thereof. The irrigated areas *did not include*: (a) areas previously or usually irrigated or areas left fallow during this period; and (b) crops cultivated and irrigated under nets or in tunnels.

Water use: In this study, water use was equated to consumptive water use and actual ET. In this context, consumptive water use refers to all water that has been removed from a surface through the processes of transpiration (beneficial water use through plants) and evaporation (non-beneficial water use). This study considered the water use from all irrigated agricultural areas as defined above and therefore excluded the consumptive water use of crops cultivated under nets or in tunnels.

1.3 Report structure

This report is structured into seven chapters. This first chapter introduces the rationale of the study and gives a synopsis of the project aims and objectives. Additional background to the research is provided in the next chapter, along with its contextualisation within the existing literature. This is followed by Chapters 3 to 6, which respectively report on the datasets developed, irrigated area maps produced, water use quantification carried out and WA implemented. The final chapter, Chapter 7, lists the main findings of this study, possibilities for future research and recommendations for operational mapping of the irrigated area and associated water consumption in SA. Details of each of these activities and how they relate to the project aims are provided at the end of the next chapter.

2 LITERATURE OVERVIEW AND BACKGROUND

This chapter provides an overview of the existing knowledge about the land and water used for irrigated agriculture in SA. It starts by highlighting uncertainties in previous estimations and the importance of improved estimations. This is followed by an overview of traditional crop water use modelling approaches and their limitations. Emphasis is placed on the models that produce actual (rather than potential) ET. EO methods for mapping areas under irrigated crops and for modelling the water use thereof are then discussed, with specific focus on solutions that can be applied on regional scales. The chapter concludes with a section outlining the WA process and data requirements.

2.1 Land and water used for irrigated agriculture in South Africa

2.1.1 Area and water used by irrigated agriculture

SA is classified as a water scarce country (Reinders 2010) and has an estimated average annual rainfall of 495 mm (Annandale et al. 2011). An estimated 21% of SA is considered arid, receiving less than 200 mm/yr rainfall, while 44% is regarded as semi-arid as it receives between 200 and 500 mm/yr. According to Aquastat statistics (FAO 2016), 65% of SA does not receive enough rain to support successful dryland agriculture. In addition, most (~80%) rainfall occurs within a five-month period of the year (Reinders 2010). Hence, only a fraction of the surface area of SA is suitable for crop production. An estimated 13% (approximately 14 million ha) of soils are fertile and can support dryland crop production (Annandale et al. 2011; World Wide Fund for Nature 2018); however, most of this area is considered marginal. Only 3% of the land surface of SA is considered moderate to high-potential land (World Wide Fund for Nature 2018). According to FAO (2016), the estimated area in SA with irrigation potential in 1992 was 1.5 million ha. This is similar to the 1996 NDA estimation of potential irrigable land (1.58 million ha) (Backeberg 2003).

A number of assessments since 1990 documented either the actual area under irrigated crops or the registered area under irrigation, using various approaches to derive the estimates. Examples are listed below. According to these, the estimates for the area under irrigation range between 1.29 and 1.59 million ha and the area registered for irrigation use between 1.44 and 1.68 million ha. The area equipped for irrigation is estimated to range between 1.27 and 1.5 million ha.

1. The 1990 estimate of 1.29 million ha by the Committee for the development of a food and nutrition strategy for Southern Africa (1990), as cited in Backeberg et al. (1996), is still considered as the last authoritative empirical estimate of the *actual area under irrigated agriculture* in SA.
2. FAO (2016) estimated that, in 1994, the *water managed* was 1.21 million ha. This area consists of government water schemes (329 000 ha), irrigation boards (155 000 ha), private schemes (660 000 ha) and small-scale farmers (70 000 ha). FAO (2016) also states that 82% of irrigation was sourced from surface water and 18% from groundwater. Backeberg (2010) provides a historic overview of the changes in the area under irrigation from 1910 to 1990.

3. Nell & Van den Berg (2001) estimated the *area under irrigation* at 1.59 million ha. This estimate exceeded the 1996 NDA *potential irrigable land estimate* of 1.58 million ha (Niewoudt & Groenewald 2003).
4. Freydank & Siebert (2008) mapped irrigation expansion in SA over 100 years using various data sources (EUROSTAT, AQUASTAT & FAOSTAT). They estimated the *area equipped for irrigation* at 404 000 ha in 1900, 1 million ha in 1970, 1.2 million ha in 1990 and 1.5 million ha in 2000.
5. The Department of Water Affairs (DWA) estimated the *area registered for irrigation use* as 1.68 million ha (Van der Stoep et al. 2008).
6. Annandale et al. (2011), citing FAO (2005), estimated *area under irrigation* as 1.5 million ha.
7. Department of Agriculture, Forestry and Fisheries (DAFF) reported the *total area under irrigation* (including mainly crops and orchards) in 1991 as 1.35 million ha (Development Bank of South Africa 1991 in DAFF 2012). Field boundaries mapped for DAFF from Satellite Pour l'Observation de la Terre (SPOT) 5 recorded in 2011 (2007 for the Eastern Cape) showed 14 million hectare of fields in SA (excluding sugar cane), with 660 000 hectares of centre pivot irrigation and almost 430 000 ha of horticulture/viticulture.
8. Van der Stoep & Tylcoat (2014) provided an estimate of the *registered area under irrigation* in 2014, according to the WARMS database, as 1.44 million ha.

Given the uncertainty about the area currently irrigated, the estimated amount of water used by irrigated agriculture is also unclear. It is estimated that irrigated agriculture uses between 51% (Backeberg et al. 1996) and 63% (Water Accounts for South Africa (2000), in Reinders (2010)) of SA's water resources. According to Statistics South Africa (2010), 62% of water is being used by irrigation, 23% for meeting urban requirements and the remaining 15% is shared by other users (rural users, mining and bulk industrial, power generation and afforestation). The water use by irrigated agriculture is affected by assurance of supply, varies regionally across SA and the source of water (surface or groundwater) differs, as outlined below.

1. Water use by irrigated agriculture was estimated to be 10 740 million m^3/yr in 1996 (BKS report by Basson et al. 1997) and 7 836 million m^3/yr in 2000 (as part of the draft report on the National Water Resources Strategy – NWRS). The latter estimate is based on a 98% assurance of supply (Backeberg 2003; DWAF 2004).
2. In the year 2000 it was estimated that irrigated agriculture uses 7 900 million m^3 of annual runoff per year, which constitutes about 61% of the runoff used by all sectors or just under 40% of the estimated 20 000 million m^3 exploitable runoff (Annandale et al. 2011). In addition, with only 8% of the total rainfall contributing to runoff in SA, the water that is truly used for irrigation is estimated at only 2.5% of the total rainfall (Bennie et al. (1998) in Backeberg (2005)).
3. Nationally, irrigation comprises over 64% of water use (Statistics South Africa 2010). According to Dennis & Nel (2002), groundwater provides water for 24% of the irrigable area. The rest is obtained from surface water (76%).

4. Backeberg (2005) points out that there are large regional variations in water use, with the contribution of water to irrigation as low as 9.5% in the Upper Vaal areas and as high as 93.5% in the Lower Orange region.

2.1.2 Importance of irrigated agriculture

Despite the fact that irrigated agriculture uses a large proportion of the available surface and groundwater resources, the importance of this sector for the economy and food security is undisputed. Irrigation supports approximately 25 to 30% of national agricultural production; it is estimated that up to 90% of irrigated areas are planted with high-value crops (e.g. potatoes, vegetables, grapes and other fruit and tobacco), of which 25 to 40% are industrial crops such as sugarcane and cotton (Backeberg 2005).

According to Greyling (2015), there has over the last five decades been a clear shift in SA from the production of low value primary food crops to high-value export crops (e.g. fruit and wine). This resulted in SA becoming a net importer of food (e.g. meat, cereals, milk, cheese and vegetables) in terms of quantity in the middle 1990s. The shift towards high-value export products resulted in SA still being a net exporter of agricultural products by value.

Overall, the direct contribution of agriculture to SA's GDP is relatively low, estimated to be between 4 and 5.3% (Backeberg et al. 1996; NDA 1996). A more recent estimate indicates a contribution of 2.5% (Greyling 2015). However, through linkages to the manufacturing sector and its contribution to employment it is estimated that the indirect contribution of agriculture to the GDP is much higher at 14% (World Wide Fund for Nature 2018) and even 20-30% (Fenyes & Meyer (2003) in Backeberg (2005)).

2.1.3 A vulnerable irrigated agriculture sector

In view of a clear need for irrigated agriculture to support crop production, food security and economic growth, it is alarming to note that in the year 2000, 12 out of the 19 WMAs[2] in SA already faced a water deficit (Reinders 2010; Statistics South Africa 2010). There consequently seems to be little room for increased surface water extraction or abstraction. WWF estimated that 98% of the available water resources are already allocated (World Wide Fund for Nature 2018). In addition, SA has few exploitable aquifers and groundwater, which currently only contribute to a small portion of the total water supply (13%) (World Wide Fund for Nature 2018). New groundwater contributions will be limited, since the overexploitation of groundwater and substantial drops in the water table have already been reported in a number of areas (Burger 2008). Irrigation in some areas is made possible – and will remain possible – only through significant water transfer between the various WMAs (Statistics South Africa 2010).

Apart from limited land and water resources outlined above, food production in SA faces several additional challenges. This includes changes in the climate, a decline of water quality due to salinisation and population increases. The expectation is that climate change will increasingly affect crop production

[2] The 19 WMAs were since amalgamated into 9 WMAs (South Africa 2016).

worldwide. Climate change prediction models for SA suggest that average temperatures will rise and rainfall events will become both more infrequent and more intense, thereby increasing the unpredictability of (water availability for) agricultural production (World Wide Fund for Nature 2018). A general decrease of five to 10% in rainfall is predicted, with longer dry spells in the interior and north-eastern areas of the country, coupled with more frequent and severe flood events (Statistics South Africa 2010). The increased temperatures will also result in the increase of ET, which will exacerbate the already high drought risk and increasing water deficits in arid and marginal zones (Statistics South Africa 2010). All of these factors will increase production risks to both dryland (rainfed) and irrigated agriculture.

Irrigation used to expand crop production in rainfed areas can reduce soil fertility through salinisation of soils (World Wide Fund for Nature 2018) and have a negative impact on water quality (Backeberg 2005). Waterlogging (the hypersaturation of soil due to over irrigation) and salinisation already affect large areas in SA. (Nell et al. 2015) found that as much as 6% of irrigation schemes are severely affected. Due to the severity of the salinisation impact, approximately 15 000 ha of SA's irrigated farmland is only suitable to salt tolerant crops (World Wide Fund for Nature 2018). Increased salinisation is extremely problematic given the limited land available for irrigated agricultural crop production.

At present, the annual population of SA is growing by approximately 2% and it is estimated that the 2013 population of 53 million will increase to 82 million by 2035 (Statistics South Africa 2013). It is estimated that food production (or imports) will have to more than double to feed this growing population. Local production will consequently need to increase without using additional natural resources (World Wide Fund for Nature 2018). It is predicted that, to meet the food demand by 2050, farmers will be required to double their current use of water or produce more with the water available to them. To meet this need, water supply and WUE will have to be increased (World Wide Fund for Nature 2018). With the currently full or over allocation of water in many catchments, expanding the area under irrigated agriculture will likely not be sustainable. Improved WUE in crop production is thus the most viable solution.

2.1.4 Legislation and irrigated agriculture

In the light of the current pressure and future demands on water, the importance of adherence to current legislation related to water resource management are recognised, especially in the context of economic growth and development and secure food production. The National Water Act of South Africa (Act 36) (1998) prescribes that water resources should be protected, used, developed, conserved, managed and controlled in a sustainable and equitable manner. This directly implies knowledge of who (various sectors), where (geographic space), when (time) and for what (purpose) water are used. With knowledge on water use, the available water demand can be managed against supply, water can be allocated fairly between users, the environment be can protected and water tariffs can be efficiently allocated.

Backeberg (2005) suggested measures whereby the NWRS can reconcile water demand with supply.

The NWRS requires knowledge of water use over space and in time. Backeberg (2005) emphasised that, although the National Water Act (NWA of 1998) does not make provision for water conservation and demand management, the definition of water conservation makes these measures an essential component of water resource management (DWAF 2004); Backeberg (2005) and relates the efficient and effective use of water to the minimisation of loss and wastage of water. Backeberg (2005) further highlights that water demand management is not only about reducing water use; it is also about the economic valuation of a scarce resource in the context of irrigated agricultural crop production.

The concern about the inefficient use of water for irrigation is also highlighted in the Water for Growth and Development framework compiled in 2009 by the Department of Water Affairs and Forestry (DAFF). This framework states that the inefficient use of water in commercial irrigation must be urgently addressed. This, too, requires spatial and temporal information on the allocation of water to different users and quantifying the amounts used by specific crops (Backeberg & Reinders 2009). Adding to the competition for water resources in already well-allocated WMAs, the Water for Growth and Development framework refers to proposals by the Department of Agriculture (2007) in the Irrigation Strategy for South Africa (Backeberg & Reinders 2009). This strategy proposes that new farms be established and an estimated extra 600 000 ha of land developed. It proposes that the areal expansion can be achieved by savings in water losses and improved irrigation efficiency. Backeberg & Reinders (2009) estimated that the DAFF targets for expansion of the irrigated area, based on water savings, are too ambitious and need to be adjusted downwards, with 282 000 ha being a more realistic target.

It is clear that the availability of suitable land and adequate water resources for irrigated crop production is limited in SA. With the added pressures of climate change, population growth and decline in water quality due to for example salinisation, the need for improved assessments of the current water resources and land uses is critical. Actions related to improved WUE and irrigation expansion, or water reallocation, can only follow once this information is available. With irrigated agriculture being labelled the largest water user, it is important to obtain recent and accurate data on water used by different irrigated crops over time (i.e. throughout the growing season) and space (i.e. in different geographical areas). Combining these datasets into a WA framework will improve our understanding of the true pressures on SA's water resources and will better inform the expansion of irrigated agriculture.

2.2 Traditional models for estimating crop water use

Numerous methods have been developed, both locally and internationally, to estimate crop water use (consumption) through the processes of transpiration and soil evaporation, as reflected by evapotranspiration (ET). Methods include both field-based measurements and models. The field-based methods for measuring or estimating ET include the soil water balance approach, pan methods (e.g. Class A pan), the reference evaporation and crop factor approach, lysimetry, atmometers (e.g. ETgage), the eddy covariance method and a range of aerodynamic methods that estimate sensible heat from which evaporation is estimated as a residual, using the shortened energy balance equation (Jarmain et al. 2009b). The latter includes the one sensor eddy covariance, Bowen Ratio, surface renewal, scintillometry and other methods. A number of methods are also used to estimate transpiration directly, e.g. the sapflow and heat pulse velocity methods (Jarmain et al. 2009b). Many of the methods listed above have been used to estimate ET in SA, as part of Water Research Commission (WRC) funded projects. In this context, see for example Bristow & De Jager (1981); Green & Clothier (1988); Dye et al. (1997); Savage et al. (1997); Everson et al. (1998); Everson (1999); Savage et al. (2004); Jarmain et al. (2009a); and Jarmain et al. (2014).

Numerous field-based models for estimating ET and crop irrigation water requirements have been developed in SA, for example the soil water balance (SWB) model, SAPWAT, BEWAB, and CANESIM®. Annandale et al. (2011) provide a comprehensive overview of different methods developed over the past 40 years and used in irrigation scheduling and to determine crop water requirements. These models have been evaluated extensively in completed WRC funded projects. See for example Bennie et al. (1998); Annandale et al. (2005); Bezuidenhout & Singels (2007); Ehlers et al. (2007); Van Heerden et al. (2009); Jarmain et al. (2014). Of these, the most commonly used and often recommended by DWAF (2006a), is the South African procedure for estimating irrigation water requirements (SAPWAT). SAPWAT is a South African irrigation planning and management tool based on the United Nations' (UN) FAO planning model CROPWAT (Smith 1992; Van Heerden et al. 2001; Woyessa et al. 2004). The latest version, SAPWAT4, was released in 2016 (Van Heerden & Walker 2016). Several international models are based on a similar approach. Many hydrological models similarly provide estimates of ET, however, in a spatial manner. In SA, the Agricultural Catchments Research Unit (ACRU) model (Schulze 1995) was designed to determine water use by a wide range of agricultural crops and other vegetation. ACRU is a multi-purpose, integrated physical-conceptual model that consists of a multi-layer model for soil water content. Various studies (Warburton et al. 2010; Graham et al. 2011; Ngcobo et al. 2012; Warburton et al. 2012; Kusangaya et al. 2014) have used the ACRU hydrologic model to gain insight into the effect of land use and climate change on SA's available surface water resources.

Given that many of the abovementioned methods are point- or field-based, their ET estimates have a limited spatial "footprint". Spatially explicit methods developed to estimate ET fill the need for geographical estimates of ET. Advances in remotely sensed data enable pixel-based assessments of ET at resolutions ranging from 1000 m to as small as 20 m. Such EO methods for estimating ET over large areas are discussed in the next section.

2.3 Earth observation

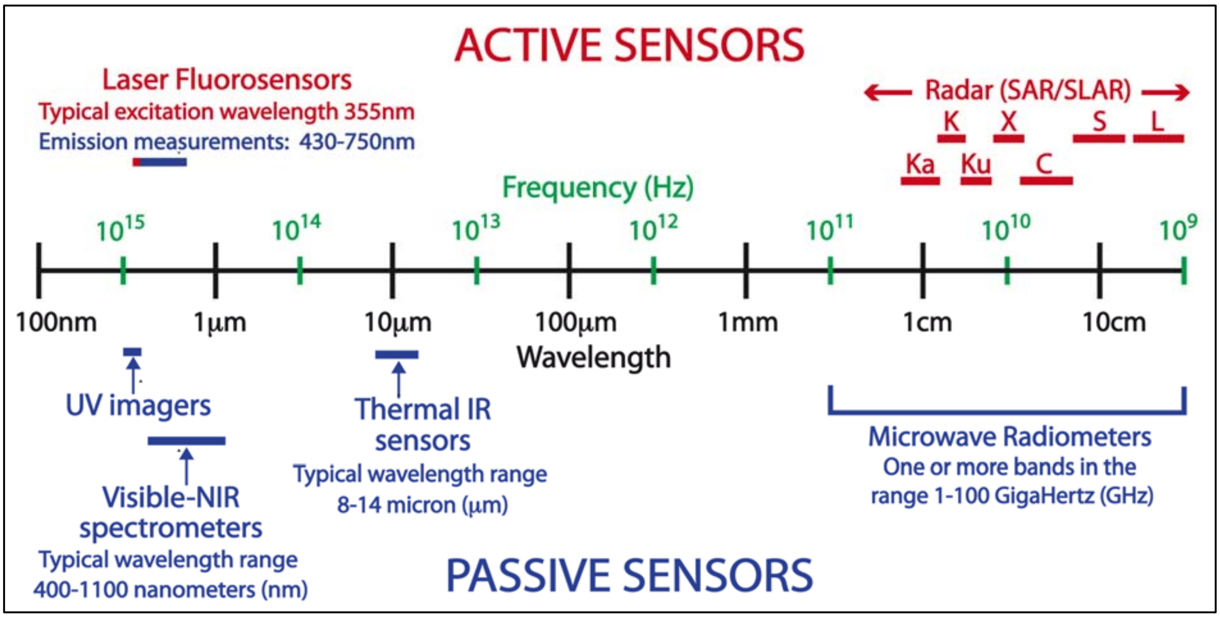
The previous sections highlighted the need for crop water use (ET) information for aiding the understanding and management of water demands across SA. The availability of spatially explicit methods to generate these datasets necessitates the use of geospatial technologies such as GIS and remote sensing. The following sections provide an overview of the geospatial technologies and data used in this project. The discussion starts with GIS and spatial modelling, as these were the fundamental technologies used to quantify crop water use. This is followed by a section on the remote sensing technologies used to collect the necessary data. An outline of existing data are followed by an overview of the fundamental EO techniques employed, specifically image classification and object-based image analysis techniques.

2.3.1 GIS and spatial modelling

GIS is used to manage and analyse spatially referenced or geographical data (Heywood et al. 2006) and provides quick and easy access to large volumes of data for analysis purposes. Over the last twenty years, GIS has established itself as a mature technology, with particular value in answering questions about location, patterns, trends, conditions and the implications thereof. Within GIS, datasets of different formats at varying scales can be incorporated into a single database, which can be stored as vector and/or raster data. Using such data, spatial modelling can be employed, where models can be constructed to predict spatial outcomes that simulate the dynamics of natural processes (O'Sullivan & Unwin 2010). Spatial modelling in GIS embraces techniques that apply quantitative structures to systems in which the variables of interest vary across space. Spatio-temporal models simulate change over time using equations that represent real-world processes while taking spatial patterns and spatial interaction in the system into account (Karssenberg et al. 2008). Such spatial and temporal process models can be used for decision-making regarding spatial phenomena (e.g. in spatial decision support systems) but are also used to evaluate our understanding of complex spatial systems (Heywood et al. 2006). Furthermore, models can be used to establish (*a priori*) or explore (*a posteriori*) spatial theory (Hardisty et al. 1993). However, when modelling in GIS, the questions of validation and the roles of scale and accuracy need to be carefully considered (Goodchild 2005).

2.3.2 Remote sensing and Earth observation background

Remote sensing is the process of acquiring information from a distance (i.e. without being in contact with the observed target). EO combines *in situ* data with remote sensing techniques to derive information about the Earth's land and water surfaces. The remotely sensed data, usually acquired from an overhead perspective, record electromagnetic (EM) radiation in one or more regions of the EM spectrum, reflected or emitted from the Earth's surface (Campbell 2007). Passive sensors, which only receive EM radiation, mainly operate in the visible and the infrared regions of the EM spectrum (Figure 2.1). The visible spectrum contains those wavelengths of radiation that can be perceived by human vision, *i.e.* from violet to red light. Wavelengths longer than those of the visible spectrum (but shorter than those of microwave radiation) are termed infrared, and this spectrum can be subdivided into near-, mid- and far-infrared. The primary source of near- and mid-infrared radiation is the sun, and EM radiation in these wavelengths are reflected by the Earth's surface in the same manner as EM radiation in the visible wavelengths. Hence, the near- and mid-infrared wavebands, together with the visible bands, are often collectively known as the optical bands. Far-infrared radiation, however, is absorbed and then emitted by the Earth's surface in the form of heat, or thermal energy, and is sometimes known as thermal infrared radiation. Thermal infrared bands are generally less common in multispectral satellite imaging platforms than visible, near- and mid-infrared bands (Campbell 2002; Mather 2004).



Source: SEOS (2016)

Figure 2.1 Electromagnetic spectrum and its relation to passive and active remote sensors

The longest wavelengths commonly used in remote sensing fall in the microwave spectrum, where solar irradiance is negligible. Although the Earth itself emits a small amount of microwave energy, this emitted energy is rarely measured in remote sensing as most microwave sensors are active. As opposed to passive sensors, which measure energy generated by an external source (usually the sun), active sensors use their own energy to irradiate the ground and then measure the portion of that energy reflected back to them (Campbell 2002; Mather 2004). Active microwave sensors are radar (radio detection and ranging) sensors. An imaging radar system typically consists of a transmitter, receiver, antenna array and a recorder. The transmitter transmits repetitive microwave pulses at a specific frequency through the antenna array, which controls the propagation of the EM wave through devices known as waveguides. Usually, the same antenna then receives the echo of the signal. This is then accepted by the receiver, which filters and amplifies it as required, and passes it on to the recorder (Campbell 2002).

A feasibility study carried out during the first phases of the project found that the use microwave remote sensing was not cost-effective for regional or national implementation. It was therefore not employed in this study. However, in light of recent developments (e.g. availability of Sentinel-1 data at no cost), microwave data should be considered in future research activities (especially for crop type mapping and monitoring).

The following subsections consequently focus on optical and thermal remote sensing, which were the primary remote sensing datasets used in this study.

2.3.3 Optical remote sensing

A large number of passive (optical) EO sensors are available. Choosing the most appropriate sensor for a particular application depends on several factors, including:

- spatial resolution (also known as the pixel size), which is often related to the size of the object that can be recognised using the imagery;
- spectral resolution, referring to the number of spectral bands available and range of the EM spectrum captured;
- temporal resolution (also called revisit cycle), which denotes the interval between image acquisitions for the same area; and
- swath width (also called image extent), which describes the square kilometre area covered by one scene.

The scale of mapping and the minimum mapping unit (MMU) of the application are often the main criteria considered when deciding on the appropriate imagery to use, and these characteristics relate directly to the spatial resolution of the imagery. However, another very important factor that has to be considered when selecting a specific source of EO data for a project, is cost. Table 2.1 summarises current prominent optical (passive) satellite sensors and their respective spectral and spatial resolution, extent and cost.

Landsat 5 (TM), Landsat 7 (ETM+), Landsat 8 (OLI) and Advanced Spaceborne Thermal Emmission and Reflection Radiometer (ASTER) are by far the most popular sensors for scientific purposes, mainly because archived data from these sensors are freely available via a number of web-portals. Unfortunately, the scan-line corrector of ETM+ has been inoperative since 2003, rendering large areas of any image unuseable. ASTER data are only acquired on request, which means that limited areas in SA have recent data available. Furthermore, since May 2008, ASTER's shortwave infrared sensor (which acquires the most useful information for agricultural science) is no longer operational. Although the relatively low spatial resolutions of the Landsat (30 m) and ASTER (15 m) sensors make them less suitable for many applications, their relatively high spectral and temporal resolutions are of great value for land cover and crop type mapping applications. Very high resolution (VHR) sensors such as IKONOS, Quickbird, Worldview and GeoEye offer sub-metre spatial resolution (in panchromatic bands at least) and are consequently highly suitable for analysing the structural/spatial properties of agricultural fields (e.g. orchard rows, size of trees). However, compared to sensors with slightly lower spatial resolutions (e.g. SPOT 5), the VHR sensors have smaller image footprints and are significantly more expensive.

Table 2.1 Commonly used optical Earth observation satellite sensors and their characteristics

		Satellite (launch year)	Sensors	Spectral bands	Spatial resolution	Revisit time	Availability
Low resolution OI	**MODIS**	TERRA (1999) AQUA (2002)	Moderate-Resolution Imaging Spectro-radiometer (MODIS)	36	Red, Near-infrared (NIR) (250 m) Blue, Green, IR (500 m) Thermal (1 km)	2 times, daily	Freely available
	AVHRR	NOAA (1978 - 2009) multiple	Advanced Very High Resolution Radiometer (AVHRR)	6	VIS, NIR, Thermal, (1 km)	2 times, daily	Freely available
	MSG	MSG-1 (2002) MSG-4 (2012)	Spinning Enhanced Visible and Infrared Imager (SEVIRI)	13	VIS (1 km) VIS, NIR, Thermal, (3 km)	15 min	Freely available
Medium resolution OI	**Landsat**	Landsat 4 (1982)	Multispectral Scanner (MSS); Thematic Mapper	4	VIS, NIR, Thermal (68 m by 83 m)	18 days	Freely available
			Thematic Mapper (TM)	7	VIR, NIR, Mid-IR (30 m), Thermal (120 m)	16 days	Freely available
		Landsat 5 (1985)	MSS	4	VIS, NIR, Thermal (68 m by 83 m)	18 days	Freely available
			TM	7	VIR, NIR, Mid-IR (30 m), Thermal (120 m)	16 days	Freely available
		Landsat 7 (1999)	Enhanced Thematic Mapper Plus (ETM+)	8	Panchromatic (15 m), VIR, NIR, Mid-IR, SWIR (30 m) Thermal (60 m)	14 days	Freely available
		Landsat 8 (2013)	Operational Land Imager (OLI)	9	Panchromatic (15 m), VIR, NIR, Mid-IR, SWIR (30 m)	15 days	Freely available
			Thermal Infrared Sensor (TIRS)	2	Thermal (100 m)	16 days	Freely available
	ASTER	TERRA (1999)	Advance Space-borne Thermal Emission and Reflection Radiometer (ASTER)	14	VIS, NIR (15 m), SWIR (30 m), Thermal (90 m)	16 days	Commercial, Research
	CBERS	China-Brazil Earth Resources satellite CBERS (1999) multiple	High Resolution charged coupled device (CCD) Camera (HRCCD)	5	Panchromatic, VIR, NIR (20 m)	26 days	Freely available
			Infrared Multispectral Scanner	4	Panchromatic, SWIR (80 m), Thermal (160 m)	26 days	Freely available
	IRS	IRS-1A (1988)	Linear Imaging Self Scanning Sensor (LISS)- I	4	VIR, NIR, (72.5 m)	22 days	Commercial, Research
			LISS – II	4	VIR, NIR (36.25 m)	22 days	Commercial, Research
		IRS-1B (1991)	LISS – I	4	VIR, NIR, (72.5 m)	22 days	Commercial, Research
			LISS – II	4	VIR, NIR (36.25 m)	22 days	Commercial, Research
		IRS-1C (1995)	LISS – III	4	Panchromatic (5.8 m), VIR, NIR (23 m)	24 days	Commercial, Research
High resolution OI	**IRS**	Resourcesat - 1 (2003)	LISS – IV	4	Panchromatic, VIR, NIR (5.8 m)	5 days	Commercial, Research
		Resourcesat - 2 (2011)	LISS – IV	4	Panchromatic, VIR, NIR (5.8 m)	5 days	Commercial, Research
	Sentinel	Sentinel -2 (A & B)(2015 & 2016)	Multispectral Instrument (MSI)	13	VIS, NIR (10 m), SWIR (20 m), other (60 m)	5 days	Freely available
	SPOT	SPOT 1 (1986)	Visible High Resolution sensor (HRV)	4	Panchromatic (10 m), VIS, NIR (20 m)	26 days	Commercial, Research
		SPOT 2 (1990)	Visible High Resolution sensor (HRV)	4	Panchromatic (10 m), VIS, NIR (20 m)	27 days	Commercial, Research
		SPOT 3 (1993)	Visible High Resolution sensor (HRV)	4	Panchromatic (10 m), VIS, NIR (20 m)	28 days	Commercial, Research
		SPOT 4 (1998)	Visible and Infrared High Resolution sensor (HRVIR)	5	Mono-spectral (10 m), VIS, NIR, SWIR (20 m)	26 days	Commercial, Research
		SPOT 5 (2002)	High Resolution Geometric sensor (HRG)	5	Panchromatic (2,5 m), VIS, NIR (10m), SWIR (20 m)	26 days	Commercial, Research
		SPOT 6 & 7 (2012 & 2014)	New AstroSat Optical Modular Instrument (NAOMI)		Panchromatic (1,5 m), VIS, NIR (6 m)	5 days	Commercial, Research
Very high resolution OI	**IKONOS**	IKONOS (1999)	Optical Sensor Assembly (OSA)	5	Panchromatic (0.82 m), VIS, NIR (3.2 m)	Approx. 3 days	Commercial
	Quickbird	QuickBird (2001)	Ball's Global Imaging System (BGIS 2000) sensor	5	Panchromatic (0.65 m), VIS,NIR (2.6 m)	3.5 days	Commercial
	RapidEye	RapidEye (2008)	RapidEye Earth Imaging System (REIS)	5	VIS, NIR (5 m)	5.5 days	Commercial
	GeoEye -1	GeoEye-1 (2008)	GeoEye Imaging System (GIS)	5	Panchromatic (0.41 m), VIS, NIR (1.65 m)	8 to 10 days	Commercial
	WorldView	WorldView-1 (2007)	WorldView-60 camera	1	Panchromatic (0.5 m)	2 to 6 days	Commercial
		WorldView -2 (2009)	WorldView -110 camera	9	Panchromatic (0.5 m), VIS, NIR (2 m)	1 to 3 days	Commercial
		WorldView - 3 (2014)	WV-3 imager, CAVIS	17	Panchromatic (0.3 m), VIS, NIR (1.2 m), SWIR (3.7 m)	1 to 5 days	Commercial

The main EO satellites used in this project included MSG, MODIS, Landsat 8, SPOT 5 and SPOT 6/7. Detailed specifications for each of these satellite sensors are provided in the succeeding subsections.

2.3.3.1 Meteosat Second Generation (MSG)

MSG is a geostationary satellite that makes observations of the Earth's surface at 15 minutes intervals. MSG is primarily used for monitoring atmospheric processes such as weather systems, but is also frequently applied to observe other terrestrial phenomena such as active wildfires. In this project, MSG provided cloud cover information used to quantify the transmissivity of the atmosphere, which was subsequently used in modelling the shortwave solar radiation in the ETLook model. The characteristics of the Spinning Enhanced Visible and Infrared Imager (SEVIRI) sensor on MSG are provided in Table 2.1 and were gained from Aminou (2002).

2.3.3.2 MODerate-resolution Imaging Spectroradiometer (MODIS)

MODIS is a key instrument aboard both the TERRA (EOS AM) and AQUA (EOS PM) satellites, in orbit at 705 km above the Earth. TERRA was launched on 18 December 1999, while AQUA was launched on 4 May 2002[3]. The direction of the satellites differ in that TERRA orbits the Earth north-to-south, timed to pass over the equator in the morning (10:30 am). AQUA orbits the Earth, south-to-north, timed to pass over the equator in the afternoon (1:30 pm). Together, TERRA MODIS and AQUA MODIS view the entire Earth's surface every 1 to 2 days, acquiring data in 36 spectral bands[4].

Spectral characteristics of the MODIS sensor are summarised in Table 2.1. The sensor's first two bands (red and NIR) have a resolution of 250 m, allowing the generation of the normalised difference vegetation index (NDVI) at this resolution. The sensor also has five 500 m resolution bands in the visible and NIR region of the EM spectrum, and several bands in the thermal infrared spectrum. Two of these bands, at 11 and 12 μm respectively, can be used to calculate the Earth's surface temperature. These bands have a resolution of 1000 m.

NASA offers readily available remote sensing products, including MODIS images, through Distributed Active Archive Centres. These centres process, archive, document, and distribute data from NASA's past and current research satellites and field programs. For example, the NDVI and albedo products are available as cloud free composites of a series of atmospherically corrected radiance images.[5]

2.3.3.3 Landsat 8

Landsat 8 is the latest satellite in a series of satellites that span more than 40 years of remotely observing features of the Earth's surface. The spacecraft, which is also known as the Landsat Data Continuity Mission (LDCM), carries two sensors, namely the operational land imager (OLI) and thermal infrared sensor (TIRS). OLI captures panchromatic and multispectral images, while TIRS records

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[3] http://modis.gsfc.nasa.gov/about/design.php
[4] http://modis.gsfc.nasa.gov/about/
[5] More information on the MODIS products is available at https://lpdaac.usgs.gov/

thermal data. OLI provides seven multispectral bands (Table 2.1) that are particularly useful for multi-temporal vegetation studies, such as mapping actively irrigated areas (discussed in Chapter 4) and classifying crop types (Gilbertson et al. 2017; Gilbertson & Van Niekerk 2017).

2.3.3.4 SPOT 5 and 6

The SPOT family of satellites have been recording satellite imagery for almost 30 years. The latest addition is SPOT 7, which was launched on 30 June 2014. Unique off-nadir positioning allows SPOT 6 and SPOT 7 to efficiently cover large areas and collect frequent images of individual targets.

Archival SPOT 5 data are free to South African academic and research use, making it an ideal source of imagery for this research. In addition, the country-wide, pan-sharpened mosaic datasets that are annually released to government departments and research institutions were also used in this project.

2.3.4 Thermal remote sensing

Thermal remote sensing deals with the acquisition, processing and interpretation of data acquired primarily in the thermal infrared (TIR) region of the electromagnetic (EM) spectrum (3 to 35 μm). In thermal remote sensing, emitted radiation is considered, as opposed to optical remote sensing where reflected radiation is captured. One of the aspects often studied in the domain of thermal remote sensing is land surface temperature (LST). LST provides information on the temporal and spatial variations of the surface equilibrium state (Li et al. 2013) and is an important in particularly the estimation of land surface atmospheric fluxes. The strong heterogeneity of land surface characteristics such as vegetation, topography, and soil lead to a rapidly changing LST in both space and time, resulting in remote sensing satellite data offering the only option for measuring LST over the entire globe at a sufficiently high temporal resolution (Kalma et al. 2008; Li et al. 2013). For example, when using an energy balance approach to estimate ET, LST is used to estimate the net radiation and the sensible heat flux. Although it was initially unclear whether satellite-based radiometric temperature could be used in the estimation of ET (Kalma et al. 2008), it has since been determined that to estimate ET with a better than 90% accuracy, LST must be retrieved at an accuracy of 1 K or more (Li et al. 2013). This reinforced the need to obtain an accurate LST, as the estimation of a critical observation (ET) in hydrology was dependent on this number.

Apart from radiometric temperature measured by satellite sensors, land surface emissivity and atmospheric effects are generally required in the estimation of LST. However, methods have been developed where LST can be estimated despite this information being absent. The approaches reported on in the literature to retrieve LST and the related assumptions are shown in Table 2.2 (based on Li et al. (2013).

Table 2.2 LST retrieval methods, based on Li et al. (2013)

General method	Specific method	Assumptions
Retrieval with known emissivity	Single-channel algorithms	No special assumption
	Multi-channel algorithms	Different atmospheric absorptions in adjacent TIR channels
	Multi-angle algorithms	1) LSTs are independent of the view zenith angle 2) The atmosphere is horizontally uniform and stable over the observation time
Retrieval with unknown emissivity	Classification-based emissivity methods	Surface materials in the same class have the same emissivity
	NDVI-based emissivity methods	1) Surface is composed of soil and vegetation 2) Variation of land surface emissivity is linearly dependent on the fraction of vegetation in a pixel
	Day/night temperature independent spectral indices based methods	Emissivity ratios are the same or do not change significantly between two times, i.e. day and night
	Two-temperature methods	Emissivity is invariant at two times
	Physics-based day/night operational methods	1) Land surface emissivity does not change significantly between day and night 2) Angular form factor has very small variation in Mid-IR channels
	Grey body emissivity methods	There exists a flat region in the emissivity spectrum
	Temperature emissivity separation methods	Relationship between the minimum land surface emissivity and spectral contrast holds true over the entire gamut of surface materials
	Iterative spectrally smooth temperature emissivity separation methods	Land surface emissivity spectrum is smoother than the spectral absorption of the atmosphere
	Linear emissivity constraint temperature emissivity separation methods	1) Emissivity spectrum can be divided into *M* segments 2) Emissivity in each segment changes linearly with wavelength
Retrieval with unknown emissivity and unknown atmospheric quantities	Artificial neural network methods	No special assumption
	Two-step physical retrieval methods	1) Specular surface reflection and a constant angular form factor are used to simplify the radiative transfer equation 2) Principle component analysis can be used to reduce the number of unknowns without significant loss of accuracy

In this project, thermal or LST data were incorporated into the ET modelling as described in Section 3.2.

2.3.5 Image classification approaches

Conventional image classification methods comprise supervised and unsupervised procedures, which strongly rely on a variety of statistical algorithms employed in spectral feature space. Although widely used in operational applications, these more traditional classifiers have limitations. The progression of digital image analysis techniques, combined with the advancement of computer hardware and software, has led to the development and increased implementation of more advanced classifiers that combine data mining and image pattern recognition methods (Tseng et al. 2008). This is done by incorporating techniques such as artificial intelligence, logical structures and expert knowledge into the classification procedures (Brown de Colstoun et al. 2003; Mather 2004). The following sections focus on the common conventional and progressive methods used for discriminating land cover (e.g. crop types) using remotely sensed imagery.

2.3.5.1 Unsupervised, supervised and expert system classification

Unsupervised classification is defined by two distinct steps. The first step is the automatic classification of pixels into a user-specified number of classes according to their spectral properties. The second step is the manual labelling of the resulting spectral classes, usually depicted in images as areas of homogeneity, according to real-world information (Campbell 2007). Although the automated nature of the spectral delineation renders this classification method less user-intensive, it cannot be said to be truly unsupervised in nature. It is rather, as Mather (2004:203) puts it, “exploratory”, where repeated unsupervised area delineations with different parameters allow a user to ascertain which real-world (informational) classes are spectrally distinct and which are spectrally similar. This understanding of image features can inform the construction of a set of informational classes to be used in the classification, rendering unsupervised classification extremely useful where *a priori* information regarding the study area or the classification structure is unavailable or not pre-determined. Conversely, where an informational class structure is already established, it is rare that it will correspond with the automatically delineated spectral classes, resulting in the lowering of the accuracy of the outcome (Campbell 2007). This is especially true for high resolution imagery where features of interest commonly comprise multiple spectral classes shared by more than one information class. This is the primary disadvantage of unsupervised classification, and for this reason its use is often limited in operational applications.

Supervised classification is the application of *a priori* information of informational classes to determine the identity of unknown image elements. Data for informational classes are acquired from an external source and entered into the classifier in the form of designated and labelled polygons termed “training areas” or “training data”. These training areas contain statistical information regarding the spectral properties of each class, which is used by a classification algorithm to identify the class of unknown pixels (Mather 2004; Campbell 2007). Classification algorithms vary widely, but are all designed to compare the features of each of the classes with those of an unknown pixel in geometric feature space, and assign a class based on the results of that comparison. The most widely used algorithm is the maximum likelihood classification (MLC) algorithm, due to its ready accessibility, robustness, strong theoretical foundation, and high accuracies for a wide range of remote sensing applications (Bolstad & Lillisand 1991; Brown de Colstoun et al. 2003; Tseng et al. 2008). Because of these traits, a number of studies use MLC as the benchmark with which to compare newly developed classification methods (Liu et al. 2002; Nangendo et al. 2007).

Despite the advantages shown by supervised classification, it does contain a number of drawbacks. First, while accuracies achieved are generally acceptable, traditional supervised classifiers are often outperformed by more elaborate classification methods, such as classification trees or rule-based expert systems (Pal & Mather 2003). Other disadvantages pertain to the identification and delineation of training areas. Poorly developed training areas result in weak classification accuracies, and thus training data must be meticulously prepared. This can become expensive in terms of both time and money, especially for projects mapping large areas that span multiple images (Albert 2002).

Classification or decision tree (DT) classifiers are often used to solve some of the limitations of traditional supervised approaches. A DT classifier recursively applies a set of decision rules to an input dataset, categorising the dataset into a set of target classes. A DT classifier is composed of a root node (the input dataset), internal nodes (splits) and terminal nodes (the target classes, known as leaves). Each node in the tree can only have one parent node, but can have two or more descendant nodes. Decision rules are applied at each non-terminal node, splitting the data into smaller subsets until the leaf nodes are reached and the data are classified (Friedl & Brodley 1997; Chuvieco & Huete 2010). The result is a classification ruleset, inferred from training data using statistical learning algorithms (Friedl & Brodley 1997; Chuvieco & Huete 2010).

DTs have various advantages that other classifiers do not provide. A wide variety of input data can be accepted, including both continuous and categorical data. Thus, ancillary data can easily be included. The simplicity of the classifier structure has the effect that it can be easily interpreted, tested and refined (Brown de Colstoun et al. 2003). Rogan et al. (2002) found a DT to be significantly more accurate than MLC in monitoring changes in forest vegetation in California. Similarly, Friedl & Brodley (1997) reported DTs to provide significantly higher accuracies than MLC, with hybrid DT performing better than uni- or multivariate DTs. Brown de Colstoun et al. (2003) noted that the accuracy of a DT classifier was significantly higher than that of traditional classifiers and comparable to that of neural networks. Additionally, the DT in their study was significantly less computationally intensive than the neural network.

Other than supervised classification, classification rulesets can be manually created based on analyst experience. Such approaches are regarded in remote sensing as one form of expert system classification (Chuvieco & Huete 2010). The term “expert system” in remote sensing is fairly versatile and can represent a number of different techniques. Tsatsoulis (1993) defines the categories of expert systems as user-assistance systems, classifiers, low-level processing systems, data fusion systems, and GIS applications. All pertain to different procedures in remote sensing analysis, but all are defined as “expert” in that they all employ artificial intelligence (AI) inference structures that use expert knowledge (Cohen & Shosheny 2002). For this reason, expert systems are also known in the literature as knowledge-based systems.

2.3.5.2 Geographic object-based image analysis

The development of classification methodologies has been enhanced by the advent of object-based image analysis (OBIA). Traditional methods of image analysis consider each pixel as an individual unit, with little cognisance of its topological relations to its neighbours or the class structure it represents (Lira & Maletti 2002; Van Coillie et al. 2007). This individuality of pixels renders them susceptible to data noise, atmospheric effects and surface variation (Wicks et al. 2002), and limits the usability of spectral, textural and relational information (Rego & Koch 2003; Lennartz & Congalton 2004; Oruc et al. 2004). Considering these factors, Blaschke et al. (2000) argue that no form of pixel-based image analysis (PBIA) can really yield reliable, robust and accurate results. In contrast, object-oriented imagery analysis operates on pre-defined areas of the image, derived either from an external source or, more commonly, an internal region-partitioning process known as segmentation (Blaschke et al. 2000).

The increased availability of high spatial resolution satellite imagery has exposed further limitations of PBIA, as for many applications the pixels of these images are significantly smaller than the objects of interest. In such cases, the pixels often show spatial autocorrelation – the concept that features closer to each other are more similar than features further away – and will therefore belong to the same classes as their neighbours (Blaschke et al. 2000; Lang 2008). The object-based nature of OBIA is therefore inherently better suited to the analysis and classification of high resolution imagery.

Although OBIA is a relatively new technology, it is based on older segmentation, edge-detection, feature extraction and classification concepts that have been used in computer vision, image analysis and remote sensing for decades (Blaschke 2010; Quihao 2011). At its most fundamental level, OBIA is image segmentation and classification (Castillejo-González et al. 2009; Blaschke 2010; Peña-Barragán et al. 2011). Segmentation involves the delineation of areas of an image into separate objects. Although there are a variety of methods of segmentation, the bottom-up, region-growing method of multiresolution segmentation has been shown to provide good results for a variety of applications and over an array of image types (Baatz & Schäpe 1999). This method starts with pixel-objects, and repetitively merges adjacent objects according to a pairwise, mutual-best-fitting, region-growing algorithm, until a user-set homogeneity parameter is exceeded. Altering this homogeneity parameter, which consists of spectral and geometrical variable thresholds, allows the user to define a layer of image objects corresponding to actual geographical objects relative to the scale at which the image is viewed. Repeated segmentations at different scales result in layers of objects of different dimensions, which can be structured in a shape-constrained hierarchical object network. Each object in such a network will exhibit both horizontal and vertical spatial awareness, as it is cognisant of its neighbouring objects in the same object layer, the number of shared borders of its sub-objects in layers below, and its membership to super-objects in layers above (Benz et al. 2004; Karakis et al. 2006; Mallinis et al. 2008). The result could be termed a parent-child multi-scale hierarchy of object-primitives – building blocks defined though a process of repetitive testing that provides optimal information for the specific classification (Mitri & Gitas 2002). It follows that segmentation and classification must be a collaborative process, as defining appropriate segmentation parameters for different scales is challenging and often problematical (Hay et al. 2005), and the quality of the segmentation will significantly affect the outcome of the classification (Bauer & Steinnocher 2001; Kermad & Chehdi 2002; Benz et al. 2004).

To summarise, the use of OBIA offers the following advantages (Benz et al. 2004; Bock et al. 2005; Hay et al. 2005; Shiba & Itaya 2006):

- meaningful statistical calculation of spectral and textural qualities;
- the availability of feature qualities such as shape and object topology;
- the intuitive spatial relations between real-world objects and image objects; and
- the ease of integration between GIS and remote sensing environments and flexibility among different software platforms.

A number of researchers have argued that these factors contribute to producing a superior image classification result, compared to those provided by PBIA approaches. Several case studies support this view. Rego & Koch (2003) illustrated the superior accuracy of object-based over pixel-based supervised classifiers in more than 100 image classifications using IKONOS imagery in Rio de Janeiro City, Brazil. The superiority of object-oriented classification was also shown by Oruc et al. (2004) who compared the technique to three different types of pixel-based supervised classification of Landsat 7 ETM+ imagery in Zonguldak, Turkey. Gilbertson et al. (2017) compared OBIA and PBIA approaches for mapping crop types in the Swartland region using Landsat 8 data. They found that that the differences in classification accuracies between these approaches were marginal. In addition, Benz et al. (2004), Blaschke et al. (2000) and Willhauck et al. (2000) all lauded object-orientation for its superior integration between continuous remote sensing data and a vector-based GIS environment.

Most pixel-based classifiers can be adapted successfully for an object-based environment. Mansor et al. (2002) demonstrated an OBIA application using a simple supervised classification of a Landsat Thematic Mapper (TM) image for land cover mapping, with an overall accuracy of over 90%. Ali-Akbar et al. (2000) incorporated expert knowledge and ancillary data in image segmentation and applied an MLC to the resulting objects in an attempt to improve the accuracy of deforestation estimates in Chiong Mai Province in Thailand. Their method used Landsat TM data, and showed an 8-10% increase in accuracy over previously used methods. Berberoglu et al. (2000) compared maximum likelihood and ANN classifiers for a per field approach to land cover classification of Landsat TM data in the Cukurova Delta in Turkey, obtaining overall accuracies of up to 89% with eight categories.

The family of classification techniques most enhanced by the use of OBIA is that of rule-based classifiers. As stated earlier, each object in the hierarchy contains a number of inherent features, as well as relative spatial awareness, which is ideally suited to analysis by a ruleset structure. This has been demonstrated by a number of studies. Lewinsky & Bochenek (2008) undertook a land cover-based classification of a SPOT 4 image in the Kujawy region in Poland using feature thresholding in a rule-based DT. Their use of spectral, textural and relational object feature thresholds to classify objects attained a satisfactory overall accuracy of 89% with thirteen categories. Bock et al. (2005) used a hierarchical rule-based classification at multiple scales and at multiple resolutions for habitat mapping in Northern Germany and Wye Downs, UK, and lauded OBIA for its potential to incorporate expert knowledge at any stage of the analysis. Mitri & Gitas (2002) developed and tested a hierarchical object membership classifier for Landsat TM images to map burnt areas in two regions in the Mediterranean, with accuracies over 98% for both images. Bauer & Steinnocher (2001) developed a ruleset that used OBIA to classify urban areas from IKONOS imagery in Venice, Italy, also with favourable results.

However, a number of researchers have noted limitations with using rule-based expert systems. Creating an effective ruleset is complicated and time-consuming, and expert systems are often adversely influenced by increasing dimensionality of data. For these reasons, various studies have applied to OBIA either traditional classification algorithms such as MLC or more powerful, non-parametric supervised algorithms such as k nearest neighbour (k-NN), DT or support vector machines

(SVM). Li et al. (2010) compared SVM to k-NN for object-based classification and the SVM classifier was found to be more accurate. Myburgh & Van Niekerk (2013) compared MLC, nearest neighbour (NN) and SVM for an OBIA land cover mapping application and found that SVM consistently outperformed the other classifiers, particularly when a large number of features (i.e. high dimensionality) are used. Mallinis et al. (2008) compared DT to k-NN and found that the former classifier yielded a significant increase in accuracy. Straatsma & Baptist (2008) successfully used a linear discriminate analysis supervised classifier in an object-based classification for the purpose of floodplain roughness parameterisation. Platt & Rapoza (2008), in a study evaluating different aspects of object-based classification, found MLC to achieve a significantly higher user's accuracy than a k-NN classifier, but a slightly lower producer's accuracy. Yet, the k-NN classification could be significantly improved by integrating it with an expert system. Several studies have applied the principle where a k-NN (or other) classifier is combined with an expert system, thereby formalising known spatial or structural relationships (Bock et al. 2005; Conchedda et al. 2008).

2.3.6 Modern methods for estimating crop water use

The increased availability of spatially referenced GIS and remote sensing (RS) data enables crop water use or ET estimation at pixel level and at high resolutions (e.g. 20 to 1000 m). Such data can be aggregated and employed at different spatial scales and used over large areas. Because satellite data are frequently collected, estimates can regularly be made and temporal trends studied. Such spatial and temporal coverage can contribute greatly towards improved water management at national and/or regional level down to individual farms or fields.

Estimates of evapotranspiration (ET) from a surface, including water consumption by vegetation, relates to the vaporisation of water from the land surface into the lower part of the atmospheric boundary layer. ET consists of evaporation of water from the soil, evaporation of intercepted water and transpiration losses by plants and the sum of all these losses is often referred to as consumptive water use. The water volumes lost through the processes encompassed in ET form part of the hydrological cycle where no water is truly lost, just changed in form.

Advances in the interpretation of RS information enables the spatial assessment of crop water use, biomass and yield production and associated WUE for each pixel of a satellite image without having to rely on generalised crop coefficients. Different methods have been developed to provide information at a range of temporal and spatial scales and for various applications. A number of review papers describe various methods used to spatially estimate ET, including Choudhury (1997), Courault et al. (2005), Kustas & Norman (1996), Verstraeten et al. (2005), Verstraeten et al. (2008) and Gibson et al. (2013). For agricultural (field scale) applications, numerous models have been developed, for example the: Surface Energy Balance Algorithm for Land (SEBAL), Surface Energy Balance System (SEBS) model, Mapping EvapoTranspiration with high Resolution and Internalised Calibration (METRIC^{tm}) model, Vegetation Index/Temperature Trapezoid (VITT) model, Two Source Energy Balance (TSEB) model, the Atmosphere-Land Exchange Inverse (ALEXI) model, NDVI-DSTV (Normalised Difference Vegetation Index Diurnal Surface Temperature Variation) triangle mode. These methods either estimate

ET as the residual of a shortened energy balance equation using LST estimates, or use a WUE relationship to determine ET. Some of the models are used operationally for field scale agricultural water management[6], but most are used primarily in research applications. A selection of the models (SEBAL, SEBS, VITT and METRIC[tm]) was reviewed by Jarmain et al. (2009b). The review included an assessment of each model's accuracy in estimating ET and their potential for operational applications in SA. It was found that some of the components of the energy balance (like net radiation) were simulated accurately, but that the other energy balance components and ET were generally more complex. SEBAL and METRIC estimates of ET were generally lower than measured ET, while SEBS commonly overestimated ET. The VITT model yielded the least accurate evaporation estimates.

Other RS based models have been developed and provide ET estimates at lower spatial resolutions (often ~1 to 3 km), but higher temporal resolutions (30 min. to daily). The lower spatial resolution of these models makes them less suited for agricultural applications, where information at field scale is required. A number of these models use MSG satellite data and provide ET data at 30-minute intervals, at a resolution of 1-3 km resolution[7]. ET data from HYLARSMET[8] and MODIS[9] are estimated daily for the entire globe at a 1 km resolution. The global water cycle monitor[10] from Princeton University also estimates ET at a daily time step. The ALEXI model[11] can also be used to estimate energy fluxes and other parameters daily, e.g. at a 10 km spatial resolution.

New approaches and models are continually being developed and tested. For instance, the ETLook model (Pelgrum et al. 2011). This model is used in a recent initiative, The Water Productivity through Open access of Remotely sensed derived data (WaPOR)[12], which provides free access to satellite-based data on agricultural productivity in Africa and the Near East for the period 2009–2019. The purpose of the project is to allow for land and water productivity monitoring, using ET and biomass production data. Three levels of data products are available. Level 1 provides 250 m resolution data on a continental level. Level 2 provides 100 m data for a number of selected countries, including Morocco, Tunisia, Kenya and Mozambique. Additionally, Level 2 includes the Jordan/Litani river basin, the Nile Basin, the Awash basin and the Niger inner delta. Level 3 provides 30 m resolution data on irrigation scheme level. Level 3 data will be provided for selected areas in the river basins covered by Level 2. The data products provided in this project are produced by eLEAF using the ETLook model.

In this WRC study, the ETLook model was applied to create a nationwide dataset on actual ET for SA. The application of ETLook within this research is explained in more detail in Chapter 3.

[6] For instance, www.mijnakker.nl; fruitlook.co.za; www.idwr.idaho.gov/GeographicInfo/METRIC/et.htm
[7] http://landsaf.meteo.pt/ and http://www.ears.nl/
[8] http://sahg.ukzn.ac.za/soil_moisture/et/
[9] http://modis.gsfc.nasa.gov/data/dataprod/dataproducts.php?MOD_NUMBER=16
[10] http://hydrology.princeton.edu/~justin/research/project_global_monitor/
[11] http://alfi.soils.wisc.edu/cgi-bin/anderson/alexi_server.pl?region=SMEX02MOD
[12] http://www.fao.org/in-action/remote-sensing-for-water-productivity/database/database-dissemination-wapor/en/

2.4 Water accounting: A framework to assess water use and water availability at various scales

2.4.1 What is water accounting?

Coping with water scarcity and the growing competition for water among different sectors requires sound water management strategies and decision-making. Successful water management strategies are based on a clear understanding of a catchment's hydrological processes. This includes determination of manageable and unmanageable water flows and specifying the amount of water available for human use. By understanding the interaction between water and land use, the effects of land use change on the catchment water balance can be estimated. To increase the societal benefits of water use, water managers need to understand these interactions before they make decisions.

Over the last two decades, various projects have been initiated to develop a system of WA to support water managers and decision makers. WA integrates the fields of hydrology, water and environmental management, water allocations, policy decisions, reporting and communication. It facilitates identification of central problems in catchments, and constraints and opportunities for improved climate resilience. WA furthermore aids decision-making regarding carbon sequestration and safeguards sufficient water resources for a good quality of life, especially during periods of prolonged drought (Karimi et al. 2013).

A number of WA frameworks have been proposed, of which the most relevant are:

- The WA framework of the International Water Management Institute (IWMI) (Molden & Sakthivadivel 1999);
- The System of Environmental-Economic Accounting for Water of the United Nations Statistics Division (SEEAW 2012);
- The Australian WA Conceptual Framework (Water Accounting Standards Board 2006);
- The United Nations Environment Programme's (UNEP) Water Footprint, Neutrality, and Efficiency (WaFNE) (Morrison & Schulte 2009); and
- The Water use accounts framework of the Challenge Program on Water and Food (CPWF) (Kirby et al. 2010).

These frameworks have been useful in convincing policy makers that water should be considered an important resource and should be quantified in terms of supply, demand and value. There is a growing community of policymakers, water managers and donors who realise that, like the financial accountability of organisations, WA is essential to ensure sustainable use of this scarce resource. However, to date, none of these frameworks have been adopted as a generally accepted standard. The likely reasons for this lack of uptake include:

- the results of some of the frameworks are too complex to be used as supporting tools for decision-making;

- the input requirements are often not available or are based on expensive long-term monitoring activities;
- in many frameworks only abstracted water is considered, and in many areas only a small fraction of the water resources and water use is actually abstracted;
- most frameworks are location-specific rather than universally applicable; and
- there is limited focus on intervention options by decision makers. Most frameworks present results without a differentiation between managed, manageable and non-manageable water flows.

Of all these factors, the last is probably the most important reason why existing WA frameworks have not been widely adopted. A framework providing numbers without specifying how and where interventions are possible remain to a large extent an academic exercise rather than a foundation for exploring options to improve water resources management (Bastiaanssen & Drogers 2010). For a more detailed review of WA frameworks, see Clark (2015).

2.4.2 Water Accounting Plus (WA+) framework

The Water Accounting Plus (WA+) framework has been developed to simplify and communicate water resources related information in a geographical domain to policy makers. WA+ supports water managers by providing quantitative information and enabling the user to estimate the impact of their decision. WA+ is not meant to replace the UN SEEAW system, but provides an alternative to explicit spatial information on water depletion and net withdrawal processes in complex river basins.

The (WA+) framework was developed by eLEAF, with inputs from IWMI, FAO and the Technical University of Delft. A joint publication in the journal of Hydrology and Earth System Sciences (HESS) explaining the WA+ framework is available (Karimi et al. 2013). Following this initial conceptualisation, WA+ has been taken forward by wateraccounting.org, hosted by IHE Delft[13] (previously called UNESCO-IHE). At wateraccounting.org, the WA+-method is being developed further and the worldwide application of WA+ is promoted. Clark (2015) applied WA+ in Umgeni and Sabi-Sand catchments in SA, mainly focusing on water resource availability and usage. However, no remotely sensed ET data were used. In this project, the latest available version of the WA+ methodology was applied, supplemented by the use of RS data products.

The WA+ framework is largely based on global scale public domain datasets to enable its application in ungauged river basins and in areas with limited data availability. The inclusion of data obtained from EO is especially advantageous as it promotes transparency and consistency of the irrigation knowledge base, making the framework easily applicable worldwide without the need for extensive field monitoring and data collection. However, remotely sensed inputs are not a precondition for implementing the WA+

[13] https://www.un-ihe.org/

framework, as data from hydrological models and water allocation models can additionally be used as input.

Analogous to financial accounting, the first four WA+ sheets include (i) a resource base sheet, (ii) a consumption sheet, (iii) a productivity sheet, and (iv) a withdrawal sheet.

The WA+ resource base sheet (i) provides information on water volumes (Figure 2.2). Inflows are shown on the left of the resource base sheet diagram; the middle section shows information on how and through what processes the water is depleted within a domain; and information on water use and reports on total water depletion and outflows are summarised on the right. Since WA+ is focussed on supporting stakeholders in evaluating water accountability; this sheet entails a straightforward division into four primary land/water use groups:

- Conserved land use: areas where no changes in land and/or water management are possible; typical examples include tropical rainforests, wetlands and mountainous vegetation.

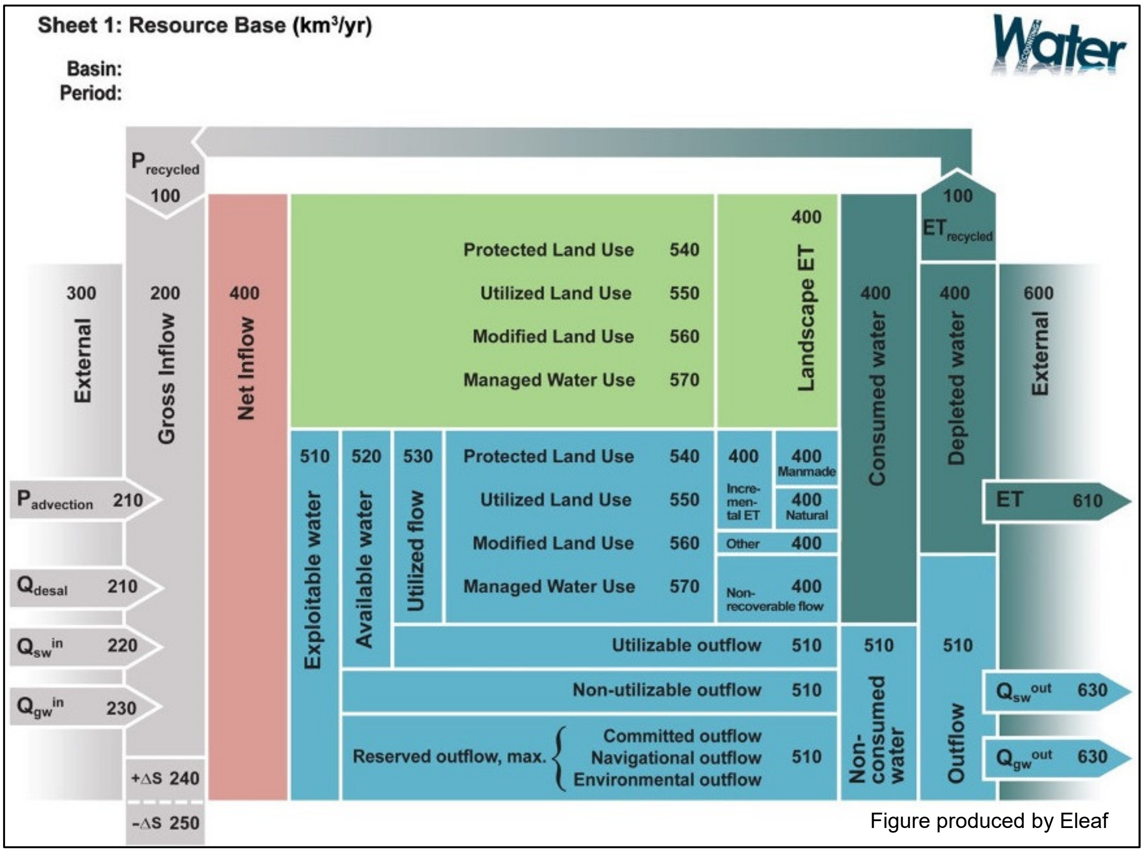
- Utilised land use: land where vegetation is not managed on a regular base; typical examples include forests, natural pastures and savannahs.

- Modified land use: areas where vegetation and/or soils are managed, but all water supply is natural (rainfall); typical examples include rainfed agriculture.

- Managed water use: all sectors that abstract water from surface water and/or groundwater; typical examples include irrigated agriculture, urban water supply and industrial extractions.

Key summarising indicators are calculated to support water managers, policy makers and donors in their task to ensure the accountable management of water resources. The resource base sheet makes it feasible to answer questions such as:

- How much rainfall is utilised by irrigated crops?
- How much water is available for allocations?
- How much water is diverted to irrigated crops?
- How much water is not utilised?
- Are irrigation systems using non-renewable water resources?



$P_{advection}$	Precipitation in the catchment	ET	Evapotranspiration
Q_{desal}	Water inflow from desalinisation plants	Q_{sw}^{out}	Surface water outflow in the catchment
Q_{sw}^{in}	Surface water inflow into the catchment	Q_{gw}^{Out}	Groundwater recharge in the catchment
Q_{gw}^{in}	Groundwater uptake in the catchment	$-\Delta S$	Water storage in storage facilities (dams) in the catchment
$+\Delta S$	Water input from storage facilities (dams) into the catchment		

Figure 2.2 The WA+ resource based sheet

The WA+ consumptive use sheet (ii) (Figure 2.3) describes which parts of the depletion processes are manageable or non-manageable. The term manageable implies that it is not actively managed yet, and that a light form of utilisation is accepted under the current situation. The consumptive sheet can be used to inform questions such as:

- Which part of the catchment's water balance is managed?
- Which component of the consumptive use of irrigation water is beneficial?
- How much water could be saved in the irrigation sector?

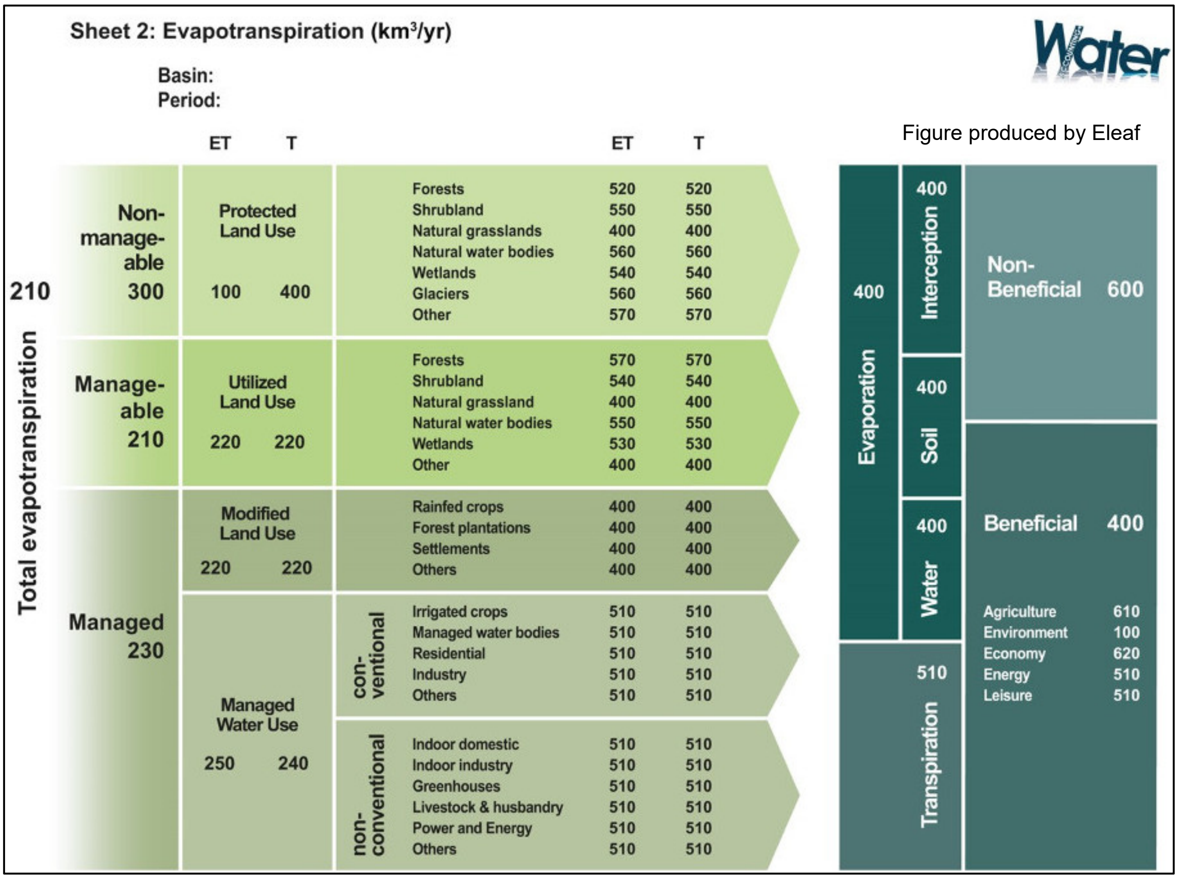


Figure 2.3 The WA+ consumptive use sheet

The WA+ productivity sheet (iii) (Figure 2.4 and Figure 2.5) is meant to describe the dry matter production and the water consumption related to that. The sheet reports on the biophysical land productivity (kg/ha) and water productivity (kg/m^3) in land use types aimed at production (agriculture, forest plantations, aquaculture, etc.). The productivity sheet makes it feasible to make fact-based decisions on:

- What is the total food equivalent production?
- What is the contribution of irrigated areas to the total food production in a catchment?
- What is the water productivity?
- How much water can be saved without affecting food security?

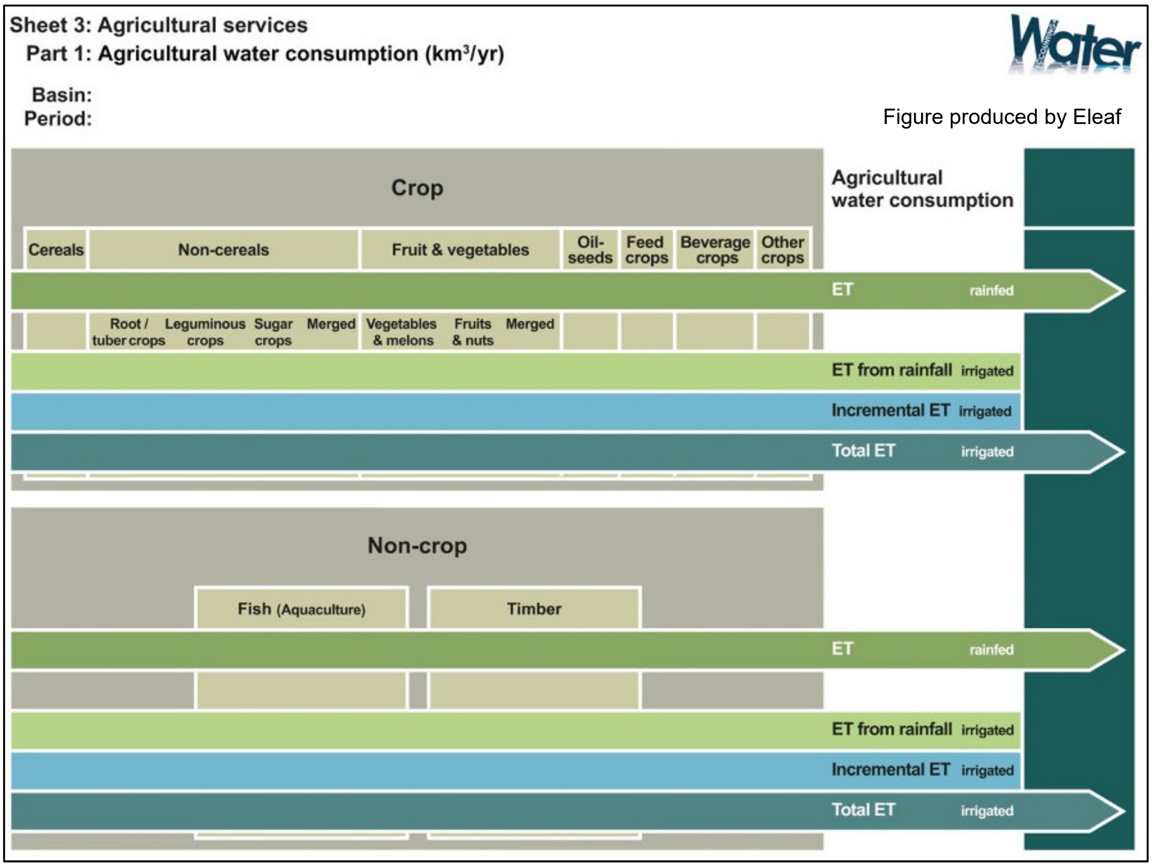


Figure 2.4 The WA+ productivity sheet part 1: Agricultural water consumption

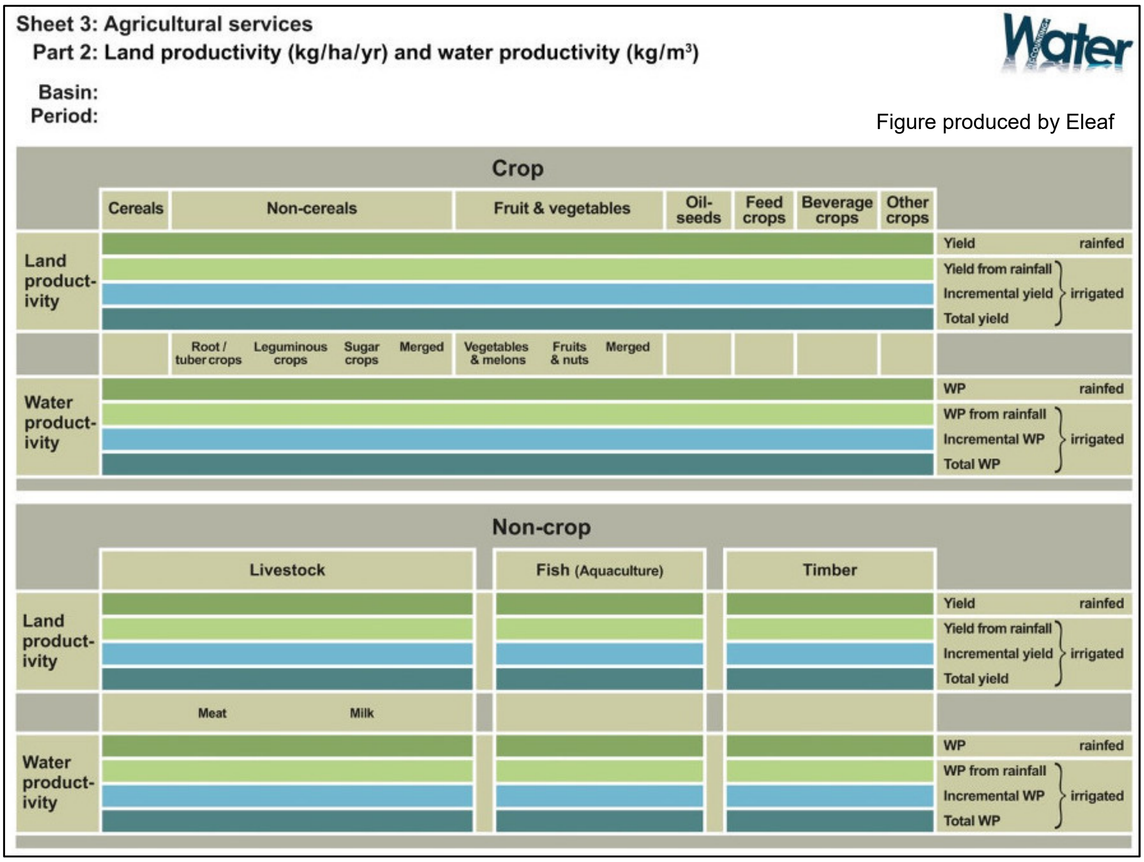


Figure 2.5 The WA+ productivity sheet part 2: Land and water productivity

While sheets (i) to (iii) can be largely populated using RS data, the WA+ withdrawal sheet (vi) (Figure 2.6 and Figure 2.7) is designed to relate consumed water to withdrawals and return flows.

The withdrawal sheet tracks water withdrawals and depletions (i.e. incremental ET), and returns separated surface water and groundwater systems. The management options for surface and groundwater resources are significantly different. Surface water can, for example, be used for hydropower, while groundwater is more suited for domestic drinking water and irrigation. Streams and rivers can be seasonal, while groundwater resources are accessible on demand and contain water throughout the year. As an example of the need for flexible management strategies, (Quereshi et al. 2010) found that the seasonality of surface water resulted in an increase in the use of groundwater, especially for irrigated crops. Considering the importance of groundwater and the variation in management options compared to surface water, it is essential to consider groundwater and surface water systems separately.

The aim of the WA+ withdrawal sheet is to provide an overview of flows in the managed water use category. Typical water users are reservoirs, irrigated agriculture, aquaculture, domestic use and industries. Incremental ET from reservoirs mostly takes the form of evaporation from free water surfaces. Given that this data cannot be derived from satellite measurements, the withdrawal sheet requires mostly conventional input data and thus can only be prepared for basins where public databases on surface water diversions and groundwater abstractions are available. Other sources, such as secondary statistics and hydrological model outputs, can also be used if available.

Apart from the four sheets described above, four additional sheets have been developed in recent years: v) surface water; vi) groundwater; vii) ecosystem services; and viii) sustainability. Sheets (v) and (vi) provide in-depth descriptions of the surface water and groundwater components. Sheet (vii) shows how water supports local ecosystems under different types of land utilisation, and sheet (viii) provides insight into how sustainable the current usage of water is in the long run, based on long-term averages. These sheets have not been included in the demonstration of WA+ performed in this study as they require additional data that were unavailable. The sheets were also only recently developed (and are still in development).

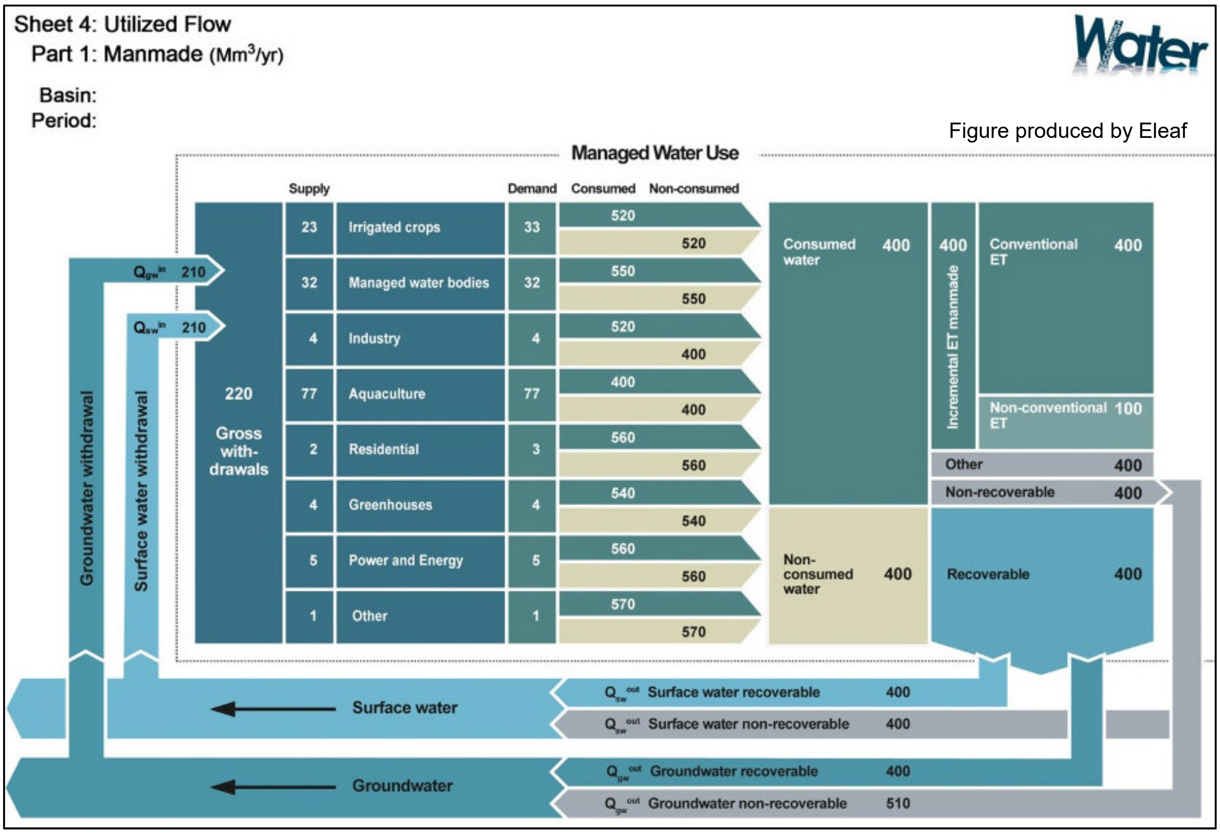


Figure 2.6 The WA+ withdrawal sheet describing manmade water withdrawals

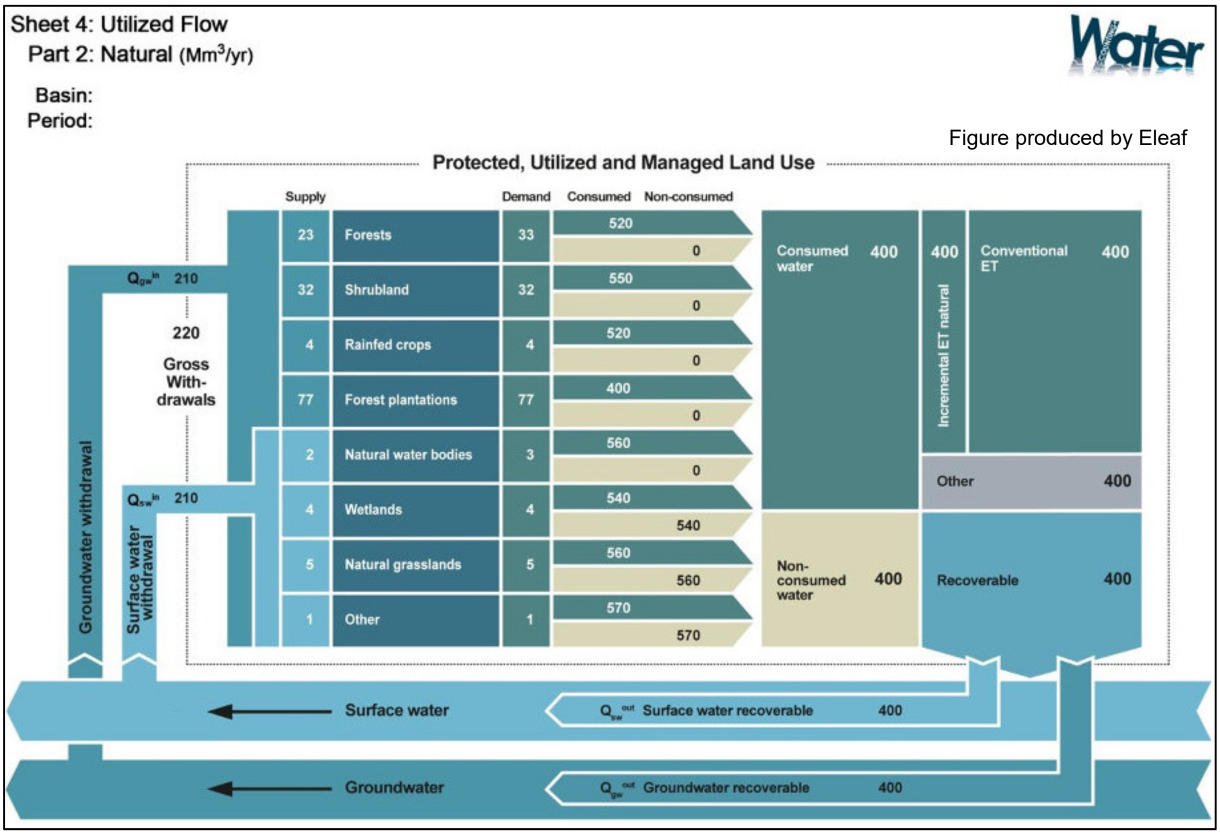


Figure 2.7 The WA+ withdrawal sheet describing natural water withdrawals

2.5 Synthesis

This chapter provided background to this research and introduced some concepts and techniques used in the study. It shows that there is a large degree of uncertainty about the area and water utilised by irrigated crops in SA's. One of the main reasons for this uncertainty is that traditional methods for mapping irrigated areas and for quantifying crop water use are laborious and costly to apply over large areas, and that most of the existing estimates at national level are based on qualitative methods and secondary data sources. It is clear from the literature that EO is the only viable national assessment approach. The relevant RS techniques – such as ET modelling and image classification – have been suitably demonstrated and verified locally and internationally at various scales and RS can supply most of the necessary information at a comparably low cost. Mapping irrigated areas and quantifying water use by irrigated crops would be of great value, but coupling this with WA allows for determining if sufficient water resources are available for additional allocations (i.e. expansion of irrigated agriculture) and other uses.

This research project was conceptualised with this in mind and conducted in five phases:

1. Land cover, land use and crop type mapping;
2. ET dataset development;
3. Irrigated area mapping;
4. Water use estimation; and
5. WA.

Figure 2.8 outlines the relationships between the first five phases of the project, the datasets generated and their utilisation.

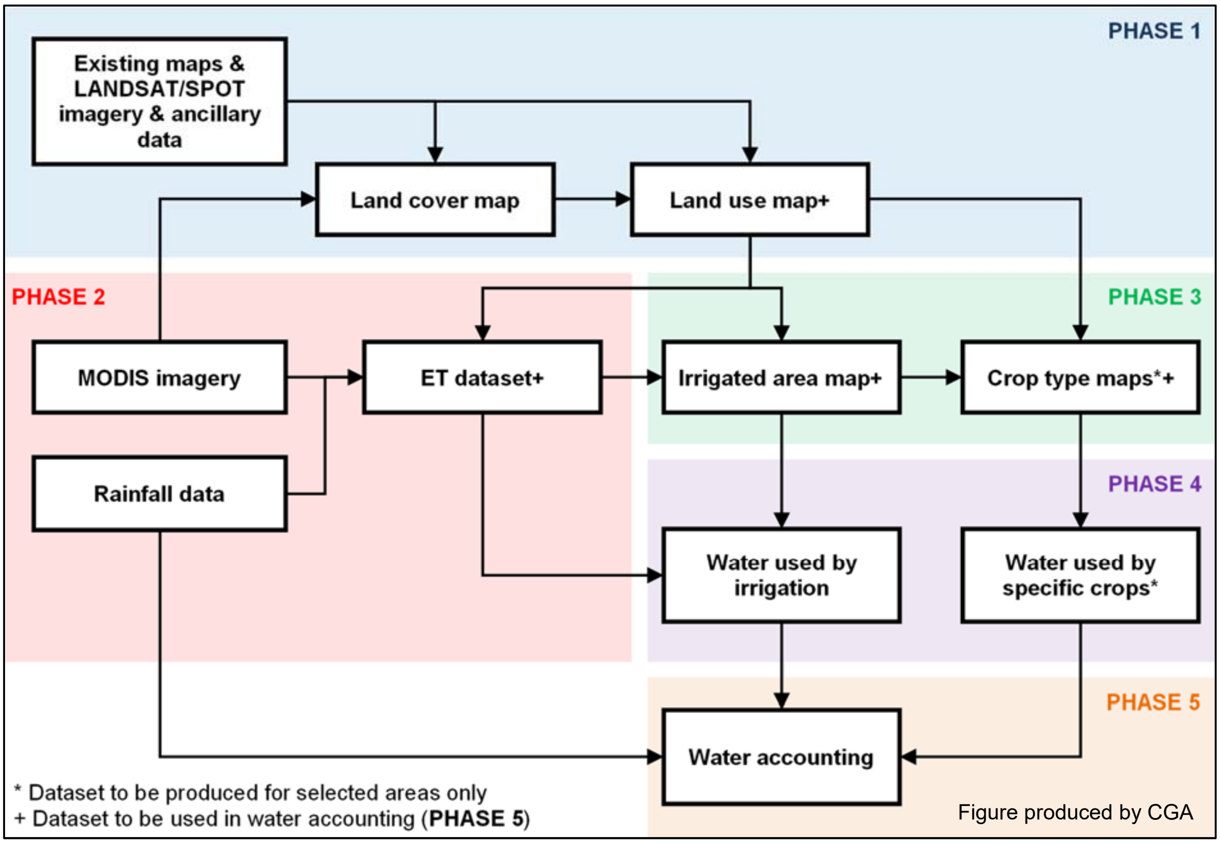


Figure 2.8 A visual representation of the key phases (with specific procedures) that formed the basis of the project plan

Phase 1 focussed mainly on land cover, land use, crop type data collection and mapping for selected areas (details are provided in Chapter 1), while ET modelling (by means of EO and rainfall data) was the main activity of Phase 2 (Chapter 3). In Phase 3, the land use map and ET dataset were used to identify and delineate irrigated areas, resulting in an irrigated area map (IAM) (Chapter 4). In the first step of Phase 4, this map, together with the ET dataset, was used to calculate the water used by irrigated agriculture. The water use by specific crop types was quantified in the same manner, using the crop type maps produced in Phase 1. The quantification of water use by irrigated agriculture and by specific crops is discussed in Chapter 5. During the WA phase (Phase 5), the land use, crop type and IAMs were combined with the ET dataset to quantify water use and availability for seven selected catchments. The WA implementation is demonstrated in Chapter 6.

The ET dataset generated during Phase 2 was a fundamental input to the following phases. Its development is explained the next chapter.

3 DEVELOPMENT OF A MONTHLY EVAPOTRANSPIRATION DATASET

3.1 The ETLook model

Surface energy balance models such as the SEBAL (Bastiaanssen et al. 1998; Bastiaanssen et al. 2005) and ETLook models (Pelgrum et al. 2011; Bastiaanssen et al. 2012) eliminate the need for generalised crop information (e.g. coefficients) in describing ET.

SEBAL is intended for catchment level, crop growth monitoring studies and not for application over extensive areas with widely varying climatic conditions (e.g. SA). The ETLook model addresses this limitation of SEBAL (Pelgrum et al. 2011; Bastiaanssen et al. 2012). With ETLook, the daily energy balances and biomass production of extensive areas can be estimated, making it ideally suited for the present study. In addition, ETLook has the ability to partition the consumed water (ET) into transpiration, evaporation and interception, which can be used to appraise the beneficial depletion of water for food and ecosystem services *vs*. non-beneficial losses. The ETLook outputs are consequently ideally suited for application to the WA+ methodology.

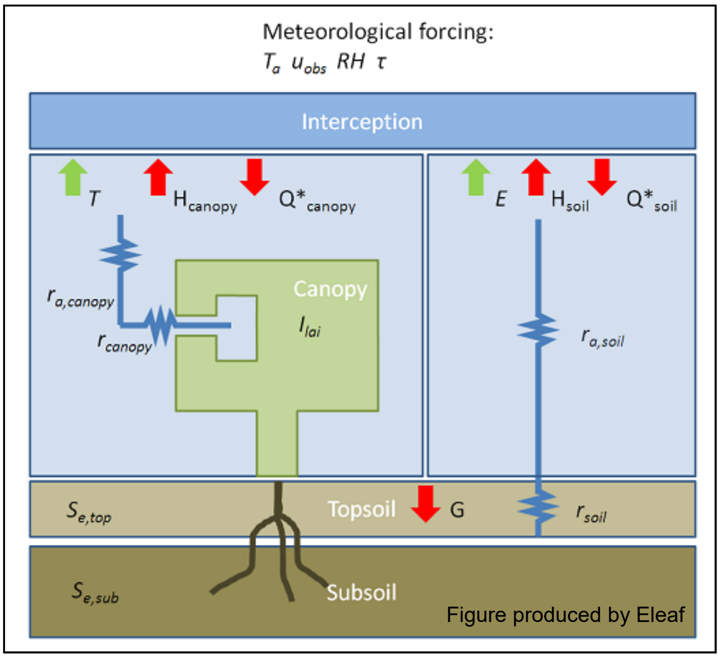
SEBAL has been widely validated internationally (Bastiaanssen et al. 1998; Morse et al. 2000; Conrad et al. 2007; Allen et al. 2011) and also in SA as part of previous WRC funded studies (Jarmain et al. 2014). In particular, SEBAL has shown great potential where crop WUE was evaluated (Klaasse et al. 2008; Jarmain et al. 2009b; Jarmain et al. 2011; CSIR 2012) and it is already used internationally (e.g. the Netherlands, Sudan, Egypt, Ethiopia) and locally to support irrigated agriculture. For example, SEBAL played a key role in the FruitLook project in the Western Cape of SA, where satellite-based ET information is provided to improve the efficiency of water use by local fruit farmers (Goudriaan 2014). Much confidence exists in the SEBAL model and its potential uses, while it is continually being improved in research. In contrast, ETLook is less well-known. It was released in 2009 and is used extensively in the Nile Basin, China, India, Pakistan, Australia, Syria, Morocco, Iran, Ukraine, Poland, Canada and the Netherlands by eLEAF. The results from a validation study carried out in the Indus Basin was presented at a conference of the International Association of Hydrological Sciences (IAHS), showing a good correlation between ETLook actual ET and other actual ET measurements in the basin (Pelgrum et al. 2011). ETLook has also since 2016 replaced the SEBAL model in the FruitLook initiative (Goudriaan 2014). Both ETLook and SEBAL consider the land surface energy balance, including net radiation (R_n), soil heat flux (G), sensible heat flux (H) and latent heat flux (E and T).

In the surface energy balance, energy flux densities, of which the latent heat flux density can be directly related to the actual ET and where 28 W/m^2 is equal to 1 mm/d, are estimated. ETLook (Pelgrum et al. 2011) is a two-layer energy balance model that calculates evaporation (E) from soil and water surfaces and transpiration (T) from canopies using transport resistances in conjunction with the Penman-Monteith (PM) equation (Equation 3.1). The PM equation typically used to estimate ET is solved separately here for vegetation and (bare) soil processes, in order to split T and E.

$$T = \frac{\Delta(Q^*_{canopy}) + \rho c_p \frac{\Delta_e}{r_{a,canopy}}}{\Delta + \gamma\left(1 + \frac{r_{canopy}}{r_{a,canopy}}\right)} \qquad E = \frac{\Delta(Q^*_{soil} - G) + \rho c_p \frac{\Delta_e}{r_{a,soil}}}{\Delta + \gamma\left(1 + \frac{r_{soil}}{r_{a,soil}}\right)} \qquad \textbf{Equation 3.1}$$

where	Δ	is the slope of saturation vapour pressure curve [mbar / K];
	Δ_e	is the vapour pressure deficit [mbar];
	P	is the air density [kg m^{-3}];
	C_p	is specific heat capacity of dry air [J/kg/K];
	γ	is a psychrometric constant [mbar/K];
	G	is soil heat flux [W/m^2];
	Q^*_{canopy}	is the radiation reaching the canopy [W/m^2];
	Q^*_{soil}	is the radiation reaching the soil [W/m^2];
	r_{canopy}	is canopy resistance [s/m];
	r_{soil}	is soil resistance [s/m];
	$r_{a,canopy}$	is aerodynamic canopy resistance [s/m]; and
	$r_{a,soil}$	represents aerodynamic soil resistance [s/m].

A basic structure of the ETLook model is illustrated in Figure 3.1. Separate and physically defined aerodynamic and evaporation resistances for bare soil and canopies are incorporated. The soil resistance (r_{soil}) is a function of the soil water content in the topsoil and is therefore characterised by a strong reflectance of microwave signals. Topsoil water content values can be obtained at a daily interval from radar-based satellite EOs. The canopy resistance (r_{canopy}) is a function of the leaf area index (LAI; [m^2 leaf / m^2 soil]) and four dimensionless stress factors. These stress factors indicate the influence of radiation, temperature, vapour pressure (meteorological conditions) and soil water content in the subsoil. The aerodynamic canopy ($r_{a,canopy}$) and aerodynamic soil resistance ($r_{a,soil}$) are functions of wind speed and surface roughness. An iteration procedure is carried out to correct for unstable conditions. The Monin-Obukhov Similarity Theory (Monin & Obukhov 1954) is used to parameterise the effects of shear stress and buoyancy. In ETLook, both the actual and potential transpiration fluxes are calculated. The difference ($T_{pot} - T_{act}$) expresses vegetation water stress induced by limited availability of soil water content in the root zone (Pelgrum et al. 2011). ETLook requires precipitation interception as input, which is calculated from spatial (interpolated) precipitation and NDVI data.



T_a	Air temperature [ºC]
U_{obs}	Wind speed at observation height [m/s]
RH	Relative humidity [%]
τ	Transmissivity [-]
T	Transpiration [mm/time step]
H_{canopy}	Sensible heat flux canopy [W/m^2]
Q^*_{canopy}	Radiation for canopy [W/m^2]
l_{lai}	Leaf area index [-]
E	Evaporation [mm/time step]
H_{soil}	Sensible heat flux soil [W/m^2]
Q^*_{soil}	Radiation for soil [W/m^2]
r_{canopy}	Canopy resistance [s/m]
$r_{a,canopy}$	Aerodynamic canopy resistance [s/m]
r_{soil}	Soil resistance [s/m]
$r_{a,soil}$	Aerodynamic soil resistance [s/m]
G	Soil heat flux [W/m^2]
$S_{e,top}$	Effective saturation topsoil [-]
$S_{e,sub}$	Effective saturation subsoil [-]

Figure 3.1 Schematic representation of the ETLook model for energy balance computations of bare soil and vegetation

The biophysical datasets required in the ETLook PM equation include surface albedo, surface emissivity, surface roughness, surface LAI and surface canopy resistance. The meteorological datasets used as input include air temperature [T_a], relative humidity [RH], wind [u_{obs}] and transmissivity [τ]. Due to atmospheric interferences (reflection, absorption, scattering), not all solar radiation at the top of the atmosphere is transmitted through the atmosphere towards the land surface; only a fraction will reach the evaporating surface of the land under clear conditions. Typically, 75% of all radiation reaches the land surface, and it will reduce to 25% when heavy clouds prevail. The exact position of the sun in combination with transmissivity values determine the net solar radiation that reaches the crops or surface where ET takes place. The biophysical parameters required in ETLook were retrieved from satellite measurements, while the meteorological data (with the exclusion of transmissivity, which was obtained from MSG) was retrieved from meteorological stations. The datasets collected and used for the implementation of ETLook in this study are described in more detail in the next section.

3.2 Data collection and preparation

3.2.1 ETLook static inputs

Several static (i.e. single-date) input datasets were required for the application of ETLook. This included a digital elevation model (DEM), a latitude raster and several other GIS layers derived from land cover data.

The Shuttle Radar Topography Mission (SRTM) DEM was used to represent the topography of SA. The SRTM DEM was generated in February 2000 using an imaging radar instrument on board of the Space Shuttle Endeavour. The DEM extends from 56° S to 60° N. During the 11-day mission, the imaging radar was used to map the surface of the Earth several times from different perspectives. All these radar measurements were combined to produce a near-global topographic map. The spatial resolution of the SRTM DEM v3 is 1/1200 degree (or approximately 90 m). Given that the intended resolution of the output of ETLook was 250 m, there was no need to make use of the 30 m version of the SRTM DEM (released for Africa in 2014). A visual representation of the SRTM DEM of SA is shown in Figure 3.2.

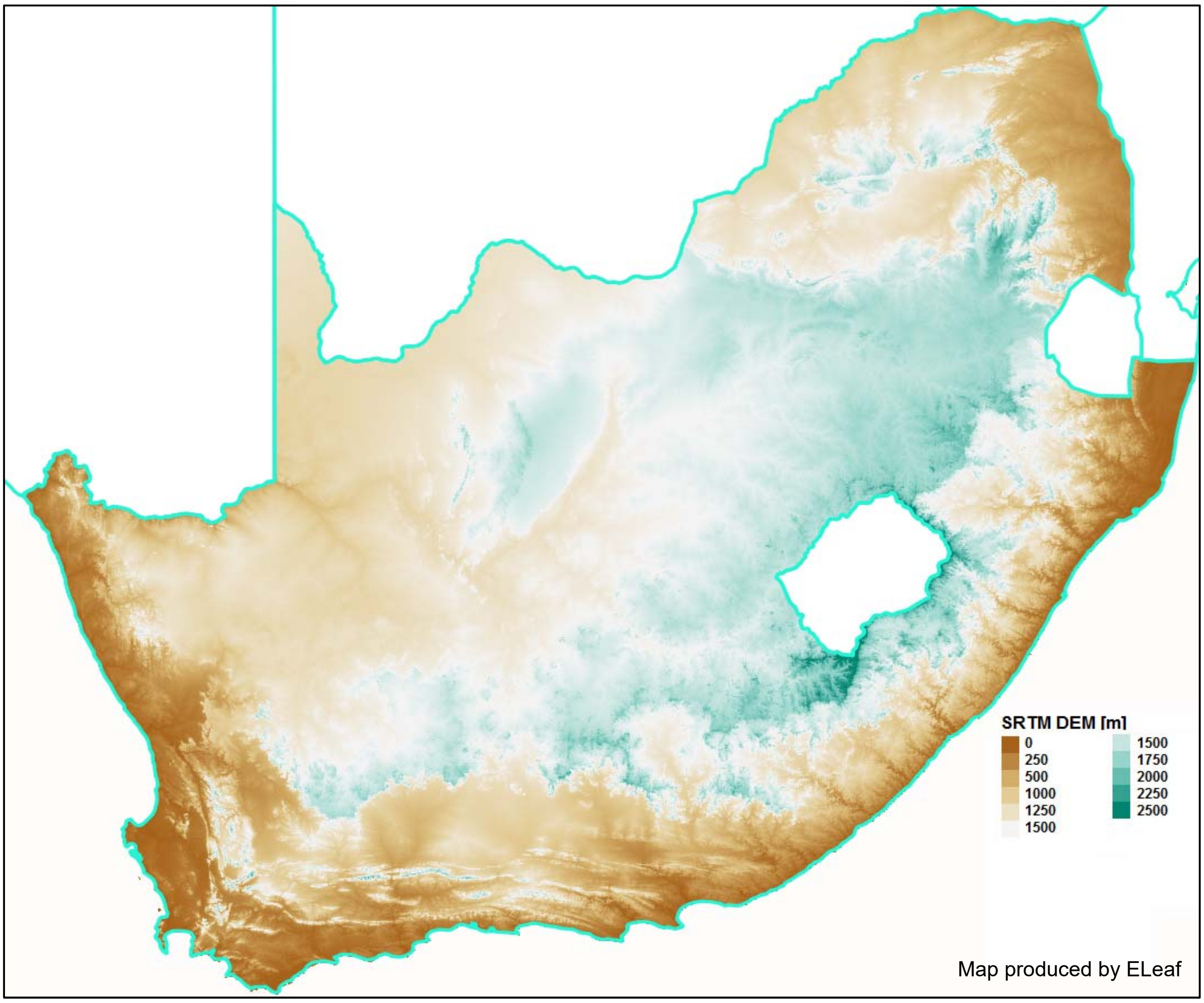


Figure 3.2 SRTM DEM shown for South Africa

A land use/cover (LULC) map was used to create look-up tables for typical biophysical parameters required for the ET computations. The parameters included minimum stomatal resistance, a standard water mask and maximum vegetation/obstacle height. The Southern African Land Cover 2013–14 (SALC1314) map, generated by GeoTerraImage for the Department of Environmental Affairs (DEA), was used for this purpose. SALC1314 was generated from multi-seasonal, 30 m resolution Landsat 8 imagery, acquired between April 2013 and June 2014, which provided seamless coverage of the entire South Africa (GeoTerraImage 2015). The SALC1314 is shown in Figure 3.3, with the class legend listed in Appendix I.

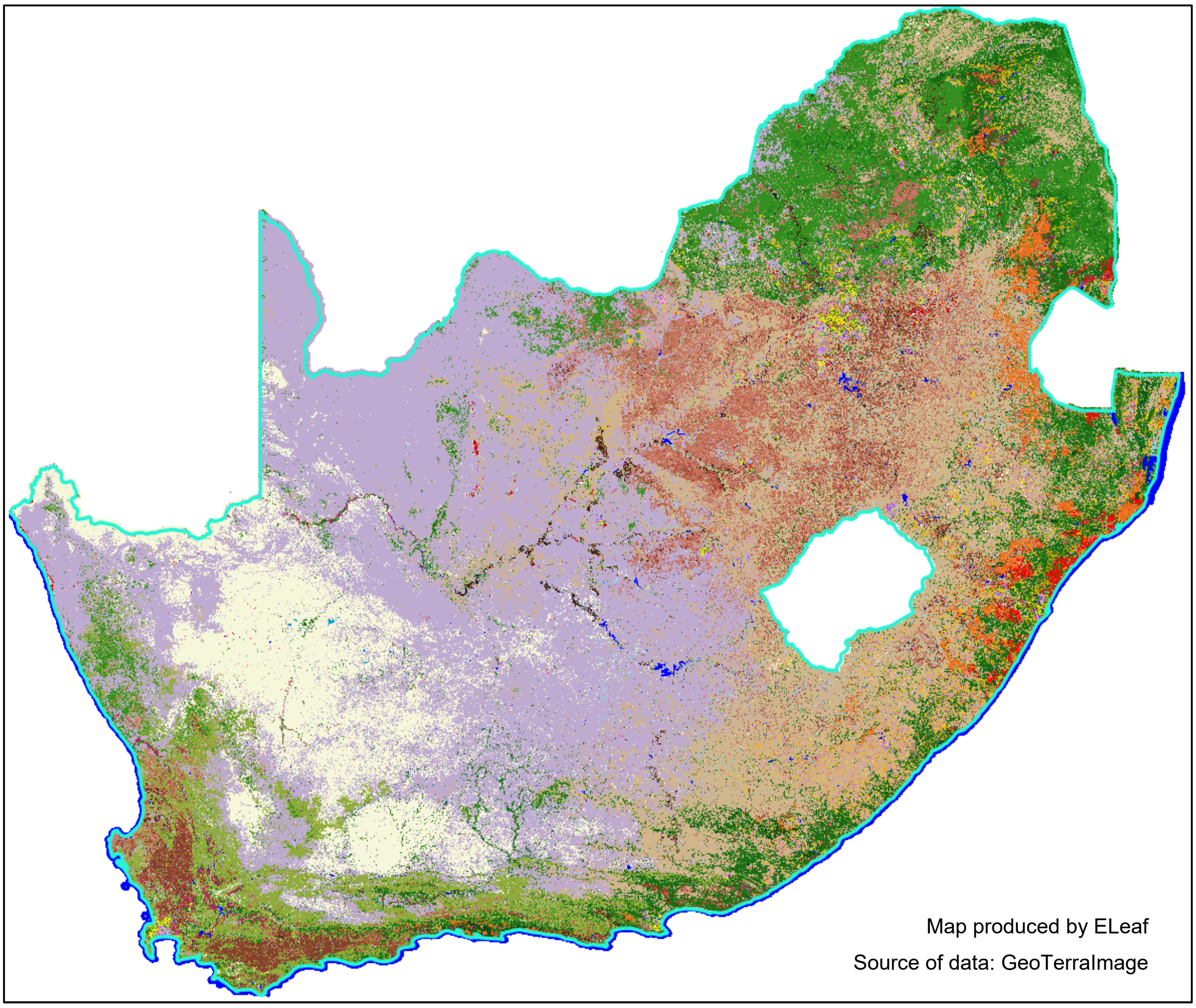


Figure 3.3 South Africa Land Cover 2013/14 (SALC1314)

SALC1314 enabled the creation of the ETLook biophysical input data and was used to model vegetation height [m]. The legend of SALC1314 gives information on vegetation heights expected in each land use class. Roughness z_0 [m] was derived on a daily time step using the maximum obstacle/vegetation height [m], the DEM [m] and NDVI [-] values. Roughness and displacement height estimates were used for the computation of the aerodynamic resistances $r_{a,canopy}$ and $r_{a,soil}$.

3.2.2 MODIS NDVI, Albedo & Thermal data

SA is covered by four MODIS tiles, namely h19v11, h19v12, h20v11 and h20v12. The spatial extent of these tiles is depicted in Figure 3.4.

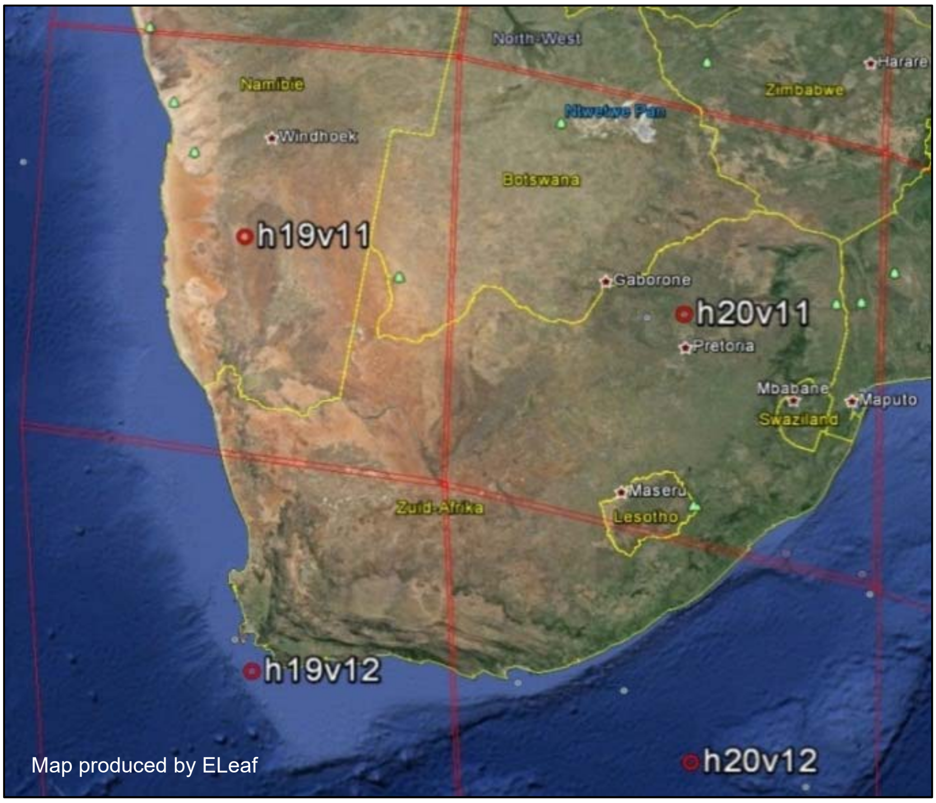


Figure 3.4 Four MODIS tiles cover SA

For each of these tiles, a number of products were obtained and prepared as inputs to ETLook. These include:

MOD09GA: The MODIS Surface-Reflectance Product (MOD 09GA) is computed from the MODIS Level 1B land bands 1, 2, 3, 4, 5, 6 and 7 (centred at 648 nm, 858 nm, 470 nm, 555 nm, 1240 nm, 1640 nm and 2130 nm respectively) on a daily basis. The product provides an estimate of the surface spectral reflectance for each band, as if measured on ground level (i.e. no atmospheric scattering or absorption).

M*D09GA provides bands 1–7 in a daily gridded L2G product in the sinusoidal projection, including 500 m reflectance values and 1 km observation and geolocation statistics. The product includes a quality rating and is used to produce albedo composites at 500 m resolution, which were subsequently converted to 250 m resolution using bilinear interpolation (Vermote et al. 2011).

MOD09GQ: MOD09GQ provides bands 1 and 2 at 250 m resolution in a daily gridded L2G product in the sinusoidal projection, as well as a quality rating. This product was used to produce daily national NDVI composites, which were used in the ETLook modelling as well as for the production of roughness input data. NDVI is used as input to calculate LAI, which in turn is used for separation of Q^*_{canopy} and $Q^*_{soil.}$ It is also used in the calculation of r_{canopy}. An example of an NDVI composite map for SA is shown in Figure 3.5. Values below 0 typically refer to water. Values between 0 and 0.2 correspond to bare soil and an NDVI of 0.2 to 0.9 refers to vegetated areas. The NDVI value increases with vegetation density and vigour.

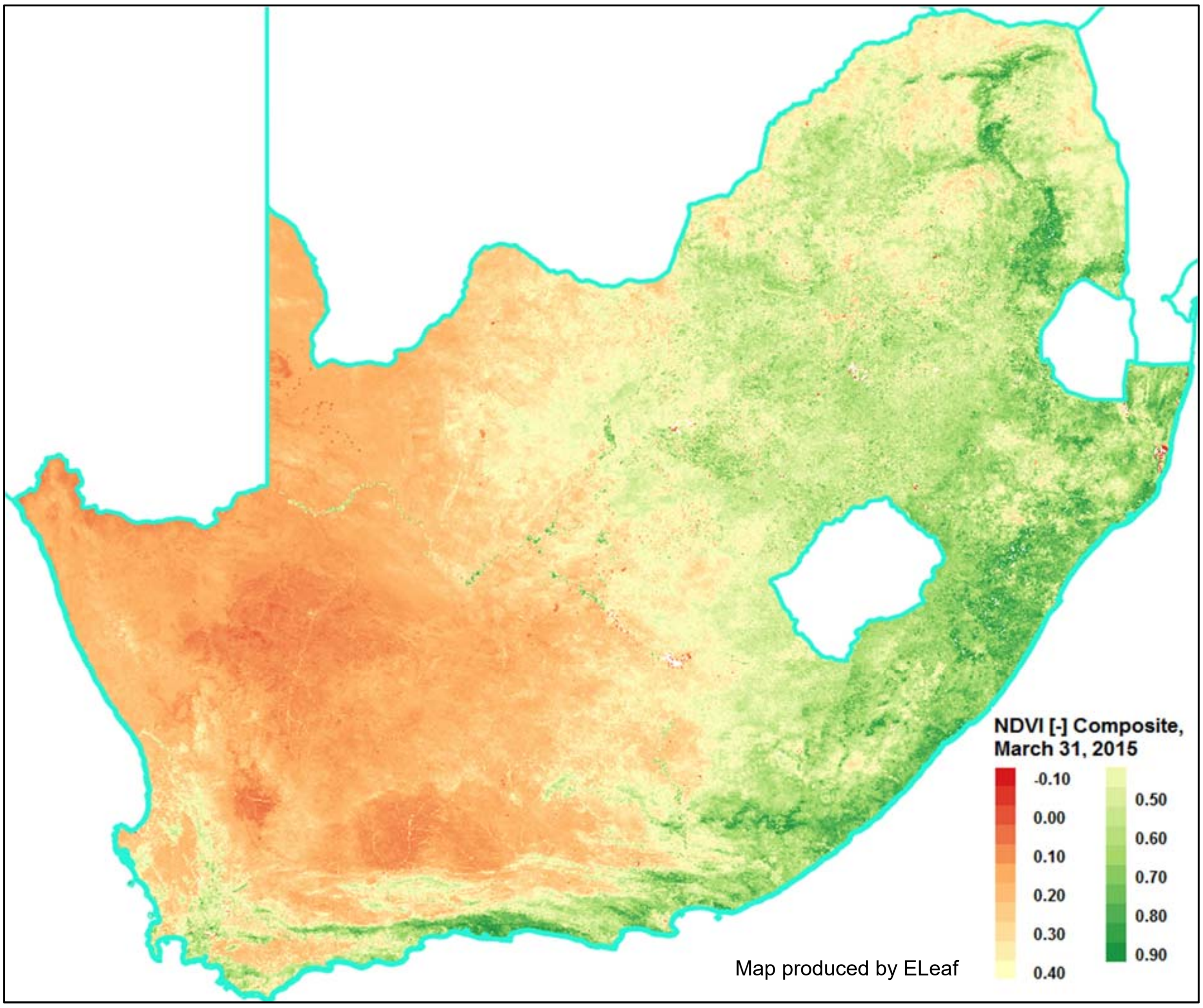


Figure 3.5 Example of an NDVI composite for 31 March 2015

MOD11A1: The MODIS/TERRA Land Surface Temperature and Emissivity (LST/E) products provide per pixel temperature and emissivity values via swath-based and grid-based global products. The MODIS/TERRA LST/E Daily L3 global 1 km grid product (MOD11A1) is tile-based and gridded in the sinusoidal projection and produced daily at 1 km spatial resolution. The thermal (LST) information is used for the estimation of soil water content required in ETLook. This soil water content serves as an input for the calculation of r_{canopy}. As with the other MODIS products, this dataset includes a quality assurance layer. The information in this layer relates to cloud cover and was used for automated cloud-masking.

3.2.3 Meteorological data

Meteorological data used in this project were obtained from two sources: the National Oceanic and Atmospheric Administration's (NOAA) *Global summary of the day* (GSOD) dataset and the Agricultural Research Council's (ARC) meteorological stations. Data from 73 ARC and 166 NOAA meteorological stations, spatially distributed over SA, were used in the modelling. The distribution of the stations used is depicted in Figure 3.6, with the complete station list provided in Appendix II.

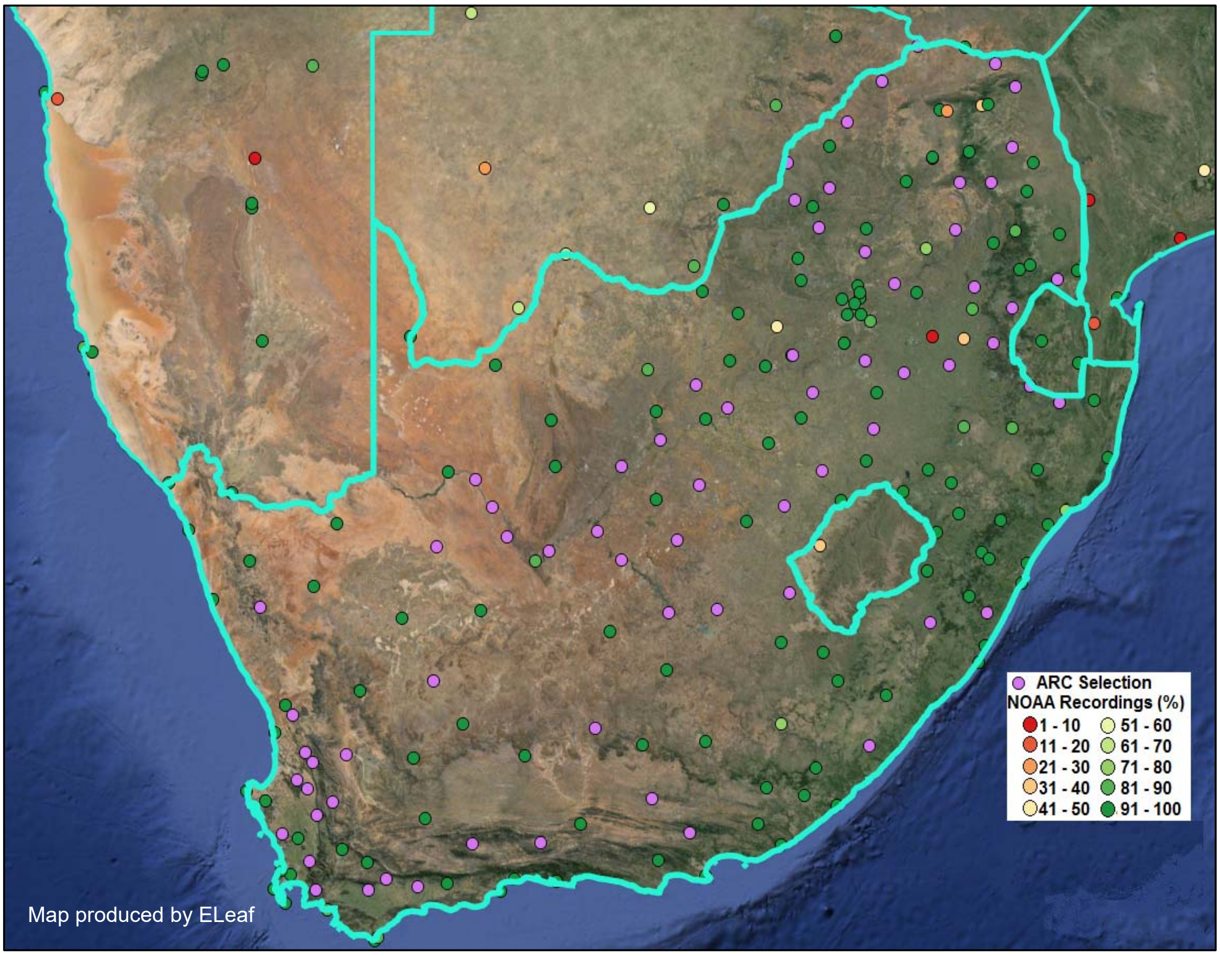


Figure 3.6 The spatial distribution of the 166 NOAA and 73 ARC meteorological stations used in this study. The colours of the NOAA station symbols indicate the consistency of data availability.

The NOAA stations' data availability between January and June 2014 was evaluated by comparing the number of completed recordings against the number of possible recordings within the evaluation period. As shown in Figure 3.6, the NOAA stations are consistent suppliers of meteorological data. The ARC stations used were strategically selected to fill geographical gaps in the NOAA monitoring network, taking into account the reliability of the NOAA stations, as displayed in Figure 3.6. Additionally, underlying land cover was taken into account and specific attention was paid to adequately represent agricultural areas.

Average daily air temperature, relative humidity, wind speed and precipitation are measured at each NOAA and ARC station. The point measurements were automatically interpolated (using Daymet) to produce daily meteorological input map datasets of air temperature, relative humidity and windspeed. Daymet comprise a collection of algorithms and computer software designed to interpolate and extrapolate from daily meteorological observations to produce gridded estimates of daily weather parameters (Thornton et al. 1997). Other inputs to the ETLook modelling relating to atmospheric conditions included transmissivity (from MSG) and precipitation (from Global Satellite Mapping of Precipitation (GSMaP)). These products are respectively described in Sections 3.2.4 and 3.2.6. An example of an interpolated and extrapolated air temperature image is provided in Figure 3.7. The meteorological information is used to calculate various stress factors to crops, which in turn are used to calculate r_{canopy}. Windspeed is used as input to the calculation of $r_{a,canopy}$ and $r_{a,soil}$.

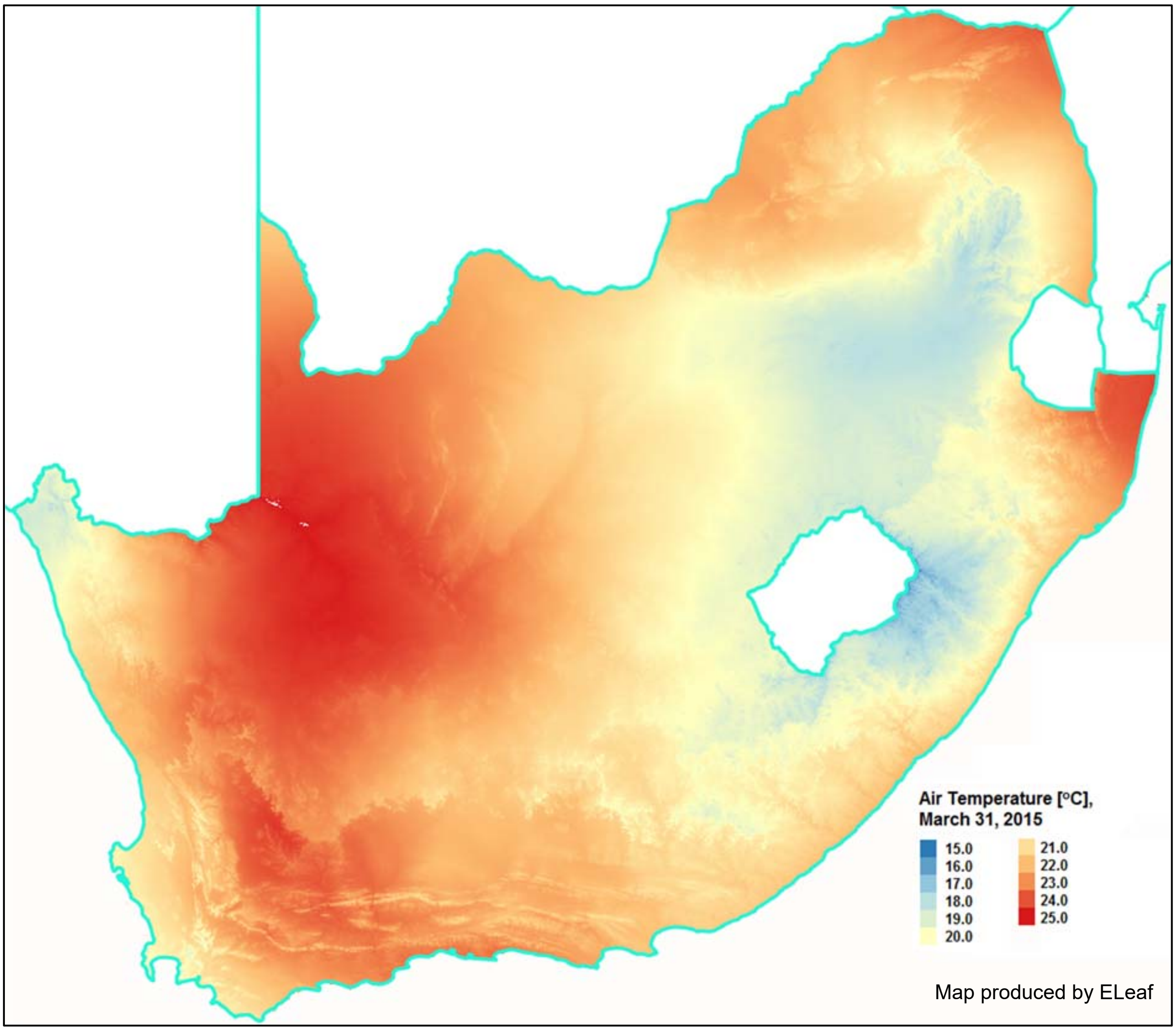


Figure 3.7 Example of an air temperature map, used as input to ETLook and generated using the Daymet model for 31 March 2015.

An example of the impact of including ARC stations in the NOAA meteorological dataset is shown in Figure 3.8. Figure 3.8a represents air temperature based on NOAA data only, while Figure 3.8b shows the result when ARC stations were included in the interpolation. The increased detail in the resulting meteorological data resulted in substantially better quality ET data.

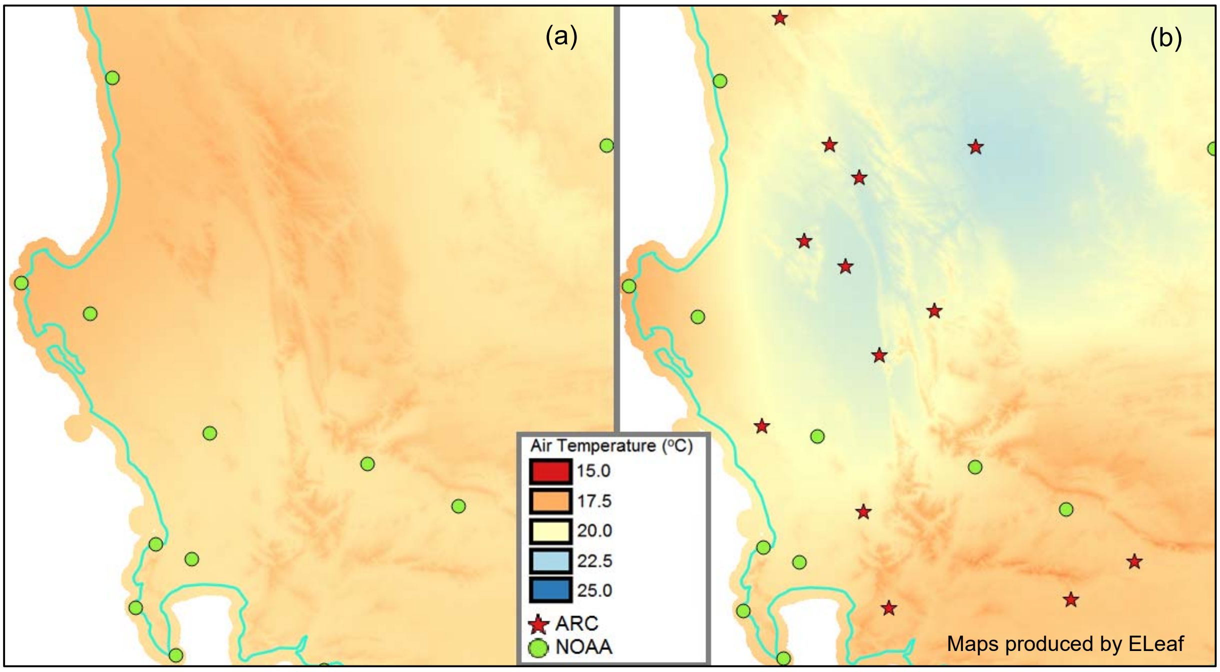


Figure 3.8 The spatial variation in extrapolated air temperature when (a) only NOAA stations were used and when (b) ARC stations were added to the NOAA dataset, for 27 December 2014

3.2.4 Meteosat Second Generation transmissivity

Daily transmissivity data are required as input to the ETLook model in order to calculate incoming radiation, which is subsequently split in Q^*_{canopy} and Q^*_{soil}. Due to atmospheric interferences (reflection, absorption, scattering), not all solar radiation is transmitted through the atmosphere and only a fraction typically reaches the evaporating land surface. This fraction of solar radiation is required to calculate crop consumptive water use (ET). Typically, about 75% of all radiation reaches the land surface under clear sky conditions, which is reduced to as little as 25% under heavy cloud cover. The net solar radiation that reaches the crops is determined by the position of the sun relative to the Earth and transmissivity measurements by satellites.

Atmospheric transmissivity determines the fraction of solar radiation that transverses through the atmosphere and reaches the Earth's surface. Cloud cover information was used to quantify the transmissivity of the atmosphere for shortwave solar radiation. The Meteosat Second Generation (MSG) geostationary satellite records cloud cover at 15 minute intervals. Cleaned-up and geo-corrected cloud cover data are provided as part of the Cloud Physical Properties (CPP) algorithm development by the Koninklijk Nederlands Meteorologisch Instituut (KNMI) in the Netherlands. The CPP algorithm is largely developed by EUMETSAT's Climate Monitoring Satellite Application Facility (CM-SAF). The down-welling surface fluxes provided by the algorithm have operational status and are reliable inputs for calculating daily transmissivity. An example of the transmissivity on 31 March 2015 is shown in Figure 3.9.

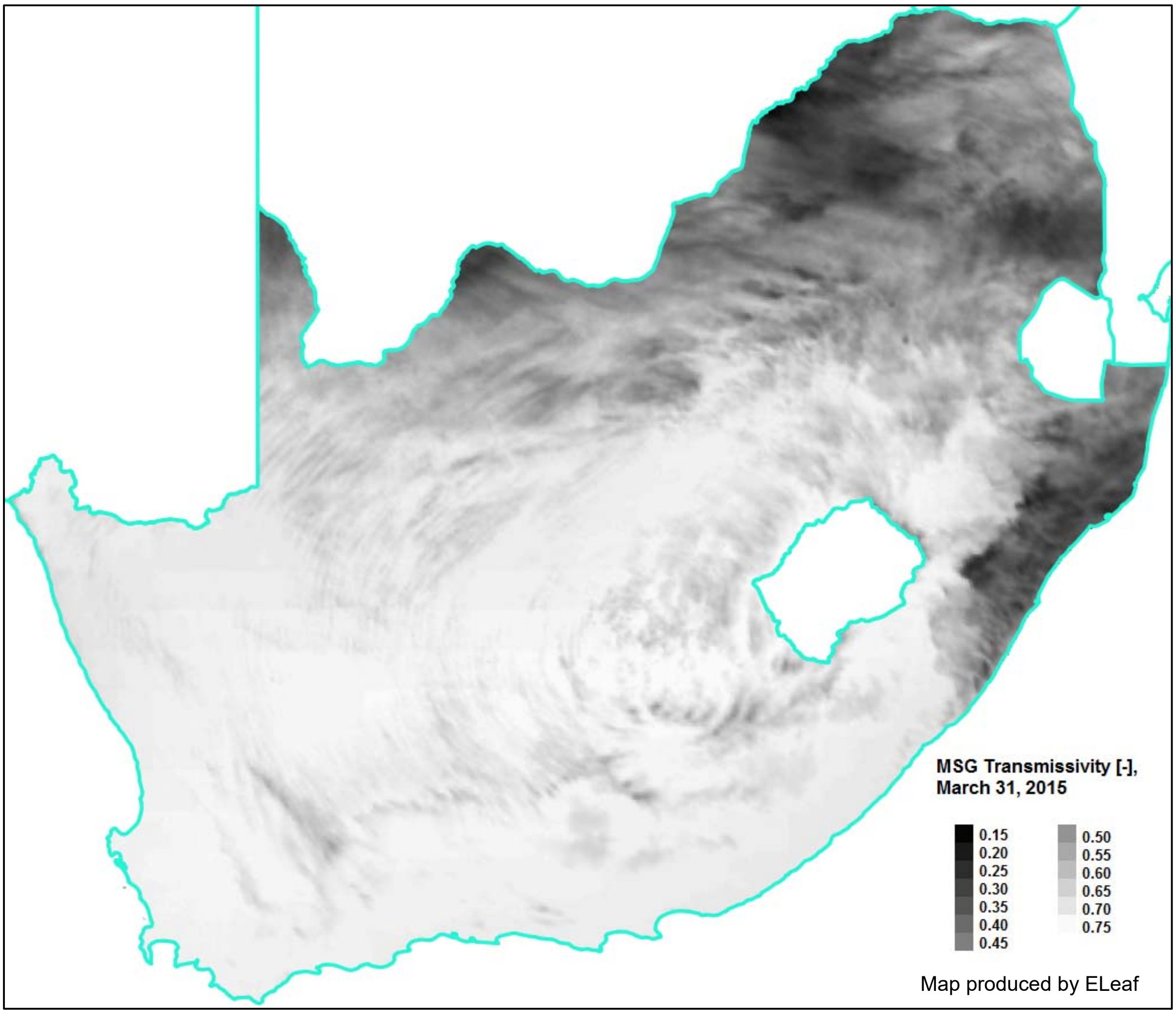


Figure 3.9 Example of transmissivity on 31 March 2015 as calculated using the CPP algorithm.

3.2.5 Topsoil soil water

The EUMETSAT data portal[14] provides soil water content products based on the Advanced SCATterometer (ASCAT) sensor on board the Meteorological Operational Satellite Program of Europe (METOP) satellite. The ASCSMR02 soil water[15] product contains surface soil water content data with a spatial resolution of 12.5 km. The algorithm used to derive soil water content is based on a linear relationship of soil water and scatterometer backscatter and uses change detection techniques to eliminate the contributions of vegetation, land cover and surface topography. The soil water content product is defined as the relative soil water content (θ) in the surface layer (~3 cm), ranging between 0 and 100% of total saturation. If θ is 100%, then the soil is completely saturated; when θ is 0%, the soil is completely dry. The ASCSMR02 data (provided in EPS HDF5 format) are disseminated on a daily basis in global swaths covering the globe. For SA, one day of data typically consisted of 14 (.h5) files that were spatially gridded to a specific projection.

[14] https://eoportal.eumetsat.int/userMgmt/login.faces
[15] For agricultural purposes the term soil water content is used, although the term soil moisture is often also used in many countries.

ASCAT was used for estimating topsoil water content, which was the main driver of soil evaporation in ETLook. It determines r_{soil} in the PM equation but was not used for calculating transpiration. The topsoil water content estimation process involved an automated quality check, after which the data were resampled from 12.5 km to 250 m using bilinear interpolation. An example of an ASCAT relative topsoil water content raster is provided in Figure 3.10.

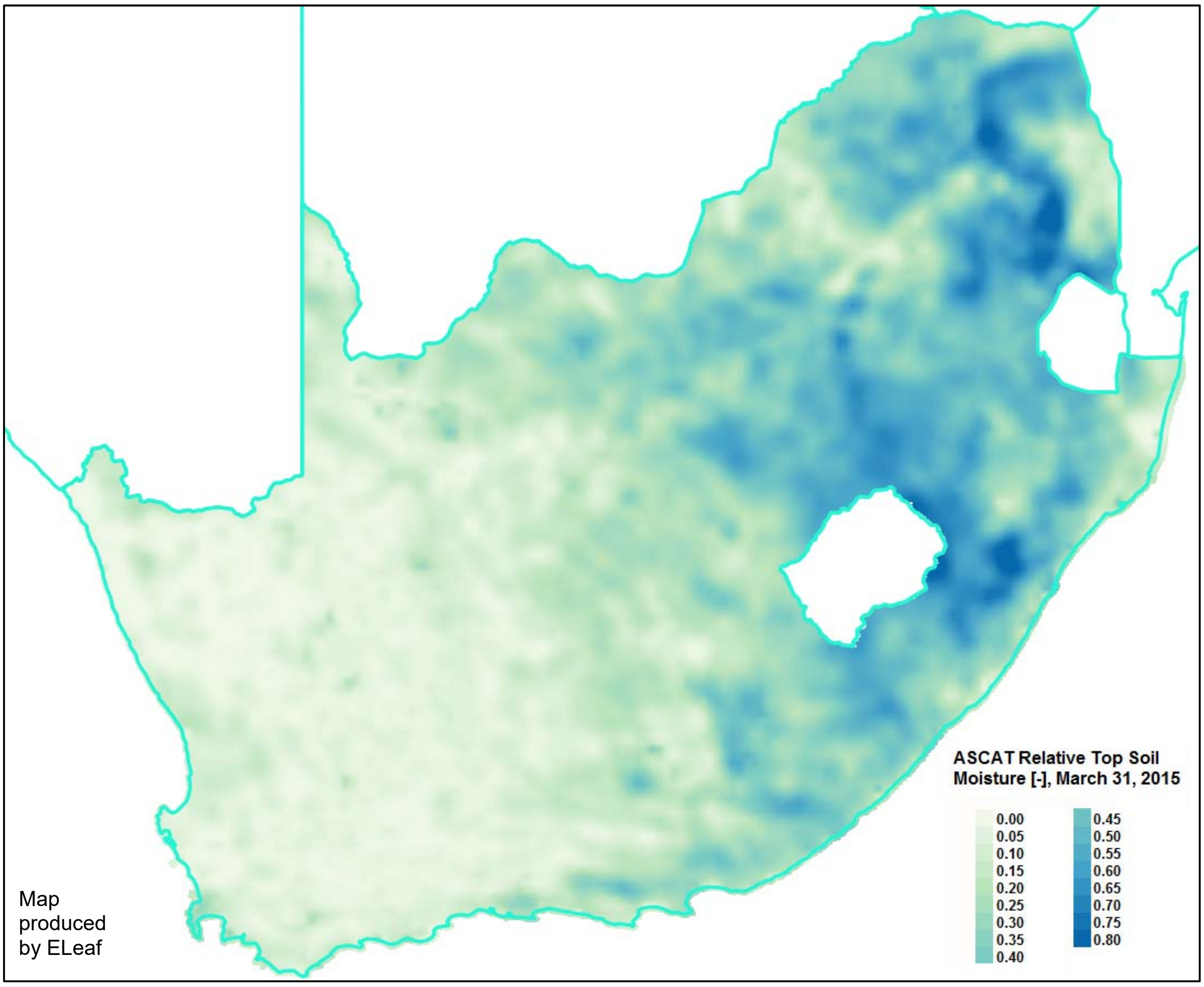


Figure 3.10 Example of ASCAT relative topsoil water content of 31 March 2015

3.2.6 Precipitation

One of the main problems with determining the spatial variability of precipitation in SA is the low density of traditional rain gauges (Van Niekerk & Joubert 2011). In this project, the hourly Global Rainfall Map of Precipitation in Near-Real-Time (GSMaP_NRT), available from the Japan Aerospace Exploration Agency (JAXA) Global Rainfall Watch System, was used to calculate interception evaporation. This product provides the rainfall rate in mm/hour and is available from 60° N to 60° S, at a resolution of 0.1 degree latitude/longitude (approximately 11 km).

The system is based on the combined microwave-infrared (MW-IR) algorithm using Global Precipitation Measurement Microwave Imager (GPM-Core GMI), Tropical Rainfall Measuring Mission Microwave Imager (TRMM TMI), Global Change Observation Mission Water Satellite 1 Advanced Microwave

Scanning Radiometer 2 (GCOM-W1 AMSR2), Defence Meteorological Satellite Program (DMSP) Special Sensor Microwave Imager/Sounder (SSMIS), NOAA Advanced Microwave Sounding Unit (AMSU), Meteorological Operational satellite programme Microwave Sounding Unit (MetOp series AMSU) and Geostationary Infrared (developed by the GSMaP project). The MW-IR algorithm consists of:

1) the *microwave imager algorithm*, which finds optimal precipitation by giving radiative transfer-model-calculated, field-of-view averaged brightness temperatures that fit best with observed brightness temperatures (Aonashi et al. 2009);

2) the *microwave sounder algorithm*, used for the retrieval of rainfall over the ocean (Shige et al. 2009); and

3) the *microwave-IR combined algorithm,* used to produce the rainfall product by combining the retrieved rainfall from microwave images and sounders with cloud information observed by infrared imagery (with high temporal and spatial resolution) aboard geostationary satellites (Ushio et al. 2009).

GPM-GSMaP Ver.6 is the latest algorithm developed by the GSMaP project, and is based on the heritage of the study *Production of a high-precision, high resolution global precipitation map using satellite data*.[16] For the purposes of this project, the hourly rainfall product was quality-checked and upscaled to 250 m resolution using bilinear interpolation and automatically summed to daily values. In combination with NDVI, the daily rainfall was used to calculate interception. This is a separate process to the PM equation used in ETLook. An example of the daily rainfall map that was used as input to calculate interception is provided in Figure 3.11.

[16] http://sharaku.eorc.jaxa.jp/GSMaP/

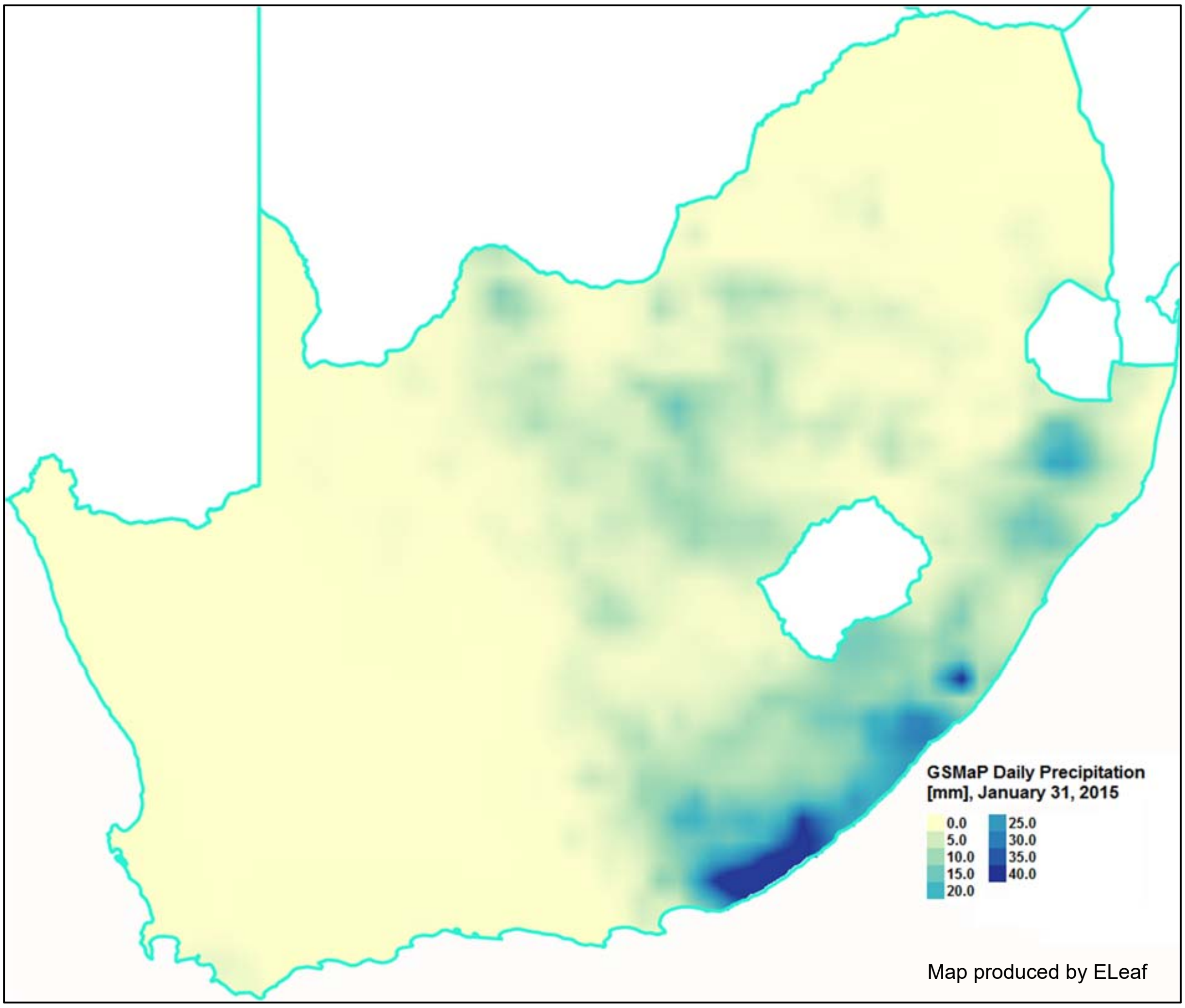


Figure 3.11 Example of GSMaP based precipitation input (mm/day) for 31 January 2015

3.3 Model implementations

The ETLook model was used to produce actual and potential transpiration, transpiration deficit, evaporation, evaporation of intercepted water and actual biomass production data (Table 3.1) for the period 1 August 2014 to 31 July 2015. The results were stored in the Albers Conical Equal Area map projection using the WGS84 ellipsoid and datum at a resolution of 250 m. ETLook was applied at a daily time step and these daily estimates were subsequently combined to produce monthly estimates of the individual datasets, which is the temporal interval reported on.

Table 3.1 List of data components produced from the ETLook modelling – first at a daily time step and then integrated to monthly intervals.

Data Component	Description
Actual Transpiration	The quantity of water vaporisation through stomata in plant leaves (mm/time step).
Potential Transpiration	The quantity of water vaporisation through stomata of the plant leaves if unlimited water were available (mm/time step).
Evaporation	The quantity of water removed from the land surface, either through evaporation of water from bare soil or open water bodies (mm/time step).
Transpiration deficit	The difference between potential and actual transpiration (mm/time step).
Interception evaporation	Interception evaporation is the direct evaporation of water from the surface of wet leaves (mm/time step).
Actual biomass production	Biomass production refers to the growth of plant material above and below the ground (such as stems, leaves, roots, fruits and grains). It is defined as *dry matter* and is measured as *incremental* biomass production per time step (kg/ha/time step) and representative of a C3 crop. Since, sugarcane areas are identified in the SALC1314 land cover classification, and sugarcane is a C4 crop, these areas were treated as a C4 crop during the ETLook calculations.

As explained in Section 3.2, ETLook requires satellite (sensor-based), land cover and meteorological data as input. Figure 3.12 provides a schematic overview of the automated ETLook process.

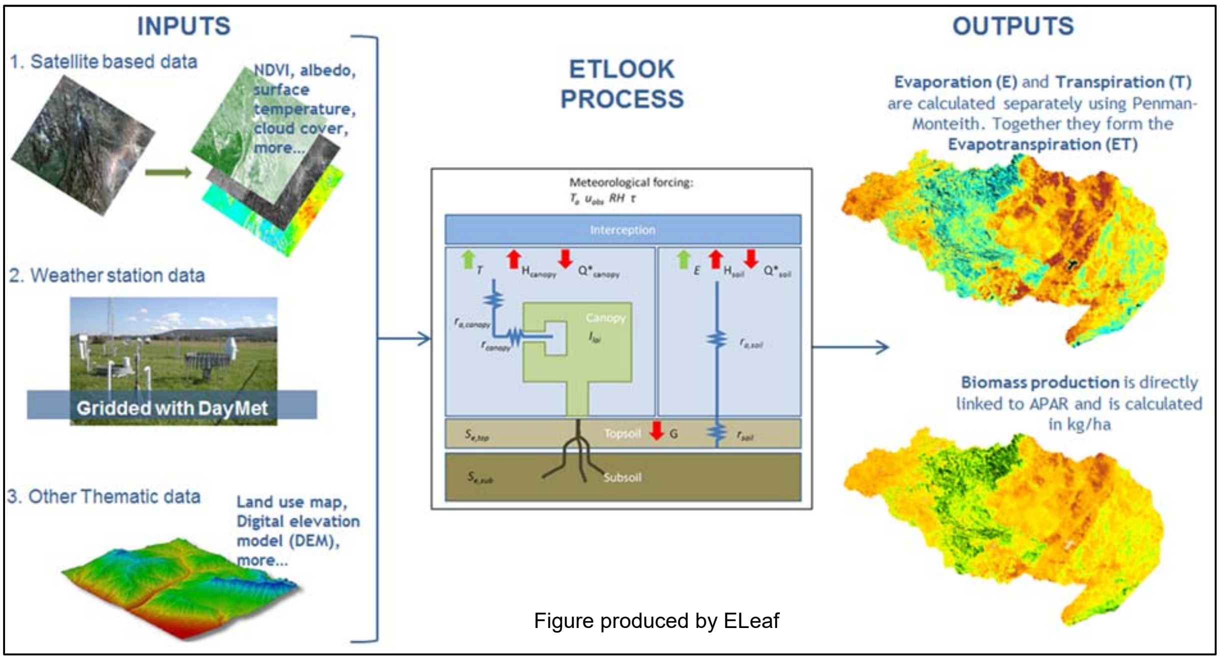


Figure 3.12 Schematic representation of the ETLook process applied to produce the ET datasets

All datasets used in ETLook were resampled to 250 m spatial resolution. Where necessary, input datasets were upscaled to 250 m resolution using bilinear interpolation to prevent abrupt changes in modelling results. Figure 3.13 describes how the different inputs/parameters within ETLook interact to solve the PM equation.

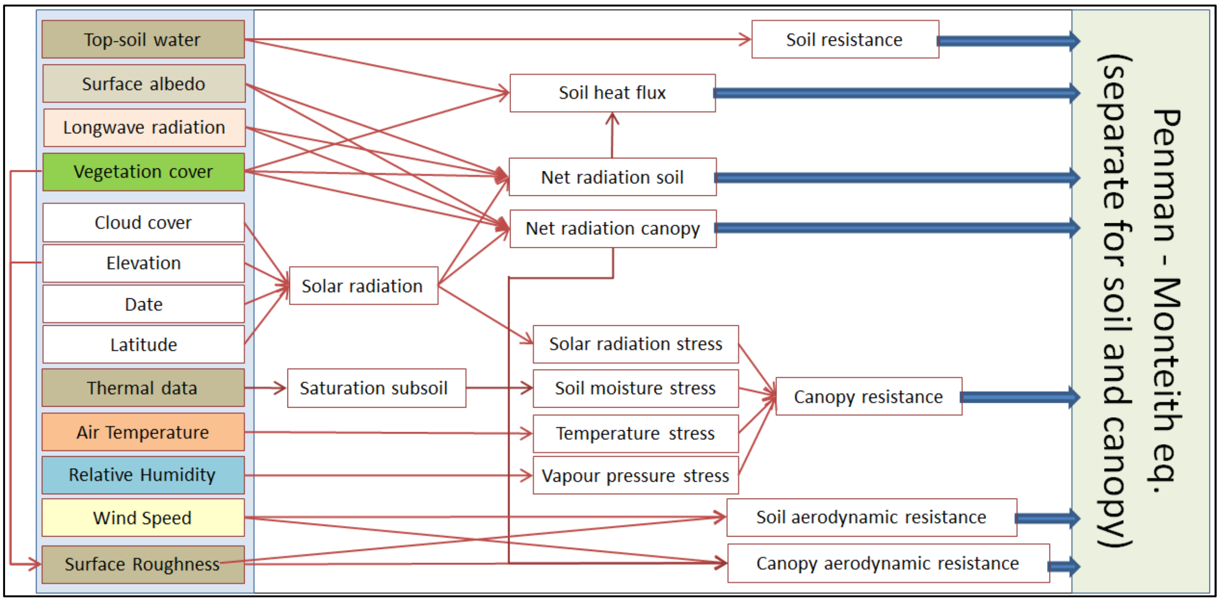


Figure 3.13 Schematic representation of the ETLook model steps Figure produced by ELeaf

The ETLook model cannot produce outputs for areas where input data are unavailable due to cloud cover. Therefore, to reduce the impact of clouds on the ETLook dataset, daily composite images were created. These nationwide daily composites of NDVI, albedo and soil water content were based on 10-daily weighted averages. Weighing factors taken into account were the age of the input data (older = less weight), the proximity to clouds (closer to clouds = less weight) and the recording angle (lower angle = less weight). If no suitable data were available for a period of 10 days, older data was used. The production of these composites was automated in the processing structure. Before ETLook was run, the created composites were inspected for omissions or errors.

A literature review on ET field measurements related to various land use classes and regions in SA was carried out to gain a better understanding of crop water use. This included measurements on horti-/viticulture (WaterWatch 2008; Dzikiti & Schachtschneider 2015; Jarmain et al. 2015), forestry (Dye & Olbrich 1993), sugarcane (Hellegers et al. 2010; Jarmain et al. 2014), irrigated maize (Jarmain et al. 2014), wheat (Jovanovic et al. 2011), grasslands (Snyman & Fouche 1993; Jarmain et al. 2009b; Everson et al. 2011), bush (Scholes et al. 2001) and fynbos (Dzikiti et al. 2014). The field measurements undertaken for these studies provided additional insight into the range of ET values for various land use types. This information is taken into account when calibrating the ETLook model.

3.4 Overview of resulting evapotranspiration dataset

This section provides examples of the ETLook datasets produced at national and provincial scale. Seasonal changes and differences related to crop development throughout the monitoring period (1 August 2014 to 31 July 2015) are highlighted. Each subsection includes a short description of the agricultural activity per province and observations of the seasonal actual ET (ETact). Most of the information related to agricultural practices per province was taken from a research report on agricultural performance (KPMG 2012) and one on crop fertiliser use (FAO 2016) in SA.

Figure 3.14 shows the actual ET (or vegetation water use) in mm/yr at national scale for the study period. Areas with high (darker blue) and low (white-pink-light green) ET are clearly visible. These differences are associated with water availability (whether through rainfall or irrigation applied), climatic conditions and the vegetation or crop type cultivated. It is clear from this map that the actual ET of agricultural crops and other types of vegetation varies greatly across SA. Understanding the spatial distribution of ET provides insights into crop water requirements in various regions.

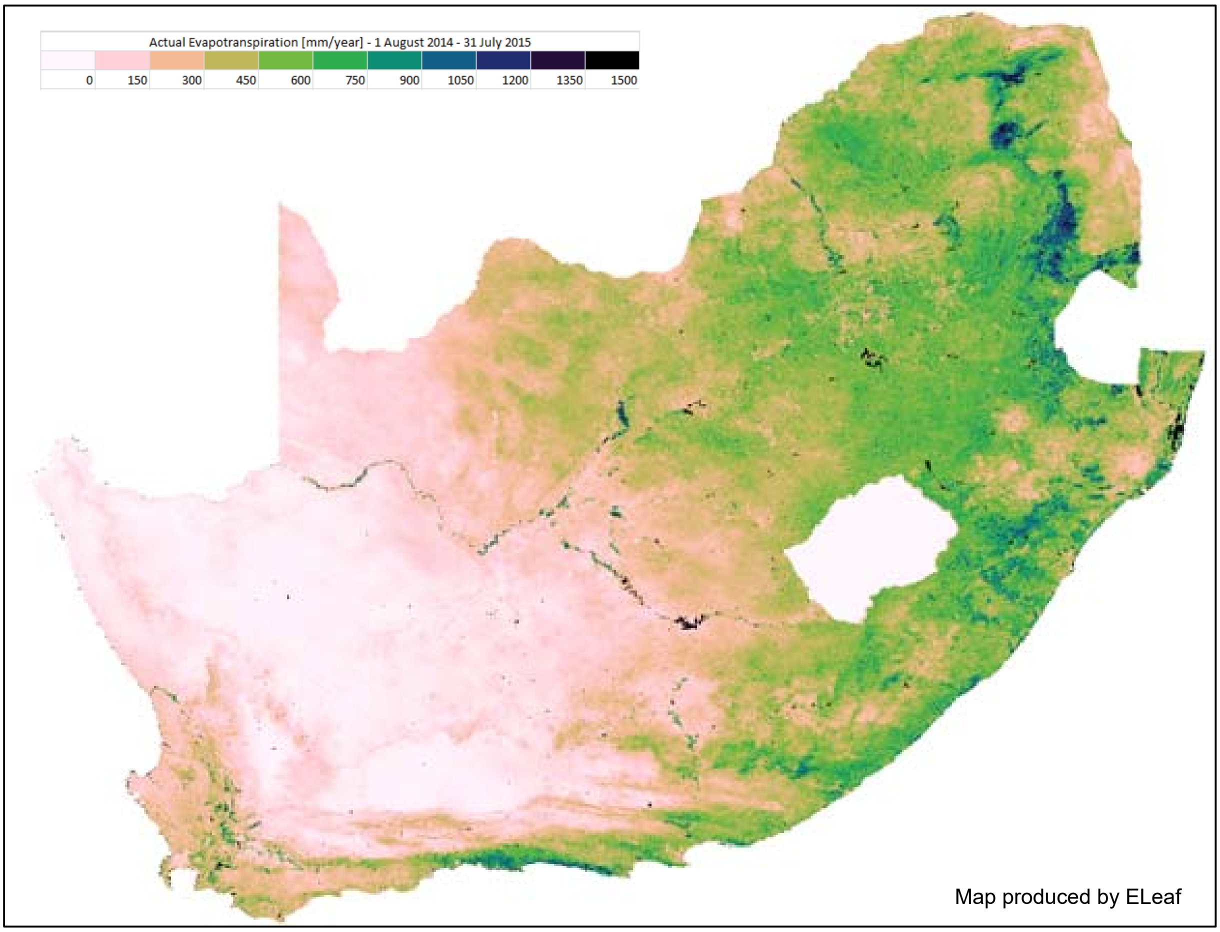


Figure 3.14 Accumulated actual ET (mm/yr) for the period 1 August 2014 to 31 July 2015, as generated by ETLook.

3.4.1 Northern Cape Province

The Northern Cape is predominantly semi-arid, with sparse rainfall throughout the year. The western parts receive most of its rainfall during the winter period, while rainfall in the eastern parts is mostly attributed to late summer thunderstorms. Only 1% of the land area is classified as arable (KPMG 2012) and agriculture is concentrated around the Orange River and Vaal River where crops are predominantly irrigated. Intensive grape and fruit cultivation takes place in the Orange River region, with some grain crops also being produced. Wheat, maize and cotton cultivation dominates the Vaal River region.

The Vaalharts irrigation scheme on the western boundary of the province (Figure 3.15) is the largest irrigation scheme in SA, with approximately 32 000 ha of land under irrigation. It is clear from the high NDVI values shown in Figure 3.15b that intensive cultivation took place throughout the scheme in October 2014. Due to high levels of solar radiation received and great amounts of irrigation applied, a large amount of water (over 200 mm/month) was consumed by the crops over this time (Figure 3.15c). Figure 3.15d shows a smaller area with high NDVI values recorded in May 2015, suggesting that a much smaller proportion of the area was actively cultivated at the time, or that the crops were growing less vigorously. Less vigorously growing vegetation in addition to lower solar radiation and vapour pressure deficit values, explain the lower Etact in May 2015 ETact (Figure 3.15e) compared to October 2014.

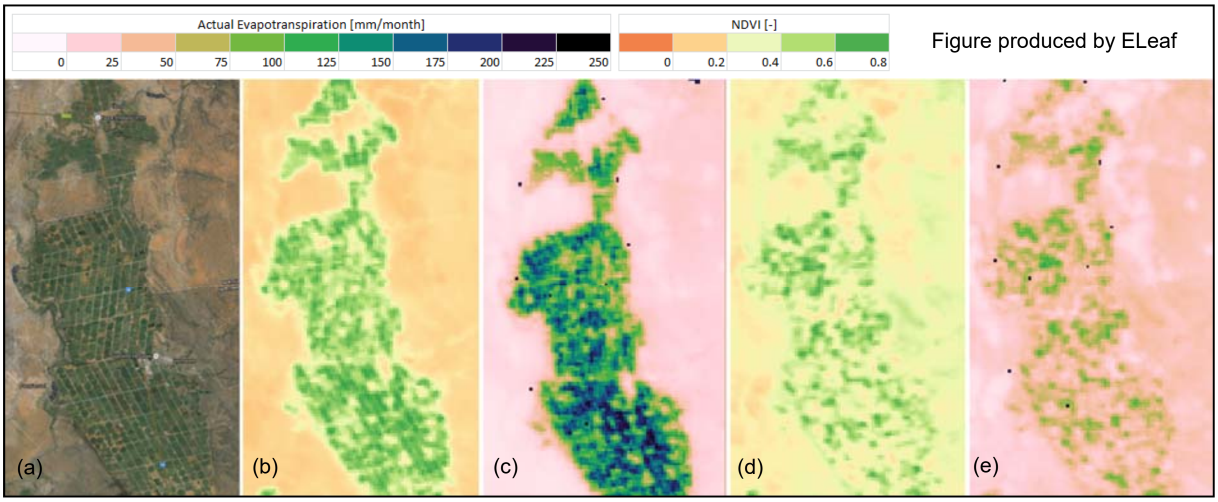


Figure 3.15 Vaalharts irrigation scheme (a) natural colour satellite image compared to an (b) NDVI and (c) ETact (actual evapotranspiration) image for 23 October 2014, and (d) NDVI and (e) ETact image of 6 May 2015.

3.4.2 North West Province

Most of the rainfall of the North West Province falls during the summer months, which corresponds to the main agricultural crop growing seasons of this region (USDA 2013). The north-eastern parts of the province receives considerably more rainfall than the central and southern region, while the western parts are considered arid.

The North West Province is predominantly rural. The eastern, north-eastern and western parts of the province are dominated by livestock farming. Extensive mixed crop farming takes place within the central and southern regions, with maize, wheat and sunflowers being most important crops cultivated. Other crops include cotton, groundnuts, citrus and tobacco (KPMG 2012).

Figure 3.16 clearly reflects the large differences in conditions experienced in spring and mid-summer. The larger cultivated areas in the southern and eastern parts of the province can be distinguished in the summer image, showing the highest actual ET (up to 200 mm/month). There is also a difference between the western and eastern parts of the province in mid-summer with the north-eastern part being the wetter part of the province.

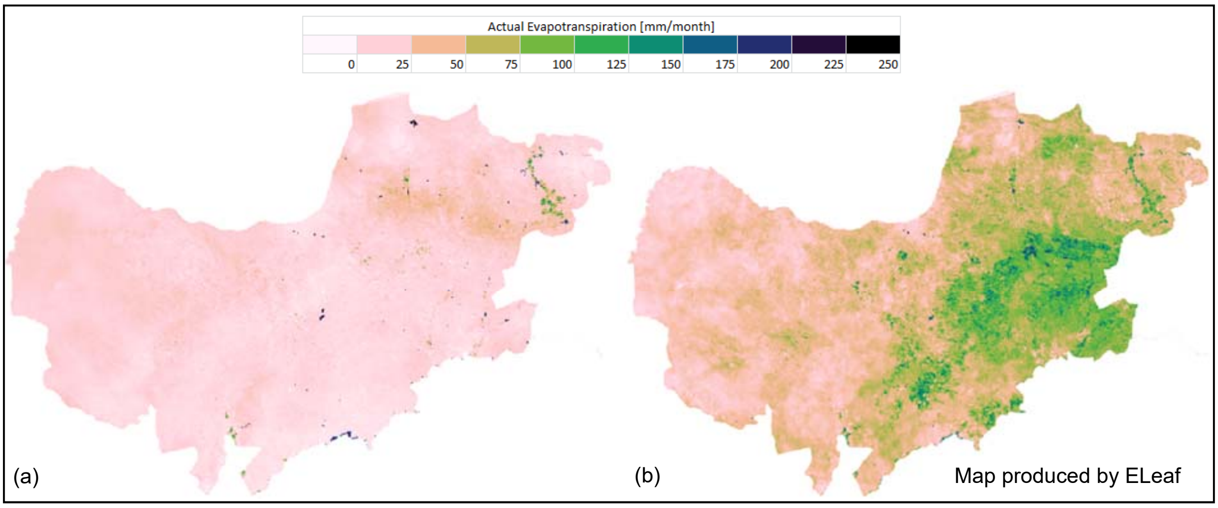


Figure 3.16 Actual ET (in mm/month) of the North West Province in (a) spring (September 2014) and (b) summer (February 2015)

3.4.3 Limpopo Province

Approximately 95% of the Limpopo Province's precipitation occurs from October to April. The province is vulnerable to changing climatic conditions and has experienced severe droughts and floods in recent years. The Limpopo Province's agricultural sector is dominated by fruit and vegetable farming, with a relatively large proportion of smallholder farmers who predominantly grow field crops such as maize and grains (KPMG 2012).

In Limpopo, the water lost through actual ET differs greatly between winter and summer. This correlates well to the water available to drive actual ET. An overview of the region just south of Soutpansberg is shown in Figure 3.17. In August, the highest ET values are found in the tree plantations in the mountainous areas on the eastern side of the image. Irrigated pivots are visible as small dots throughout the winter image. A completely different pattern is observed in the summer, with high ETact values throughout the province. This can be attributed to the abundant growth of natural vegetation, supported by summer rains and summer field crop cultivation.

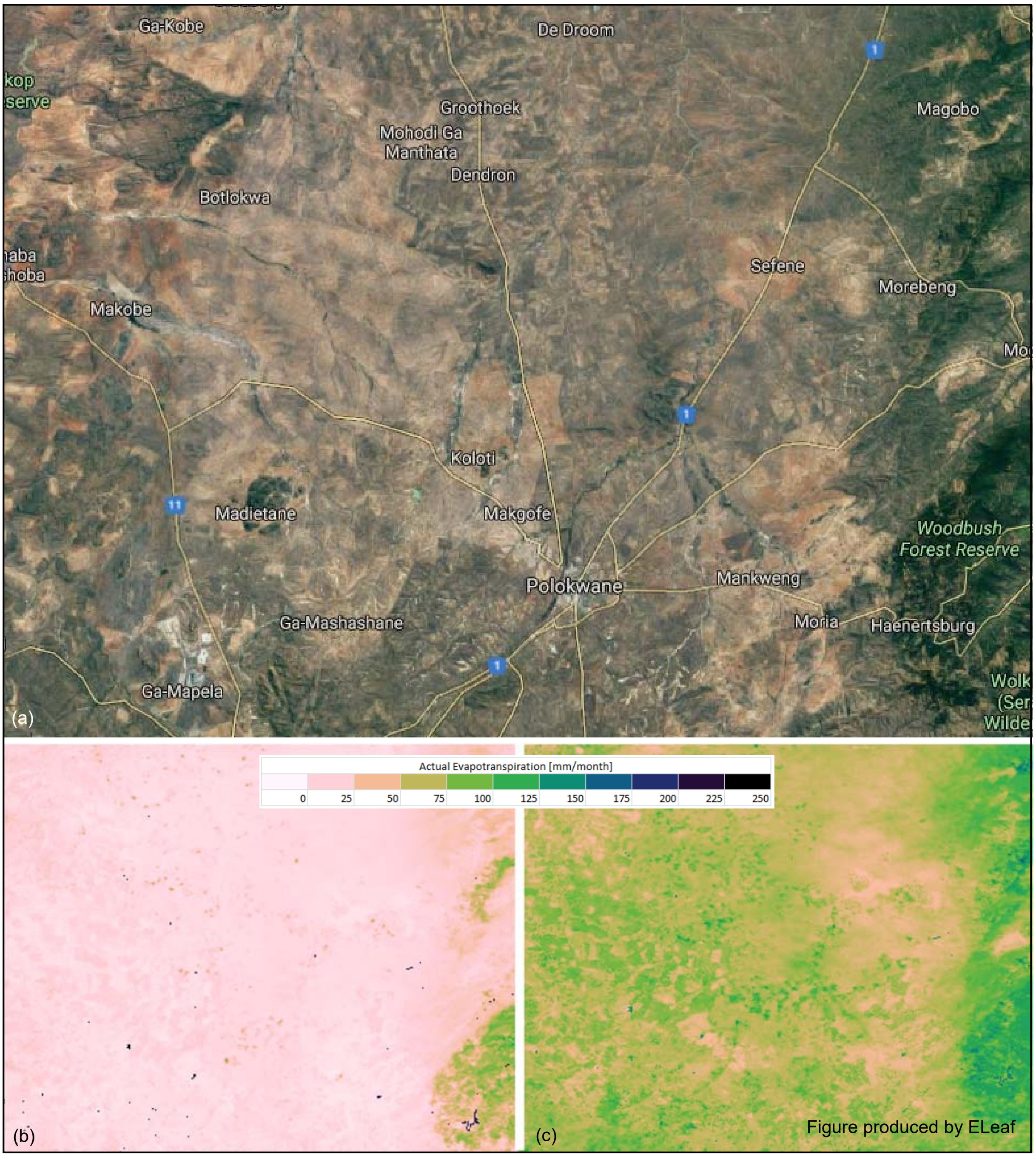


Figure 3.17 Region south of Soutpansberg shown in (a) true colour and as actual ET in (b) winter (August 2014) and (c) summer (February 2015).

3.4.4 Free State Province

The Free State experiences warm summers and cool to cold winters. Almost all its rain falls during the summer months, mainly as brief afternoon thundershowers. The province is considered the granary of SA, with extensive areas being cultivated and agriculture being a key economic driver in the province. The most predominant field crops are maize and wheat, while vegetables (potatoes) and fruits are also cultivated (KPMG 2012). Most crops are rainfed and therefore cultivated during the wet summer season, although maize, wheat and sunflower fields are irrigated in some areas (FAO 2016). In Figure 3.18, the sharp contrast between summer and winter water losses through actual ET is clearly visible.

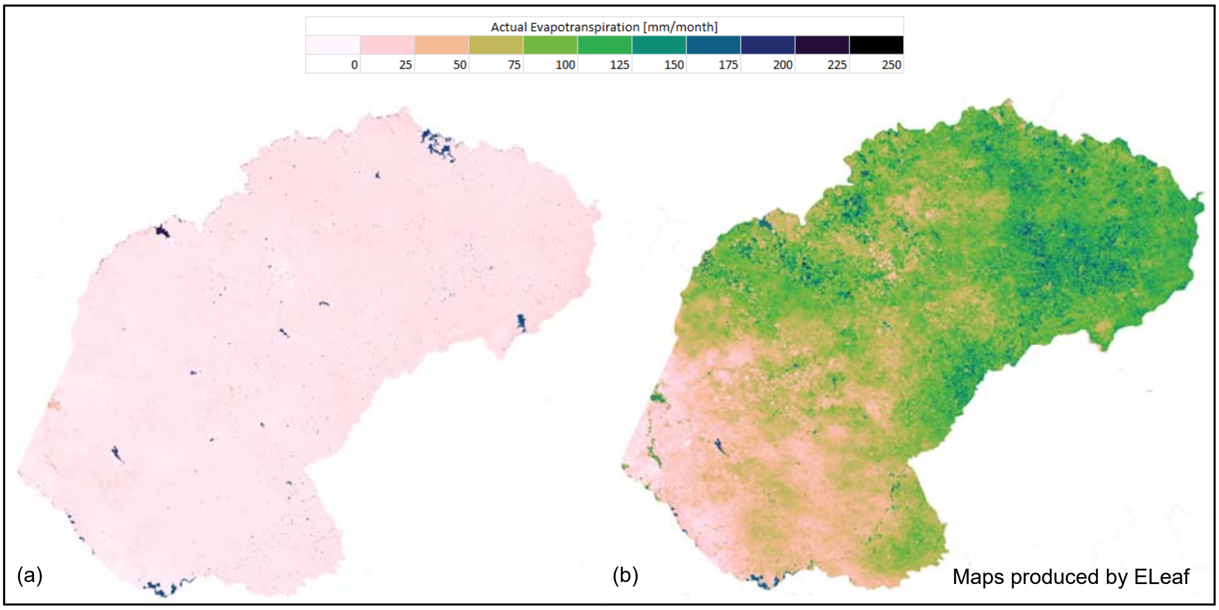


Figure 3.18 Actual ET of the Free State showing a clear difference between (a) winter and (b) summer water consumption

3.4.5 Gauteng and Mpumalanga Provinces

In Gauteng, winters are crisp and dry with frost occurring in the southern areas. Most precipitation occurs in summer as brief thundershowers. The majority of the farmland in Gauteng is arable with maize the most widely cultivated crop, supplemented by vegetable production. The growing season of most crops occurs from August to April.

Mpumalanga's climate is strongly influenced by topography. The western Highveld region is characterised by cold and frosty winters, and moderately wet summers. Winter and summer cereals are produced in the Highveld on a large-scale. Summer cereal crops include maize and sorghum, while wheat is the main cultivated winter cereal. The eastern parts of the Highveld (central Mpumalanga) contain extensive forest plantations, which use large amounts of water throughout the year. Mpumalanga's eastern Lowveld region is characterised by a subtropical climate with mild winters and high summer rainfall. The region is a major producer of sugarcane and citrus fruits, both of which are intensively irrigated. Large sugarcane plantations are found at the border with Mozambique, just north of Swaziland (Figure 3.19). These areas are irrigated year-round (FAO 2016), resulting in high water consumption in both summer and winter months. Fruit cultivation is mostly subtropical, including bananas, nuts and mangos. Potatoes are also produced throughout the province (KPMG 2012).

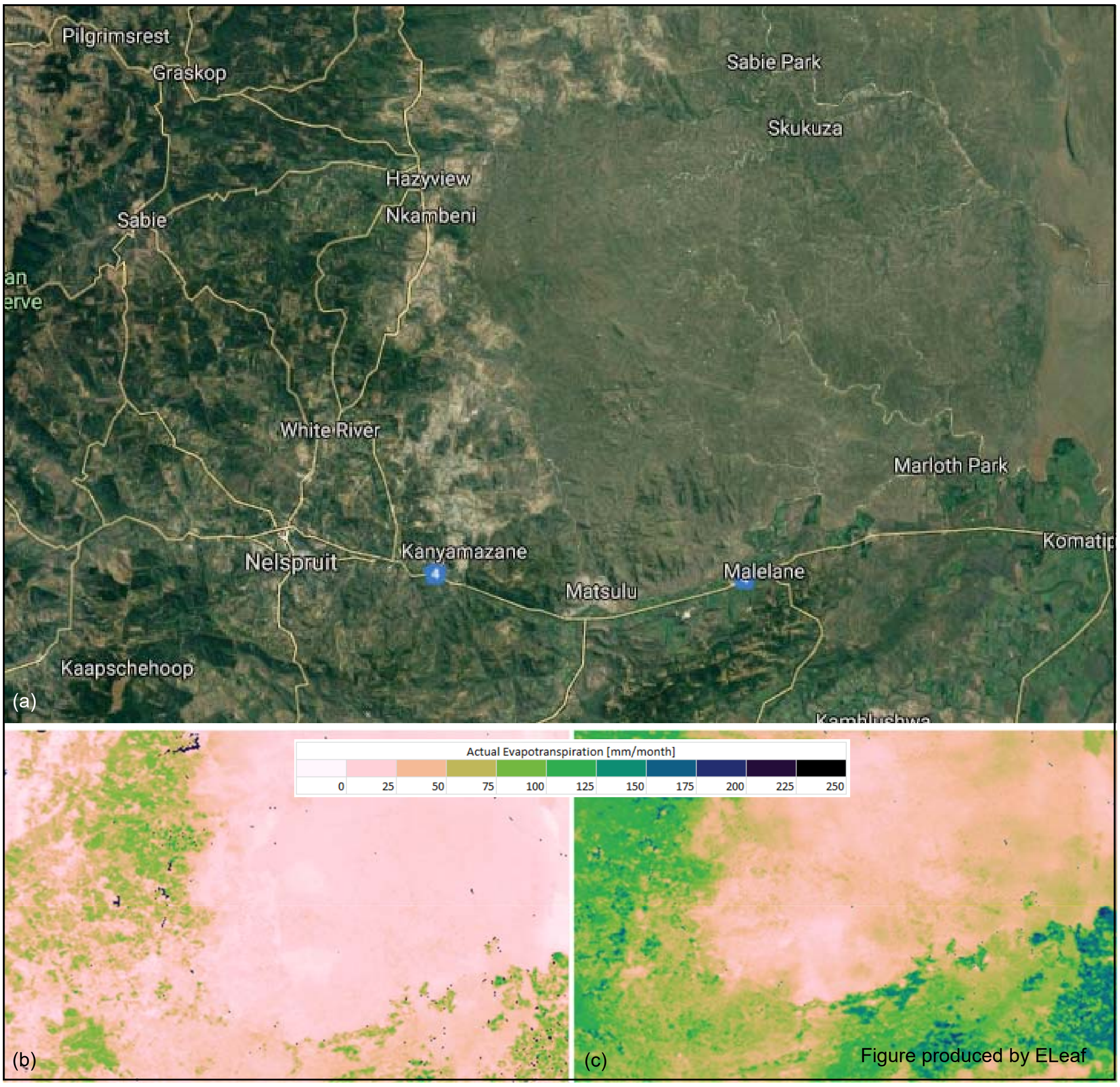


Figure 3.19 An area in Mpumalanga depicted in (a) true colour and as actual ET during (b) winter (August 2014) and (c) summer (March 2015)

3.4.6 KwaZulu-Natal Province

KwaZulu-Natal is a summer rainfall area. The coastal regions are hot and humid with a subtropical climate. The Midlands are drier, with cold conditions during winter. Forestry and the cultivation of field crops are the predominant agricultural activities in the province, with horticulture comprising 10% of agricultural activities (KPMG 2012). Large areas of sugarcane are cultivated in the province, with most of these being rainfed, with the exception of small areas in the northern Pongola region (FAO 2016). Figure 3.20 shows the actual ET for the Pongola area in northern KwaZulu-Natal during springtime. The higher ETact values on the western side of the Pongola Dam are mainly the result of irrigated sugarcane cultivation.

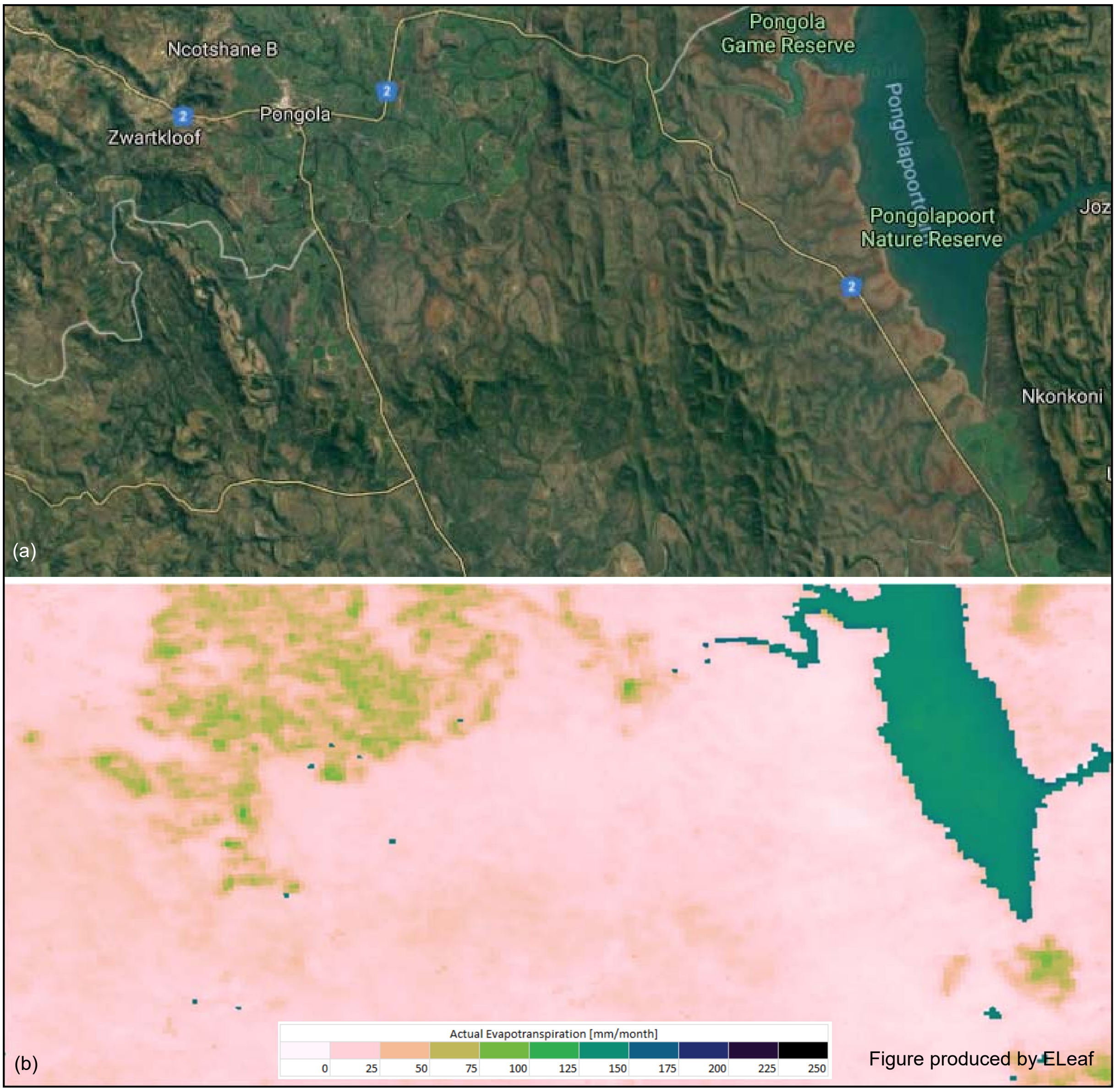


Figure 3.20 Pongola region just south of Swaziland depicted in (a) true colour and as (b) actual ET during springtime (September 2014)

3.4.7 Eastern Cape Province

The climate of the Eastern Cape is highly variable. The interior of the western area is dry throughout the year, with winter rainfall observed along the coast. Rainfall and humidity increase steadily as one moves up the coast, with a shift in precipitation patterns from winter rainfall in the west to summer rainfall in the east. The central interior shows a similar climate to that of the Free State, with wet summers and dry, cold winters. The Eastern Cape is the second largest producer of citrus in SA, though deciduous fruits are also cultivated, especially in the Langkloof Valley. Intensive irrigation is applied within the Groot Visrivier catchment where lucerne, maize and other pastures are irrigated (Figure 3.21).

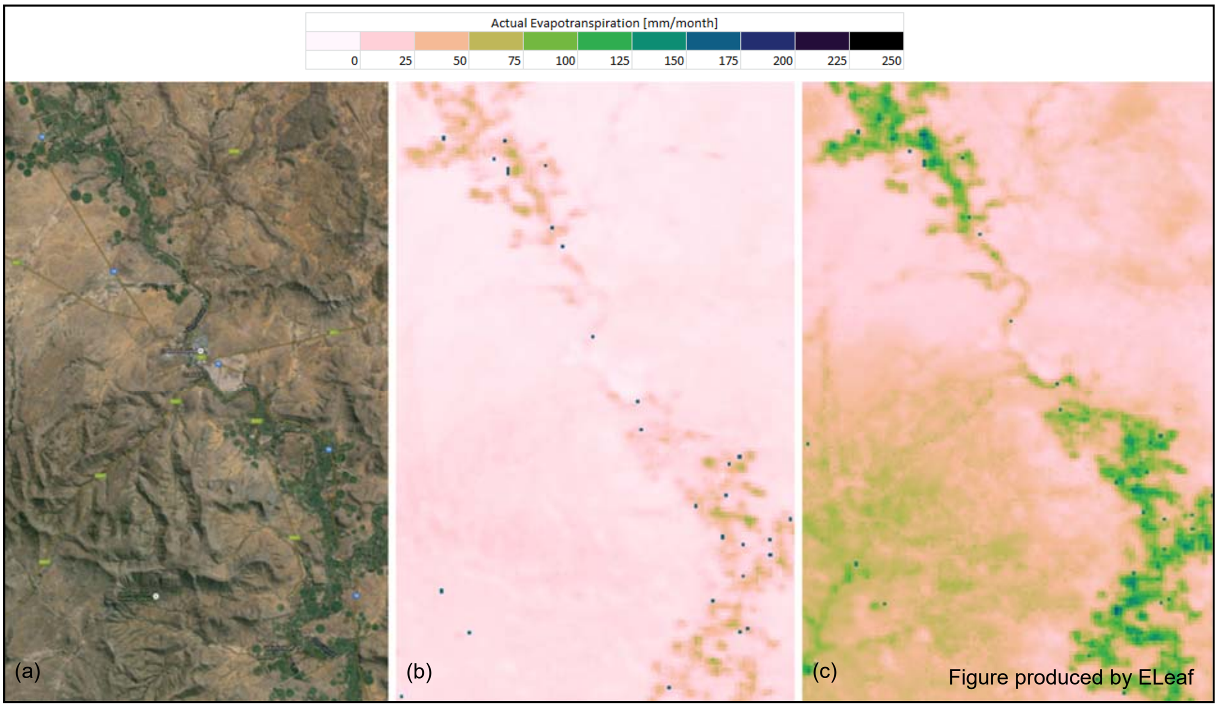


Figure 3.21 The Groot Visrivier region as depicted by (a) a colour satellite image and actual ET in (b) winter (August 2014) and (c) summer (December 2014)

3.4.8 Western Cape Province

The Western Cape is distinguished from the other provinces in SA by being mostly a winter rainfall region, although year-round rainfall is typical in the southern Cape region. During the summer period, irrigated fruit and wine grape production dominates, while rainfed wheat production is the main winter activity, especially in the Swartland and south coast region (Vink & Tregurtha 2007).

The spatial variation of actual ET during summer and winter is illustrated in Figure 3.22. The high ETact values seen in Figure 3.22a are associated with winter wheat production. These ETact values are low compared to the vineyard and orchard areas seen in Figure 3.22b, where ETact values can exceed 200 mm per month.

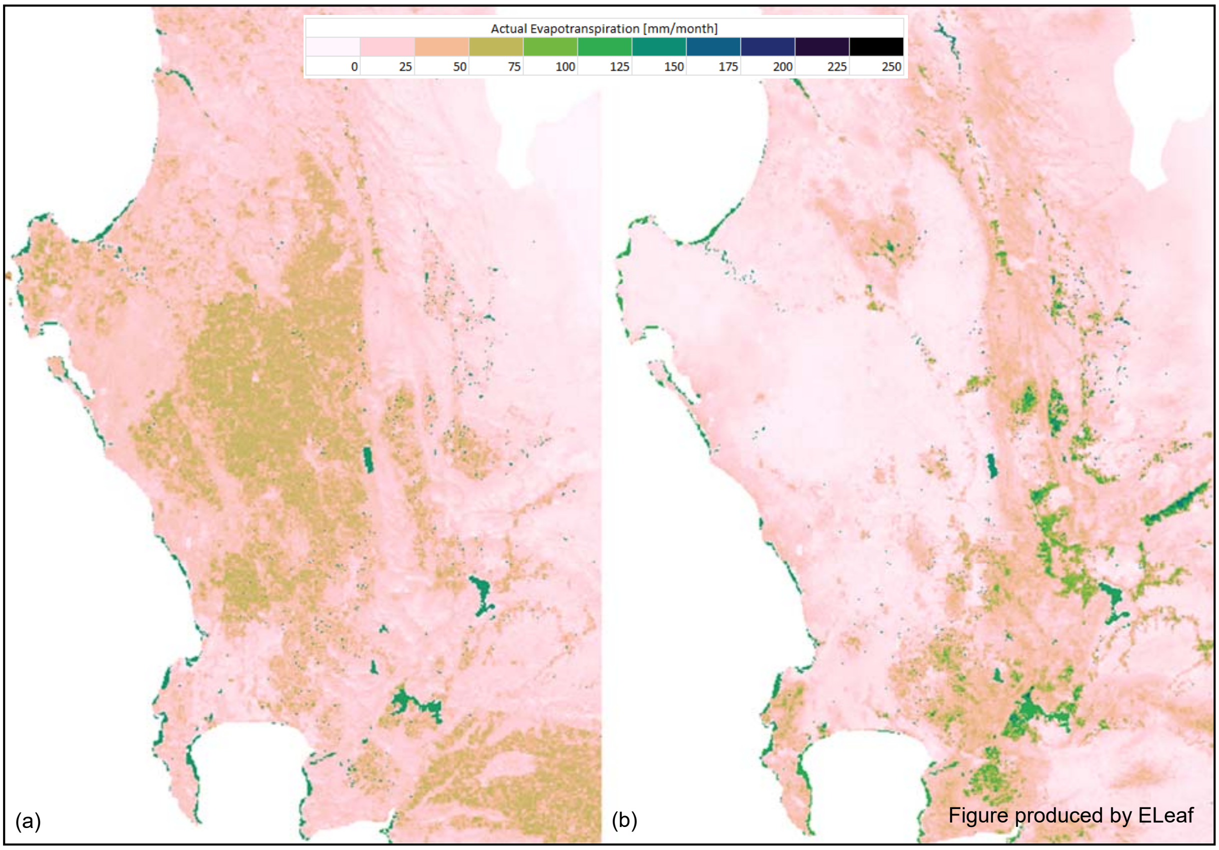


Figure 3.22 Actual ET (mm/month) in (a) August 2014 and (b) January 2015 in the western parts of the Western Cape Province

4 IRRIGATED AREA MAP (IAM) OF SOUTH AFRICA

The development of the IAM was a three-step process, resulting in three different versions of the IAM:

- IAM Version 1: rule-based classification-based on ET and rainfall;
- IAM Version 2: machine learning approach; and
- IAM Version 3: validation and verification of the irrigated areas.

For the IAM, individual fields were used as the minimum mapping and classification unit. Versions 1 and 2 of the IAM were developed independently of one another, with the more accurate product selected for the verification and validation undertaken in Version 3. The analysis performed within each step was applied to a vector polygon dataset, developed specifically for this project, consisting of up-to-date, accurate field crop boundaries named *SAFields*. The advantages of using individual fields as MMU over a pixel-based approach included:

- a higher degree of scale-independence as the resulting product would not be restricted to a specific spatial resolution (e.g. 250 m, 30 m, 10 m);
- improved compatibility with existing datasets such as land cover maps and satellite imagery, as the use of discrete boundaries enabled data extraction (without the need to resample or interpolate);
- less data storage requirements and improvements in processing time (much of the analyses could be carried out using simple database calculations); and
- allowance for straightforward manual reclassification during the verification process (i.e. only an attribute edit was required, which could be easily implemented).

The following sections explain how the *SAFields* field crop boundaries were used to produce the different versions of the IAM.

4.1 IAM Version 1: Rule-based approach

The development of Version 1 of the IAM was undertaken in three steps (Figure 4.1). Each step is described in more detail in the following subsections.

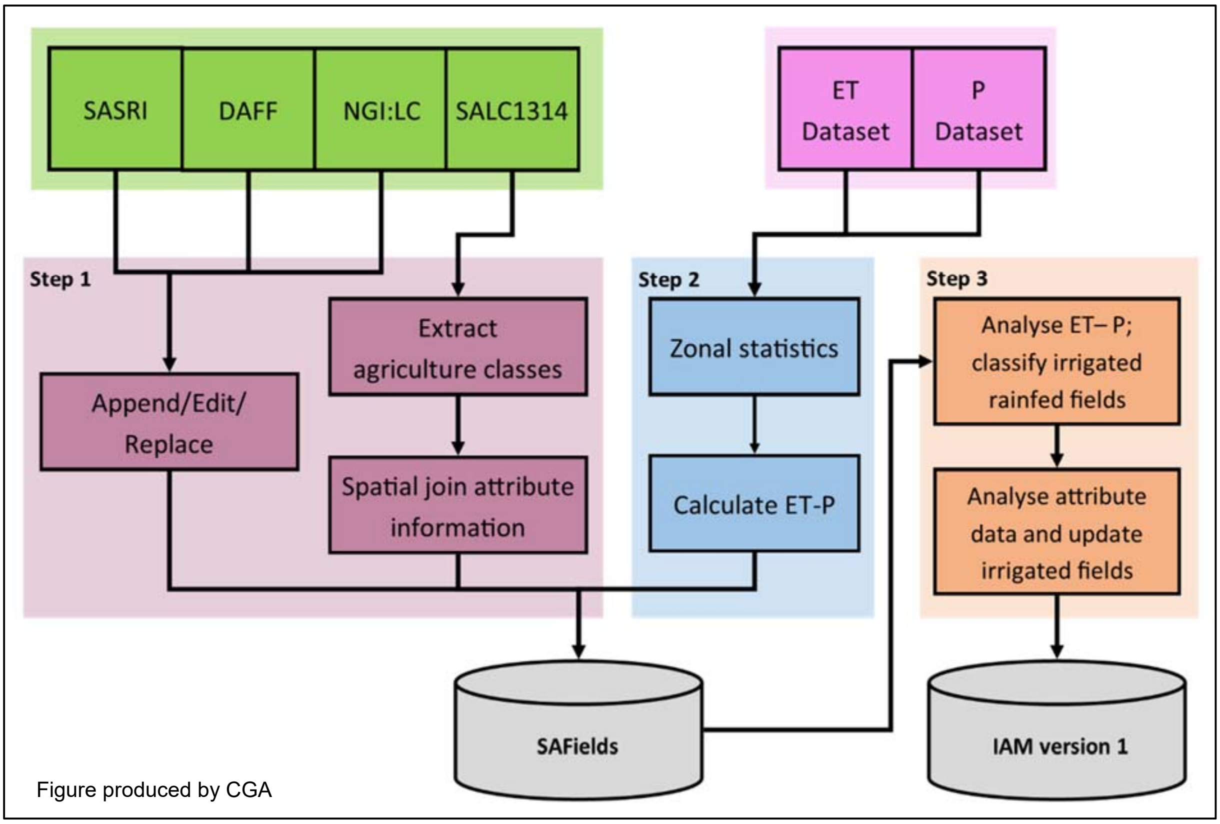


Figure 4.1 Overview of methodology for the creation of the Version 1 IAM database

4.1.1 Step 1: Data collection and preparation

The first step in the IAM methodology was to create the *SAFields* dataset. This involved the collation, manual improvement and merging of existing field boundary datasets obtained from the South African Sugarcane Research Institute (SASRI), the DAFF and National Geospatial Information (NGI). Figure 4.2 shows how these different sources of data were combined to produce the *SAFields* dataset. The quality (accuracy) of the different datasets varied considerably.

The field boundaries dataset digitised by DAFF served as the foundation for the *SAFields* field crop boundary dataset. This dataset comprises the majority of agricultural field boundaries of SA, digitised at a 1:10 000 scale from the 2.5 m SPOT 5 true colour mosaic. The dataset covers an extensive area – more than 90% of the crop fields in SA – but for the purposes of this project, it had two main drawbacks. First, the most recent update to the dataset for all provinces was undertaken in 2011, with the exception of that of the Eastern Cape, which was last updated in 2007. The second drawback was that all sugarcane fields (situated mainly in KwaZulu-Natal and Mpumalanga) are excluded. Several actions were taken to supplement and improve this DAFF dataset to form the *SAFields* dataset. During the development of the 2012 Eastern Cape Land Cover product (for NGI), the Centre for Geographical Analysis (CGA) updated and improved the existing 2007 DAFF field boundaries to 2012 by manual digitising. The manual digitising was done at scales of greater than 1:5 000 using 0.5 m aerial photographs and 2.5 m SPOT 5 data. Most of the attribute information of the original DAFF product was retained. This vector dataset was appended to the existing 2011 DAFF field boundaries to correct a large portion (71%) of the outdated 2007 Eastern Cape data. For the remainder of the Eastern Cape, a

10 m resolution land cover map obtained from NGI was used, correcting an additional 23.7% of the province. Finally, any omitted areas in the Eastern Cape were supplemented by the 2007 DAFF dataset (5.3%). Sugarcane field boundaries acquired from SASRI were used to fill some of the remaining gaps in the *SAFields* database. Sufficient metadata for the SASRI fields were not available and dates could therefore not be linked to this dataset. However, the field boundary information is being actively used by the sugarcane industry and it was assumed that this date were up-to-date.

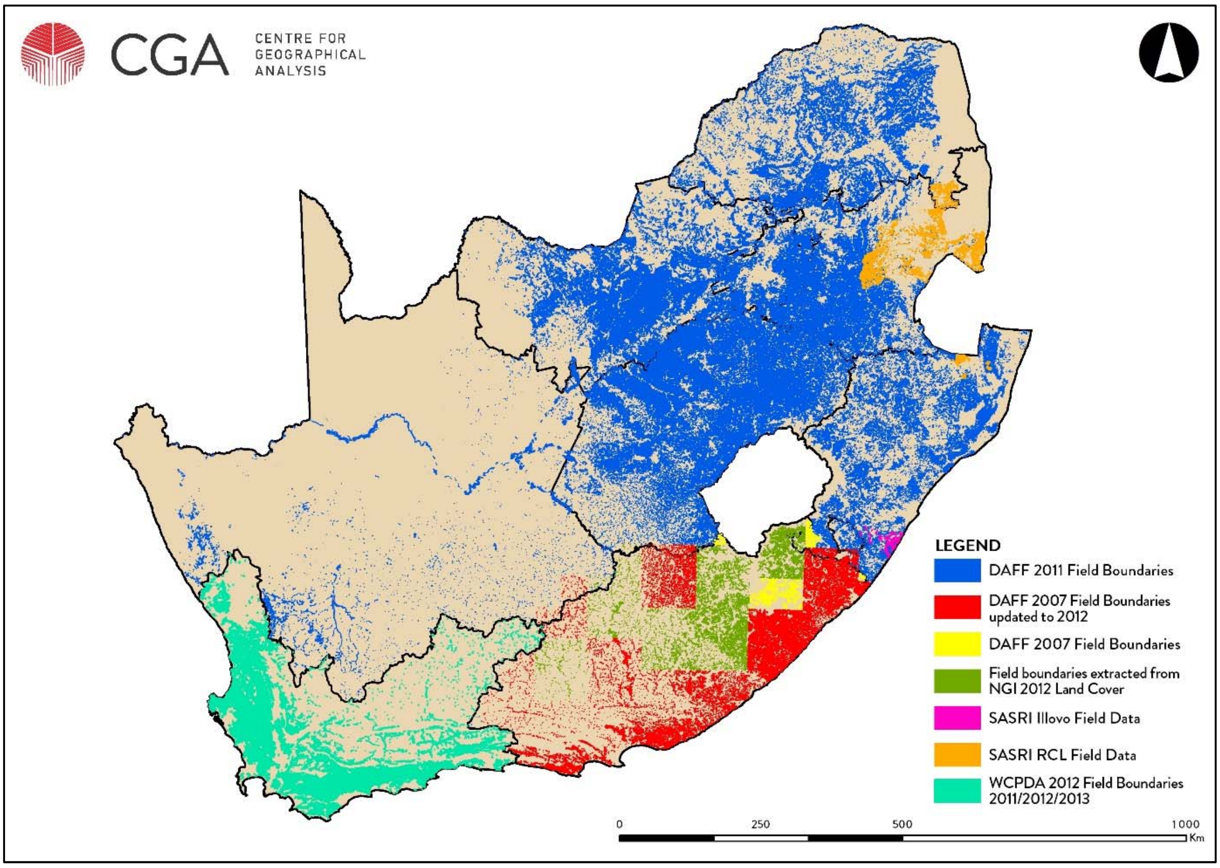


Figure 4.2 Field boundary datasets comprising *SAFields*

The agricultural field attributes of the original DAFF and SASRI datasets were retained. Additional attribute information was derived from the agricultural land cover categories of the SALC1314 (Appendix I) (GeoTerraImage 2015) and spatially joined to the *SAFields* dataset. This was visually inspected and compared to SPOT6/7 imagery of 2015 and edited where large discrepancies were noted.

The *SAFields* dataset was used to exclude all non-agricultural land covers/uses from further consideration.

4.1.2 Step 2: Zonal statistics and attribute generation

Step 2 involved the extraction of the ET and rainfall (P) data described in Chapter 3. An automated zonal statistics workflow was employed to calculate the average ET and P values for each field. This process is illustrated in Figure 4.3. The attribute information derived from Steps 1 and 2 is summarised in Table 4.1.

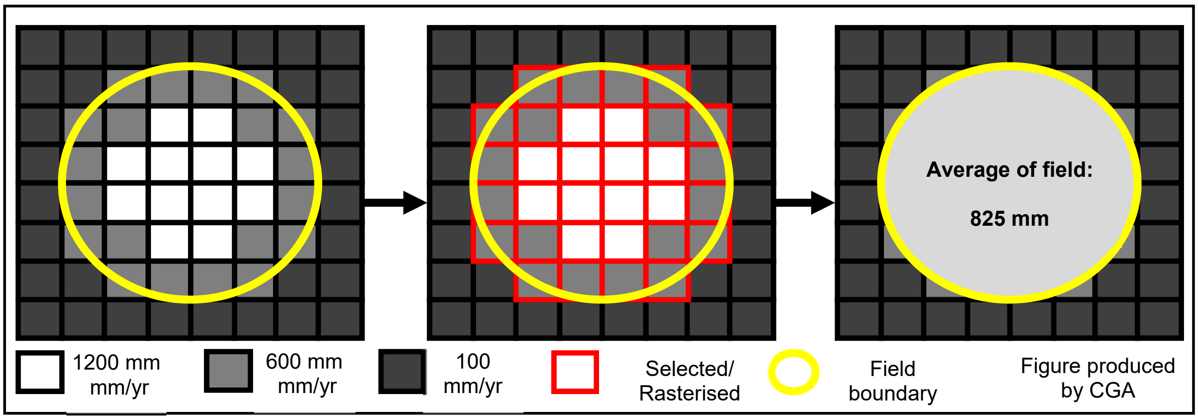


Figure 4.3 Conceptualisation of zonal statistics for extracting ET values for a hypothetical field

Table 4.1 Summary of the attribute information contained in Version 1 of *SAFields*

Data source:	Feature information	Affected fields
DAFF	Agricultural information (categorical)	Large extent (+- 88.6% of all fields)
SASRI	Agricultural information (categorical)	Only sugarcane (+- 2% of all fields)
SANLC1314	Agricultural information (categorical)	Large extent (+- 93% of all fields)
eLEAF	Yearly cumulative ET (continuous)	All fields
eLEAF	Yearly cumulative P (continuous)	All fields
Calculated (CGA)	Yearly cumulative $ET_{yr} – P_{yr}$ (continuous)	All fields

4.1.3 Step 3: ET minus P analysis

In their paper analysing water production and consumption in the Nile Basin Agro-Ecosystems, Bastiaanssen et al. (2014) concluded that open water, wetlands and irrigated fields have higher cumulative actual ET values, compared to cumulative rainfall (P), than other land cover types. Consequently, it was hypothesised that the difference between the cumulative actual ET and cumulative precipitation (ET-P) of a field would be a determining factor for distinguishing whether it was irrigated. A number of climatically diverse study areas were sampled throughout SA to identify an ET-P threshold value that would sufficiently distinguish between irrigated and rainfed fields. Figure 4.4 shows a histogram of the sampled ET-P values for three field classes: irrigated, seasonally irrigated (i.e. evidence of prior irrigation, but not irrigated during this study period) and rainfed. Visual assessment of the histogram suggests that a threshold value of 300 mm/yr is suitable for distinguishing between irrigated/seasonally irrigated and rainfed fields.

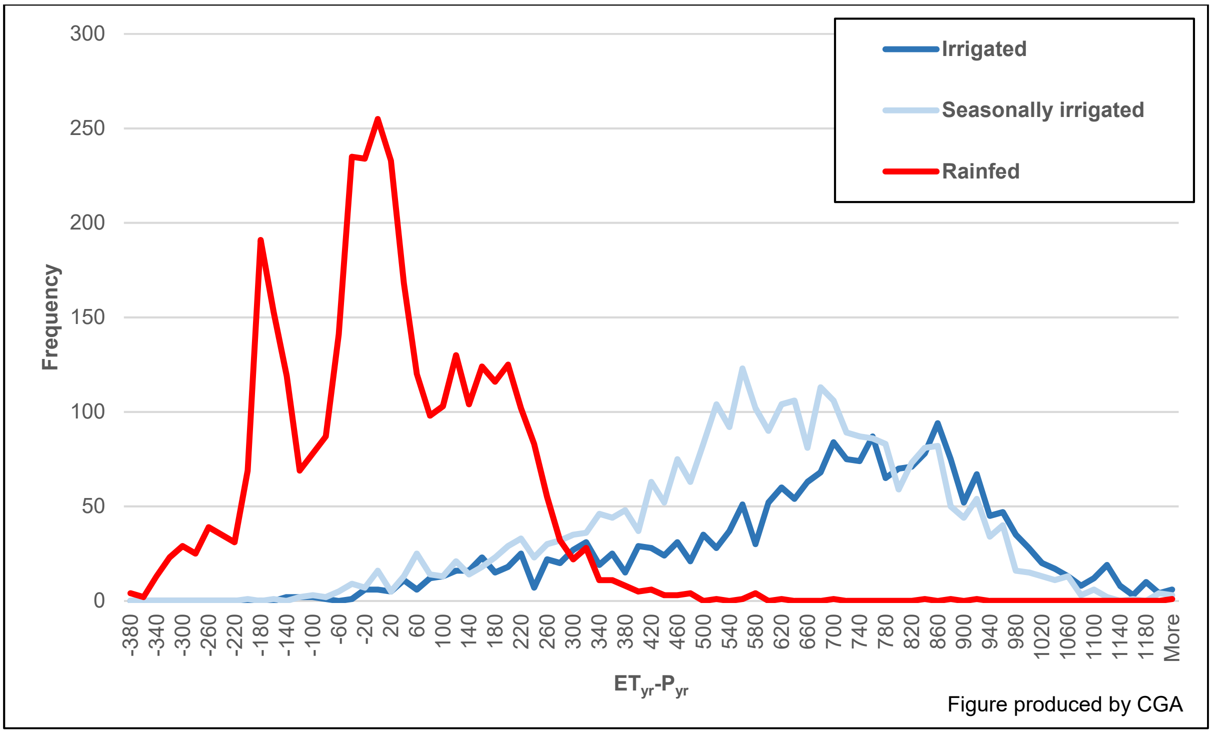


Figure 4.4 Frequency distribution of annual ET minus P for irrigated, seasonally irrigated and rainfed areas

This threshold distinguishing between rainfed and irrigated fields of sample blocks was implemented as a classification rule (Irrigated: $ET_{yr} – P_{yr}$ > 300 mm; Rainfed: $ET_{yr} – P_{yr}$ < 300 mm), applied to all the *SAFields*. The result of this classification served as the initial IAM (Figure 4.1; Step 3). The attribute information from DAFF, SASRI and SALC1314 (Table 4.1) was then used to reclassify rainfed fields to irrigated. For instance, all rainfed fields that were labelled as horticulture/viticulture were reclassified as irrigated. Table 4.2 lists the agricultural attributes used in the reclassification process.

Table 4.2 Agricultural classes in the attribute information used to classify irrigated areas

Data source	Agricultural attribute = irrigated
DAFF	Horticulture/Viticulture
DAFF	Pivot irrigation
DAFF	Tea plantation
DAFF	Shade-net
SALC1314	Cultivated commercial pivots
SALC1314	Cultivated orchards
SALC1314	Cultivated vines
SASRI	Irrigated sugarcane

The resulting Version 1 of the IAM is shown in Figure 4.5. The total estimated irrigated area based on this map was calculated to be 2.55 million ha. This is significantly higher than previous estimates of 1.35 million ha (DAFF 2012) and 1.68 million ha (Van der Stoep et al. 2008).

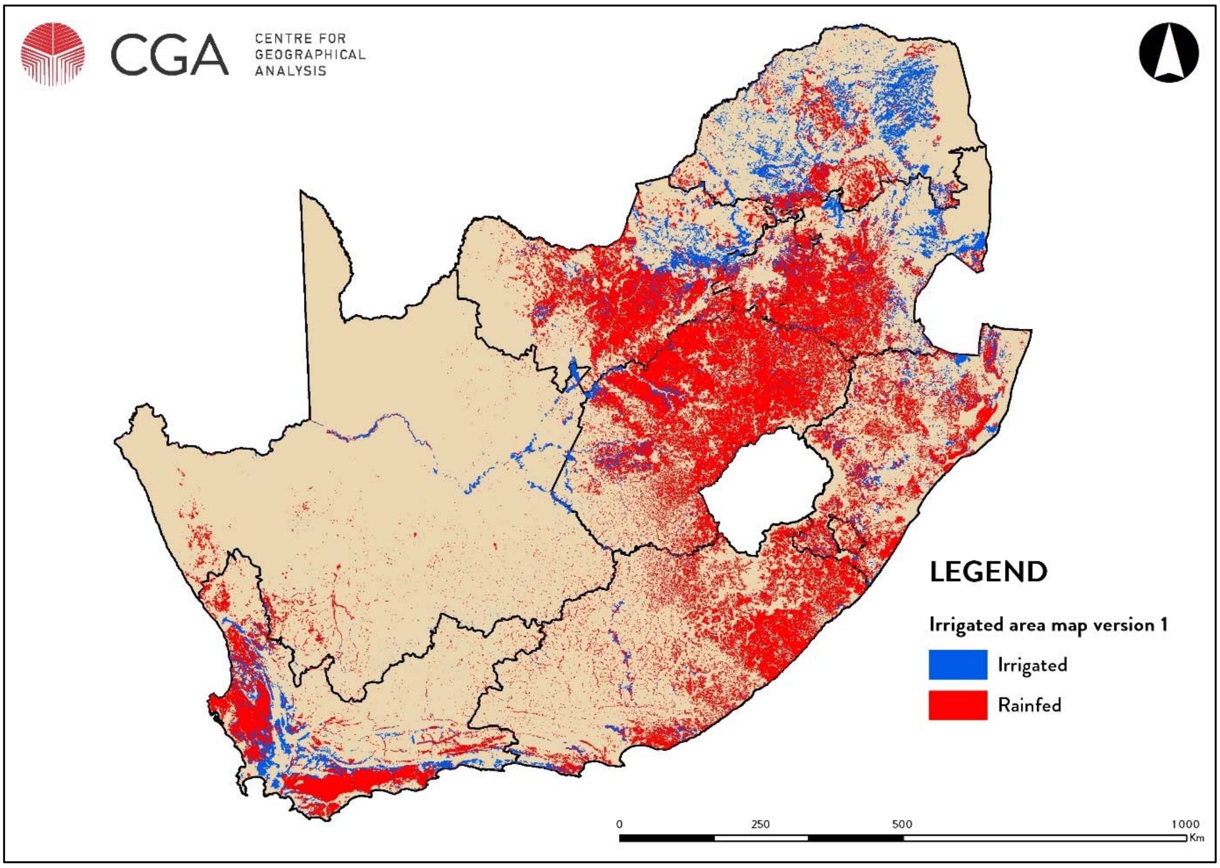


Figure 4.5 Spatial representation of Version 1 of the IAM of SA, showing irrigated (blue) and rainfed (red) fields

Version 1 of the IAM was closely scrutinised by comparing it to multi-temporal, high resolution satellite imagery and other existing data sources (e.g. of irrigation schemes). Although the 300 mm $ET_{yr} – P_{yr}$ threshold accurately identified irrigated areas in some provinces (e.g. Western Cape and Northern Cape), irrigated areas were grossly overestimated in the North West, Mpumalanga and Limpopo provinces. The main causes were:

- The large climatic differences between regions and the inaccurate estimation (interpolation) of rainfall from GSMaP. Through experimentation it was concluded that the use of a single threshold (300mm) and a single variable ($ET_{yr} – P_{yr}$) did not allow for accurate classification of irrigated and rainfed fields for the whole of SA.
- Small fields were often not accurately classified. Due to the relatively low resolution (250 m) of the $ET_{yr} – P_{yr}$ data, the spectral properties of smaller fields are mixed with surrounding land covers/uses. These mixed pixels influenced the quality of the classification.
- The agricultural attributes (Table 4.2) that were used to reclassify the IAM might have introduced error, for instance, the field *Pivot irrigation* included fallow pivots for the 2014/15 period and would have been incorrectly classified as being irrigated.

Considering the above, a logical improvement to the mapping process was make use of multiple thresholds instead of one, with each threshold fine-tuned for a particular region. The use of higher resolution satellite imagery was also expected to improve the results. However, biophysical (ET) modelling at high (e.g. 30m) resolution at national level and on a monthly basis would not have been viable in this project, since it would have been too costly and also the revisit times of available imagery are too low. Especially in cloudy months, daily imagery is preferred for optimal monitoring of crop production and associated water consumption. Alternative data and methods to improve the irrigated area map were consequently investigated, leading to a second version of the IAM.

4.2 IAM Version 2: Machine learning

Section 2.3.5.1 explained that one of the main strengths of machine learning is that the associated algorithms can analyse large, complex datasets to detect (often unnoticeable) relationships between multiple variables. This ability is ideal for irrigated area mapping as the $ET_{yr} - P_{yr}$ thresholds that best differentiate irrigated and rainfed fields vary from region to region (see previous section). Machine learning can be used to automatically identify the thresholds that would be most effective within each region. In addition, it can be used to identify other remotely sensed variables (such as those related to biomass and crop phenology) that may also contribute to distinguishing between irrigated and rainfed fields (Myburgh & Van Niekerk 2013). This approach was consequently evaluated for mapping irrigated areas at national scale. The process involved three steps (Figure 4.6), each of which is described in more detail in the following subsections.

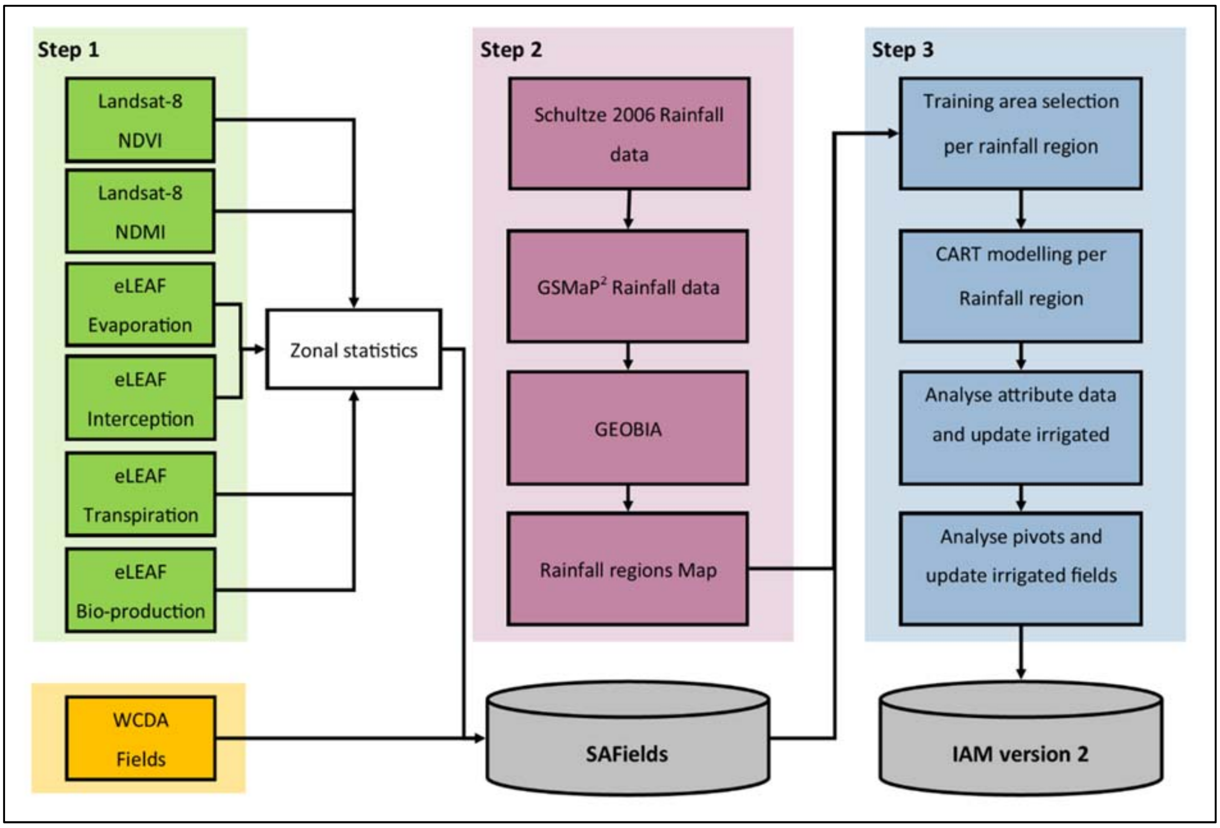


Figure 4.6 Overview of methodology for generating Version 2 of the IAM Figure produced by CGA

4.2.1 Step 1: Data collection and preparation

SAFields was updated with field boundary data acquired from the Western Cape Province Department of Agriculture (WCPDA), which replaced the field boundaries for the Western Cape. The WCPDA dataset was created from 2011 and 2012 SPOT 5 satellite imagery as well as from aerial photography of 2010. Crop type and irrigation status attribute information were added to this dataset through a visual survey, which was conducted from light aircraft in 2013.

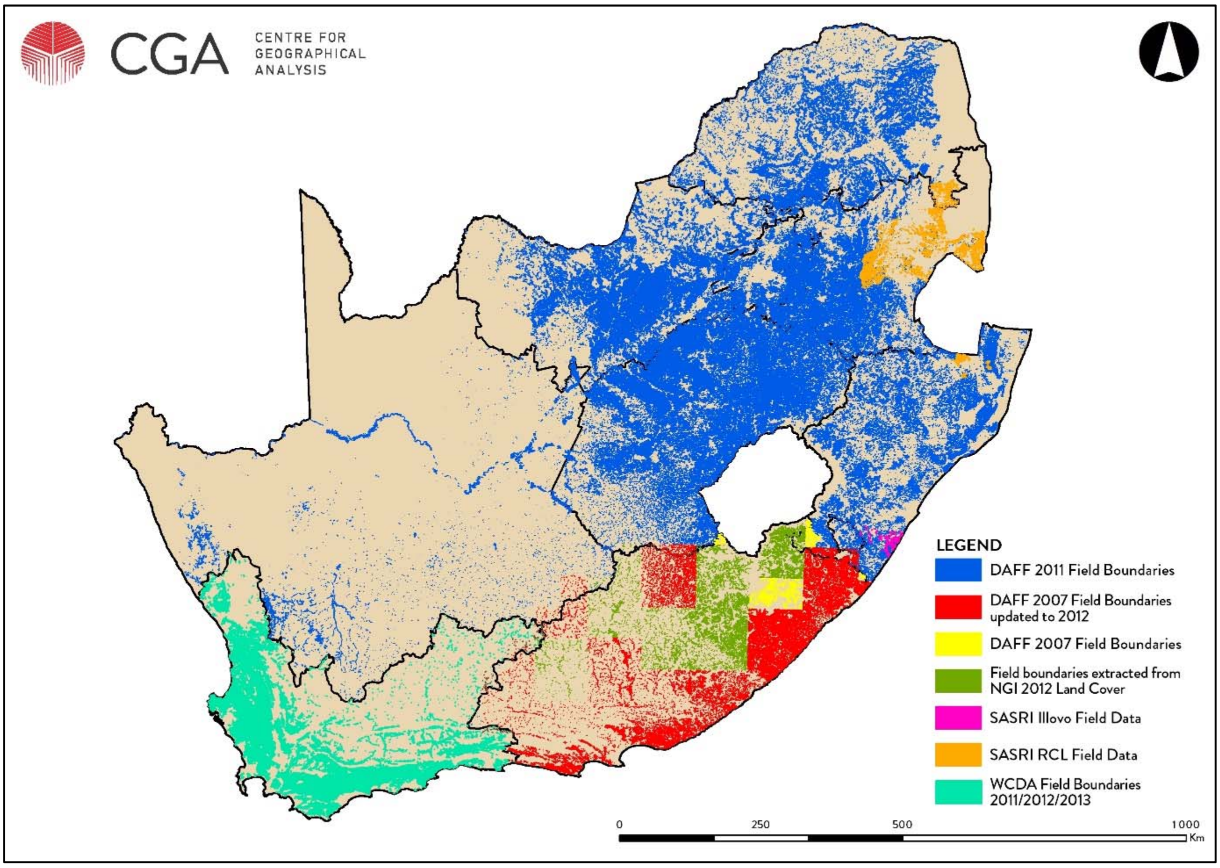


Figure 4.7 ***SAFields*** **updated with WCPDA field boundaries**

In preparation for machine learning, additional seasonal biophysical and remotely sensed variables (image features) were collected and added to the attributes of each field in the *SAFields* database. Table 4.3 summarises the type, nature and seasonality of the added features.

Table 4.3 Biophysical and remote sensing attributes added to the *SAFields* database

#	Feature information	Cumulative mean	Summer minimum	Summer maximum	Summer mean	Winter minimum	Winter maximum	Winter mean
A	NDVI (30 m)		x	x	x	x	x	x
B	NDMI (30 m)		x	x	x	x	x	
V	Evaporation (250 m)	x	x	x	x	x	x	x
D	Interception (250 m)	x	x	x	x	x	x	x
E	Actual transpiration (250 m)	x	x	x	x	x	x	x
F	Potential transpiration (250 m)	x	x	x	x	x	x	x
G	Deficit transpiration (250 m)	x	x	x	x	x	x	x
H	Actual Biomass production	x						

A total of 435 Landsat 8 images covering the extent of SA were downloaded, radiometrically corrected and processed for the period of August 2014 to July 2015. These images were used to derive seasonal (winter and summer) a NDVI (Equation 4.1) and the normalised difference moisture index (NDMI, Equation 4.2) images for winter and summer (A and B in Table 4.3 respectively) at 30 m resolution.

$$NDVI = (NIR - Red)/(NIR + Red)$$ **Equation 4.1**

Where NIR is the reflectance in the near-infrared band; and

Red is the reflectance in the red band.

Equation 4.2

$$NDMI = \frac{NIR - SWIR}{NIR + SWIR}$$

where NIR is the reflectance in the near-infrared band; and

$SWIR$ is the reflectance in the shortwave infrared band.

Additional biophysical variables (C to H in Table 4.3) generated using the ETLook model at 250 m resolution and used in the calculation of ET (as described in Chapter 2.5) were also extracted and added to the *SAFields* database to assess whether they had any significance in distinguishing between irrigated and rainfed areas. The resulting attributes in the *SAFields* database were therefore a combination of the original ancillary data (Table 4.1), the new irrigation and crop type attribute information from the WCPDA fields, and newly added biophysical and RS data (Table 4.3). A complete list of the attributes is shown in Table 4.4.

Table 4.4 Summary of updated attribute information in *SAFields*

Data source	Feature information	Information extent
DAFF	Agricultural information (categorical)	Large extent (+- 88.6% of all fields)
SASRI	Agricultural information (categorical)	Only sugarcane (+- 2% of all fields)
SANLC1314	Agricultural information (categorical)	Large extent (+- 93% of all fields)
WCPDA	Irrigation and crop type information (categorical)	Only Western Cape (+- 12% of all fields)
eLEAF	YC; ET (continuous)	Complete extent (all fields)
eLEAF	YC; P (continuous)	Complete extent (all fields)
Calculated (CGA)	YC; $ET_{yr} – P_{yr}$ (continuous)	Complete extent (all fields)
Landsat 8 (CGA)	SS NDVI (continuous)	Complete extent (all fields)
Landsat 8 (CGA)	SS NDMI (continuous)	Complete extent (all fields)
eLEAF	YC, SS Evaporation (250 m) (continuous)	Complete extent (all fields)
eLEAF	YC, SS Interception (250 m) (continuous)	Complete extent (all fields)
eLEAF	YC, SS Actual transpiration (250 m) (continuous)	Complete extent (all fields)
eLEAF	YC, SS Potential transpiration (250 m) (continuous)	Complete extent (all fields)
eLEAF	YC, SS Deficit transpiration (250 m) (continuous)	Complete extent (all fields)
eLEAF	YC, SS Actual Biomass production (continuous)	Complete extent (all fields)

YC = yearly cumulative and SS = seasonal statistics

4.2.2 Step 2: Rainfall region determination

SA has a highly variable climate, with substantial geographic differences in rainfall and temperature across its landscape. To address these variations and to overcome the limitations of the single threshold classification method used to produce Version 1 of the IAM, the granularity of the field classifications was increased by considering regions of homogenous rainfall separately. The long-term (>40 years), annual mean rainfall data from Schulze & Lynch (2006) and annual cumulative rainfall data from the

GSMaP product were used to regionalise SA into nine homogenous rainfall areas. Multiresolution segmentation (MRS) as implemented in the geographical object-based image analysis (GEOBIA) software suite eCognition was used for this purpose (Section 2.3.5.2). The resulting regions are illustrated in Figure 4.8.

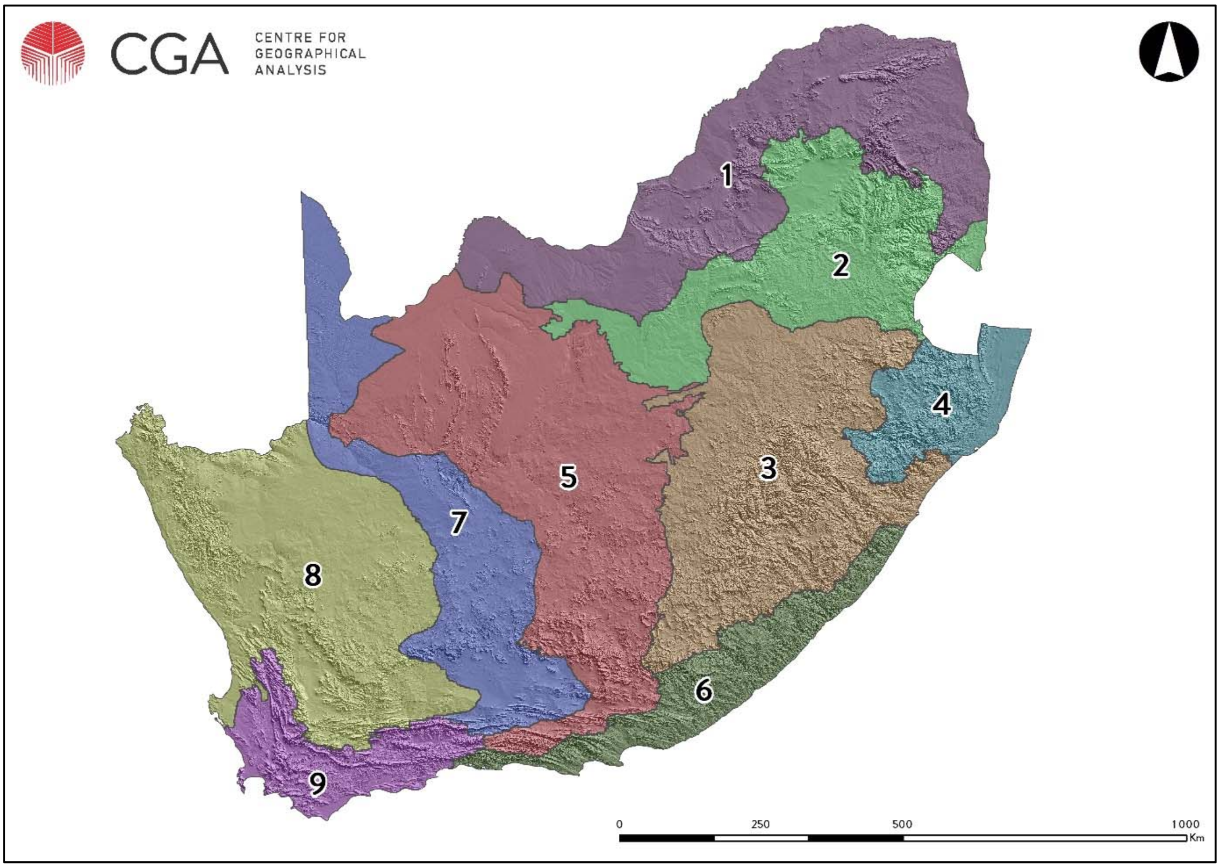


Figure 4.8 Homogenised rainfall regions created and used for carrying out machine learning

4.2.3 Step 3: Machine learning implementation

Classification and regression tree (CART) analysis – a popular machine learning algorithm – was used in Salford Predictive Modeler 8.0 to mine the data of the large set of predictors that could potentially contribute to differentiating irrigated areas from dryland fields (see Section 2.3.5.1 for an overview of DTs). A large set of training samples were selected using visual interpretation of VHR satellite (SPOT6/7 and Google Earth) and aerial (NGI) imagery. Monthly ET and NDVI datasets obtained from MODIS and Landsat 8 respectively were also used to inform sample selection. Where possible, samples were evenly distributed across each rainfall region. Attempts were also made to select samples that represented a wide spectral variation within and among irrigated crop types (i.e. intra- and inter-crop spectral variation).

The CART analysis yielded a selection of the best predictor variables and generation of an optimal set of DT rules for each region. Figure 4.9 shows an example of a ruleset produced for rainfall region 8, a winter rainfall region. The first “splitter” (rule that separates the most cases) in this region was NDMI winter minimum. The winter minimum of the transpiration potential and the summer minimum of the evaporation were used to further refine the distinction between irrigated and rainfed classes, resulting in class-node accuracy predictions of over 97%.

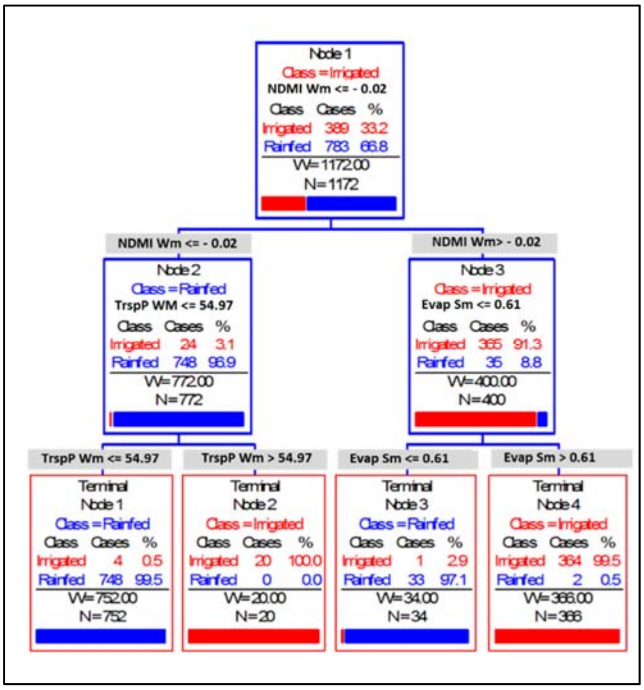


Figure produced by CGA

Figure 4.9 Example of a ruleset produced by CART, where TrspP = Transpiration potential; Evap = evaporation; Wm = winter minimum and Sm = Summer minimum

CART employs a v-fold cross-validation process to assess accuracies for DTs created. Table 4.5 summarises the accuracies of the DTs generated for each region (per class and overall). On average, the overall accuracy of all the classifications (all regions) was 96.4% (irrigated = 95.2%, rainfed = 97.7%).

Table 4.5 Summary of error matrices produced in CART, per rainfall region

Region	Irrigated		Rainfed		Overall
	Number of samples	% correct	Number of samples	% correct	% correct
1	1086	97.0	1311	97.6	97.3
2	761	95.4	1832	97.0	96.2
3	377	83.6	1 604	95.1	89.4
4	158	94.9	279	97.1	96.0
5	576	97.2	673	98.7	98.0
6	354	92.9	804	96.6	94.8
7	290	99.0	122	99.2	99.1
8	389	98.5	783	99.0	98.8
9	696	98.1	1137	98.7	98.4
Total/Average	4687	95.2	6941	97.7	96.4

The DTs were subsequently converted to rulesets for each rainfall region and systematically applied to the predictor variables to produce an initial map for each region. Although conventional DT classifiers are known for overfitting data (i.e. they produce high accuracies in areas where training date were selected, while failing to produce similar accuracies in other areas), CART minimises overfitting through an automated pruning (generalisation) and cross-validation step.

The initial IAM for each region was further refined by applying these general rules:

- From the DAFF attribute information, fields classified as *cultivated orchards* were updated to *irrigated* (0.9% change), and fields classified as *old fields* were updated to *rainfed* (0.03% change).
- From the WCPDA attribute information, fields in the Western Cape labelled as *irrigated* or *rainfed* were updated accordingly (0.6% and 0.01% change respectively). Furthermore, fields classified as *natural grazing* or *planted pastures* were updated to *rainfed* (0.03% change).
- Fields identified as a *pivot structure* (using polygon geometry) were updated to *irrigated* if clear evidence of irrigation activity was observed in the winter or summer period (NDVI > 0.6) (0.3% change).

The abovementioned general rules had little impact on the IAM; however, it did aid in eliminating obvious anomalies. Figure 4.10 shows the Version 2 of the IAM.

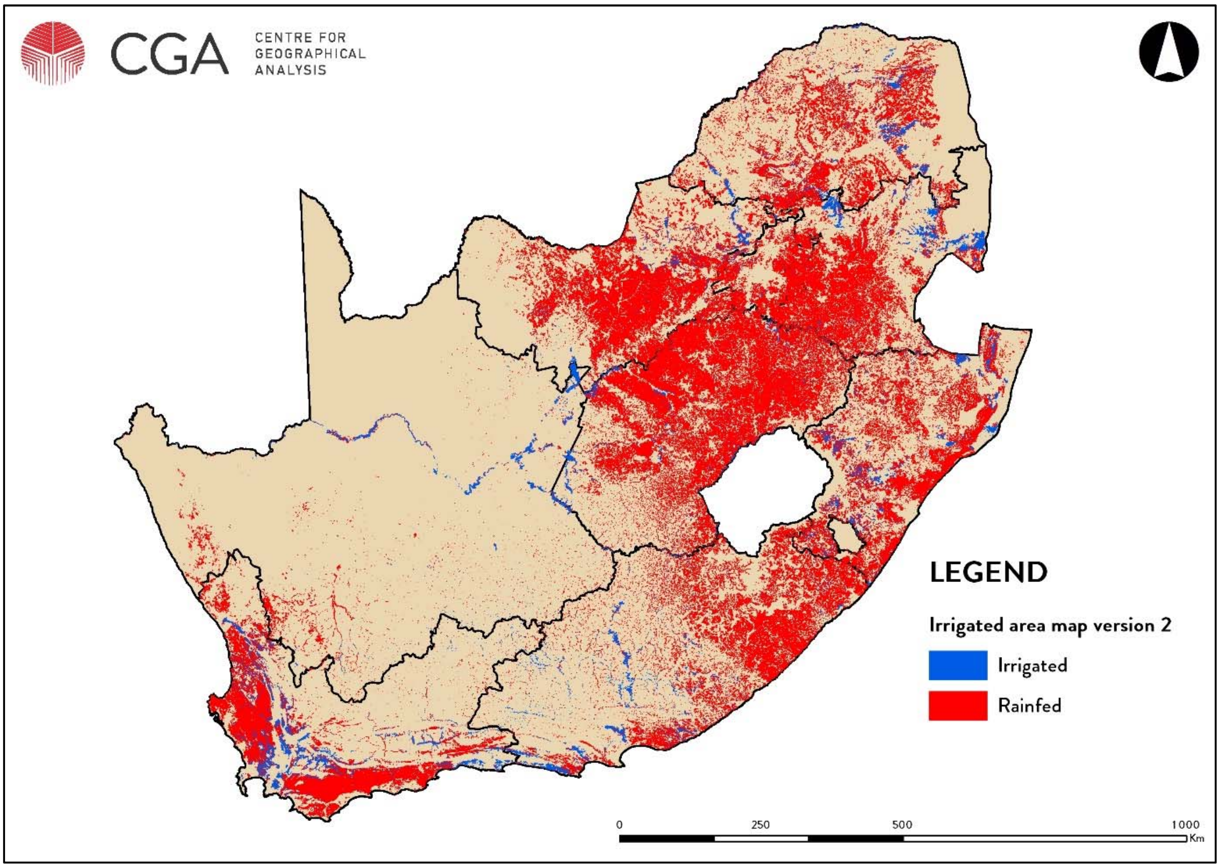


Figure 4.10 Version 2 of the IAM.

Qualitative comparisons between Version 2 and Version 1 of the IAM confirmed that most of the inaccuracies (overestimations) observed in Version 1 had been corrected in the updated version and that the regional approach was much more effective. The high (>95%) accuracies obtained during the cross-validation were also very encouraging and increased confidence in the IAM Version 2 product.

4.3 IAM Version 3: Verification and validation

Version 3 of the IAM comprised the manual verification and validation of Version 2 by the project team (Figure 4.11, Step A), and inputs obtained from stakeholders in the water and agricultural sectors (Figure 4.11, Step B). Stakeholder inputs were obtained via a purpose-built web application and a range of meetings, workshops and conferences. A number of stakeholders also provided feedback via responses to articles published in journals, magazines and online platforms. The following subsections provide more details of the different activities involved in producing Version 3 of the IAM.

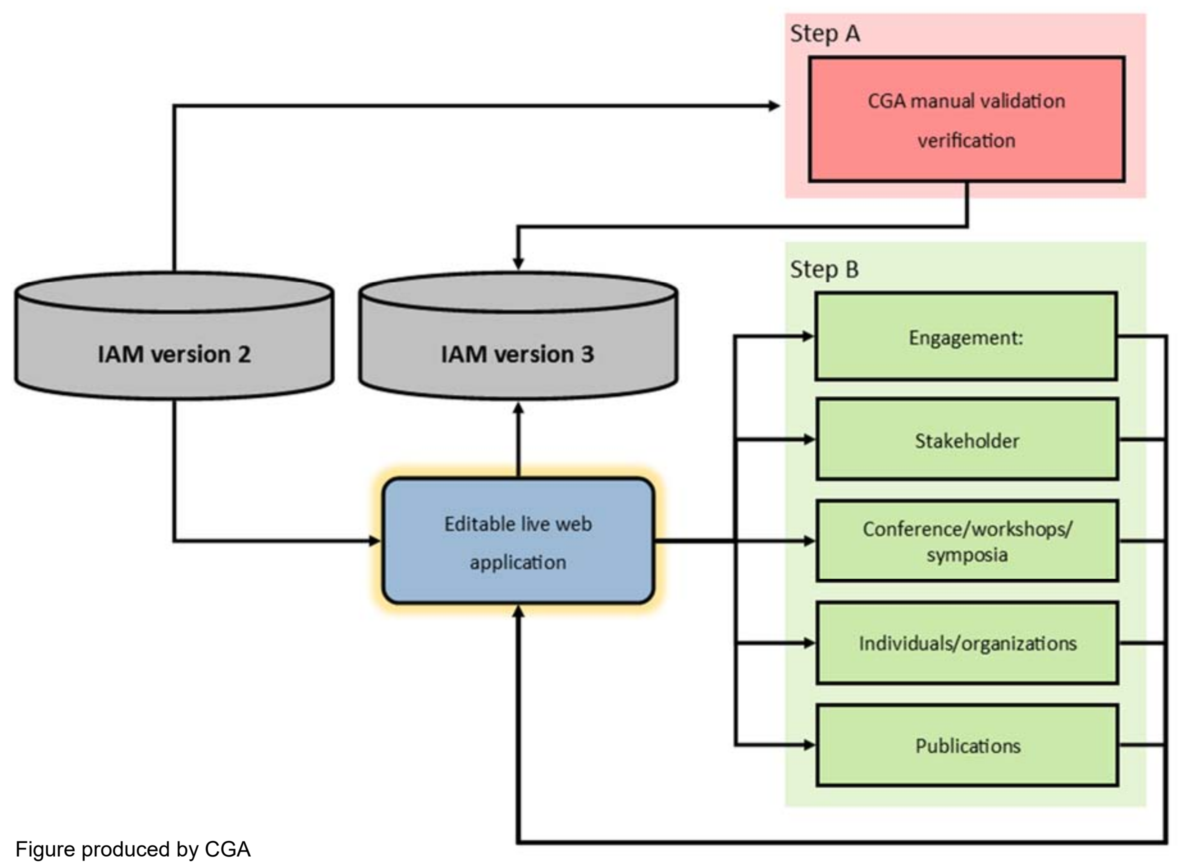


Figure produced by CGA

Figure 4.11 Methodology for creating Version 3 of the IAM

4.3.1 Web application development

A web application was developed to enable stakeholders to validate the classifications of individual fields by visually inspecting the results per water management area. It was created using HTML (Hypertext markup language) and Javascript code, while the GIS logic was implemented using the Environmental Systems Research Institute's (ESRI) ArcGIS application programming interface (API) for Javascript. The application was connected to datasets in an ArcGIS Enterprise Geodatabase (running on PostgreSQL) to enable multiple editors to concurrently access (view and edit) the data. Figure 4.12 shows an example of the view of the web application after the selection of the Breede/Gouritz water management area by the user.

Figure 4.12 View of the Breede/Gouritz water management area as shown in the web application

The application allowed the user to navigate to and zoom into specific areas of interest to evaluate the classification results (Figure 4.13). After zooming in to a specific level, all the fields from the IAM were displayed. The fields classified as irrigated were depicted with blue outlines, while rainfed fields were shown with tan outlines.

Figure 4.13 An example of fields classified as irrigated (blue boundaries) and rainfed (tan boundaries)

To assist users in navigating to areas of interest and to assess the temporal variations associated with irrigated and rainfed crops in the period of interest (1 August 2014 to 31 July 2015), various backgrounds could be selected from a menu. These included OpenStreetMap (e.g. Figure 4.13), high resolution colour imagery (ESRI satellite imagery base layer), winter NDVI and ET images, and summer NDVI and ET images. As an example, Figure 4.14 shows the summer 2014/15 NDVI layer (generated from Landsat 8 imagery) as backdrop to the fields.

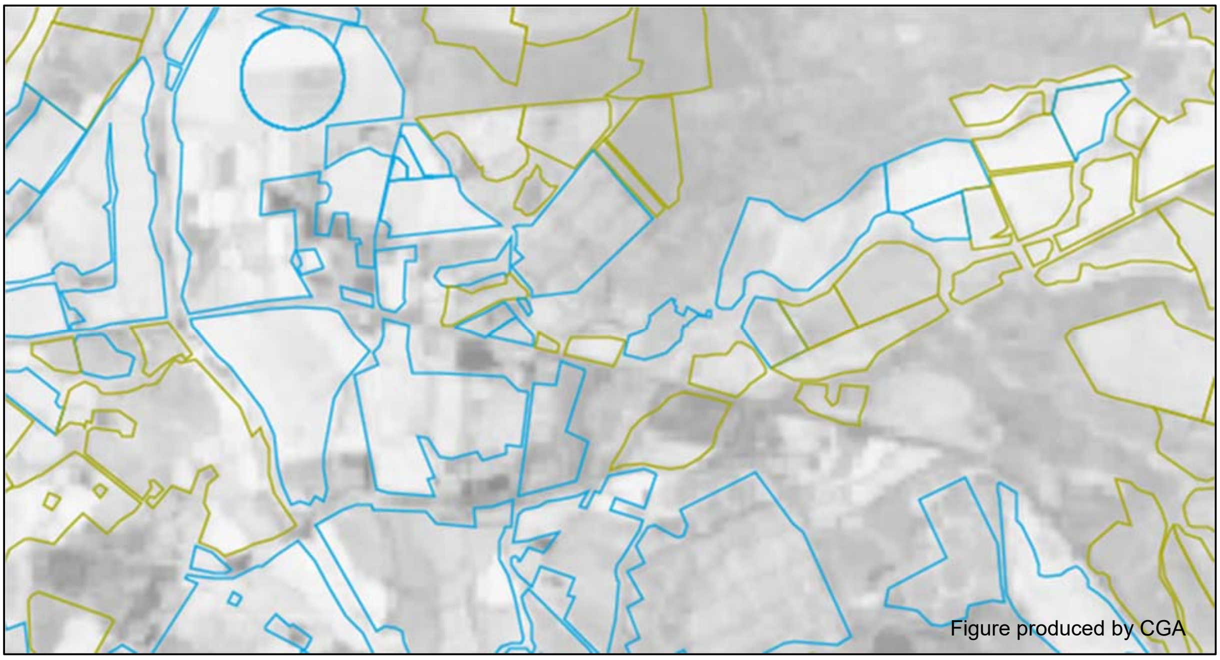


Figure 4.14 An example of the web application viewer displaying the irrigated and rainfed field boundaries, with the summer NDVI layer as background

When reviewing the classification results in the web application, users were able to select a particular field and change the classification from irrigated to rainfed (e.g. Figure 4.15), or from rainfed to irrigated. The interface also allowed users to specify irrigation duration, the presence of shade nets or any additional comments.

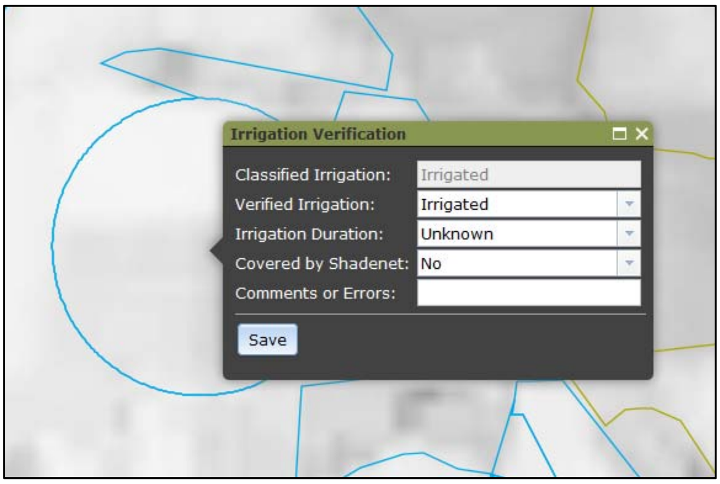


Figure produced by CGA

Figure 4.15 Pop-up window that recorded changes of land use and other information related to netting and irrigation duration

All inputs captured by the web application were recorded in a central database and used to update Version 3 of the IAM. A summary of the number of fields edited by stakeholders is presented in Appendix

III, Table 1.

4.3.2 Stakeholder engagement

This project promoted the use of remotely sensed data in support of water resources assessment and management. The utility of RS data in large-scale assessments, including various operational methodologies and frameworks for repeat studies, was proposed. Because the use of such data for water use monitoring is relatively new to the water and agricultural sectors (especially in SA), continuous engagement with relevant and key stakeholders was needed. It was also important to get feedback from stakeholders on the data products generated throughout the project. The aim of the engagement was thus twofold, namely to ensure that:

1. methods used were transparent, understood and verified; and
2. findings were verified, validated and accepted by the scientific and water and agriculture communities.

The stakeholder engagements involved presentations at group events, meetings with individuals and organisations, and media publications. A non-exhaustive, chronologic list of stakeholder engagement activities at group events is provided in Appendix III (Table 2). In addition to presentations during events, the project team engaged with individuals from government departments (water and agriculture related), agricultural industries and others in person, via email and telephonically. Valuable feedback was obtained from a number of industries/sectors and individuals (Appendix III, Table 3). A third method of engagement with stakeholders on the methodology employed and results obtained was via the publication of popular articles (Appendix IX).

4.3.3 Manual corrections

In addition to the inputs received from the stakeholders, a visual assessment of the IAM Version 2 was undertaken by the project team. This was done by comparing the irrigation/rainfed classification of every field in the IAM (Figure 4.11, step A) to the $ET_{yr} – P_{yr}$, summer NDVI and winter NDVI datasets. Four rules to scope potential misclassifications were considered by the operators during this process:

1. All fields classified as rainfed, with evidence of centre pivot irrigation and with significantly higher (compared to surrounding natural vegetation) NDVI in either the summer or winter season;

2. All fields classified as irrigated, with evidence of centre pivot irrigation and with lower or equal (compared to surrounding natural vegetation) NDVI in both the summer and winter season;

3. All fields classified as rainfed, with no evidence of centre pivot irrigation and with significantly higher (compared to surrounding natural vegetation) NDVI during the dry season; and

4. All fields classified as rainfed, with no evidence of centre pivot irrigation and with lower or equal (compared to surrounding natural vegetation) NDVI during both seasons.

A precautionary approach was followed when considering a field for correction, with the original classification (produced using machine learning) retained where the differences between the field analysed and the surrounding vegetation were not apparent. Where available, a Producer Independent Crop Estimate System (PICES) irrigated/rainfed dataset of similar date was used as a guideline. Where uncertainty remained, the 2014 and 2015 SPOT true colour mosaics were consulted and the classification only changed if there was tangible evidence of irrigation, i.e. if physical signs of irrigation were noted and the crop was significantly greener than the surrounding fields and/or natural vegetation. This approach was essential in areas where rainfall was less seasonal or bimodal, which resulted in marginal NDVI differences between summer and winter (e.g. Coastal Eastern Cape and KwaZulu-Natal).

A total of 56 263 (4.3%) of the 1 245 755 fields in the IAM were manually corrected, suggesting a 4.3% error rate for Version 2 (map produced using machine learning). Based on area, 403 533 ha out of 14 897 357 ha were reclassified, indicating an error of 2.7%. These differences correspond with the v-fold cross validations carried out during the CART analysis (Table 4.5 on page 68).

In June 2017, DAFF released a new version of the agricultural field boundaries, created from imagery of 2013, 2014 and 2015. Based on a spatial comparison between the *SAFields* dataset and the new DAFF field boundaries, the difference between the two datasets were judged to be insignificant at regional scales and not substantial enough to justify replicating the irrigated area mapping process, verification and validation on the 2017 DAFF dataset. However, it is recommended that this dataset is considered for future irrigated area mapping exercises.

4.4 Finalisation of the IAM

The final version of the IAM was created by combining the stakeholder input and the in-house manual editing (Figure 4.16). The total irrigated area (after all corrections) for SA for the period 1 August 2014 to 31 July 2015 was calculated as **1 334 562 ha**. This is slightly lower than the 1.36 million ha of Version 2 of the IAM, but in line with the previous estimations of 1.35 million ha (DAFF 2012) and 1.25 million ha (Van der Stoep et al. 2008).

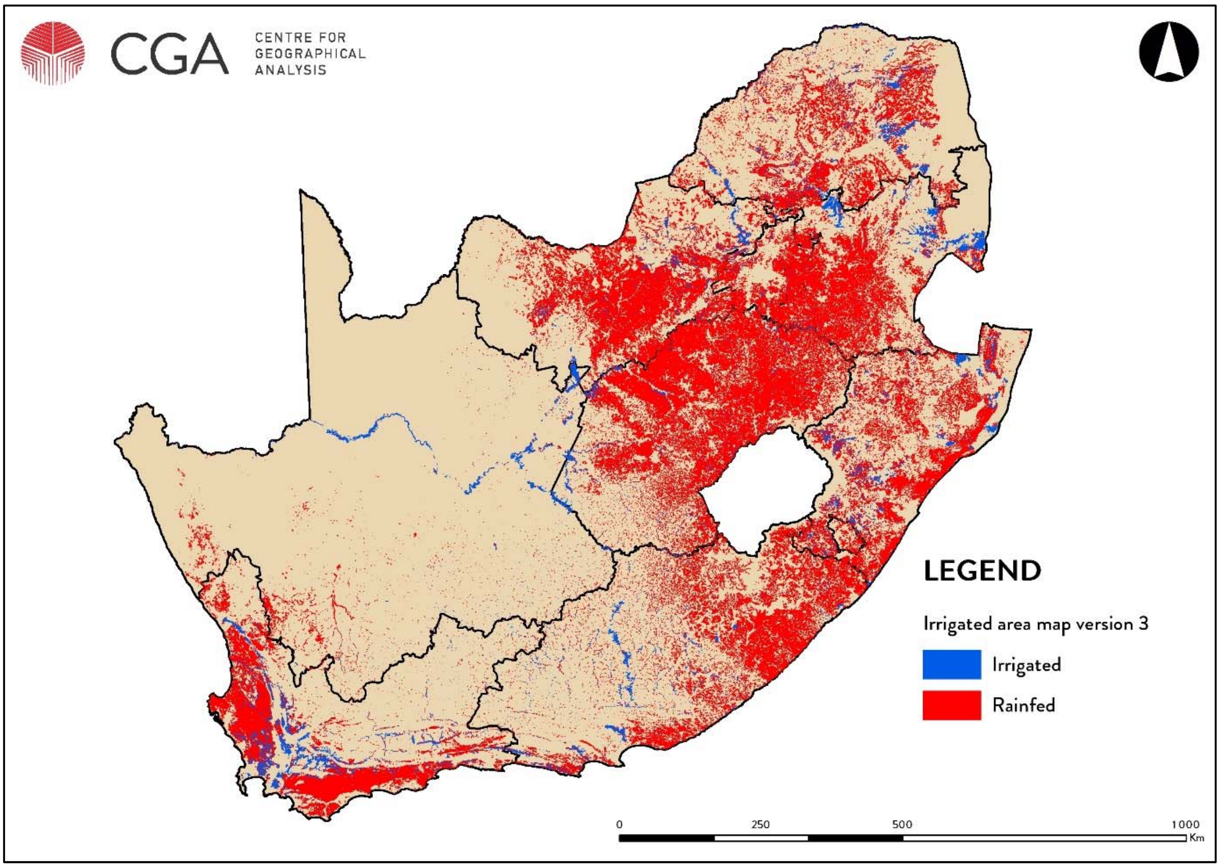


Figure 4.16 Version 3 of the IAM

The next chapter explains how the IAM was used to quantify the water used by irrigated agriculture (at both national and provincial levels) and selected crop types.

5 QUANTIFICATION OF WATER USED BY IRRIGATED AGRICULTURE

The national IAM (Version 3) together with the annual ET map were used to quantify the water use by irrigated agriculture as a whole and by selected crop types. This chapter describes the quantification methodology used and presents the results thereof.

The approach used for quantifying the water use by irrigated agriculture is largely based on the zonal statistics extraction process described in Section 4.1.1 (Figure 4.3). Zonal statistics were applied to the monthly and annual ET datasets to extract each agricultural field's water use, whether rainfed or irrigated. The main steps in the ET quantification process were:

1. Sum the water use per province and at national level using irrigated fields only, to provide provincial and national estimates of irrigated agricultural water use;
2. Sum the water use per selected crop type (using irrigated and rainfed field boundaries) to provide crop type specific example estimates; and
3. Carry out a sensitivity analysis to better understand the impact of low (250 m) resolution ET data in the ET quantification process.

Each of these steps is explained in the following subsections.

5.1 Water use by irrigated agriculture – provincial and national scales

Version 3 of the IAM was used to quantify the total water used (aggregated actual ET per field) by irrigated agriculture at national level and per province (Table 5.1). The national aggregation of ET showed that the total consumptive water use (ET) by irrigated agriculture in SA for the evaluation period, based on an irrigated area of 1 334 562 ha, was **10 221 million m^3/yr**. This compares well with previous estimations such as the 1996 Overview of Water Resource Availability and Utilisation in South Africa, which estimated the water use by irrigated agriculture to be 10 740 million m^3/yr and 7 836 million m^3/yr in 2000 (as part of the NWRS), with the latter based on a 98% assurance of supply (Backeberg 2003; DWAF 2004).

Table 5.1 Water use by irrigated agriculture, expressed nationally and per province for the 2014/15 study period.

Region	Total Area (ha)	Cultivated Area (ha) [a]	Irrigated Area (ha) [b]	Irrigated Area (% of Total Area)	Irrigated Area (% of Cultivated Area)	ET (Million m^3/yr)	ET (m^3/ha)	ET (% of tot. Use)
Eastern Cape	16 896 600	1 355 239	152 866	0.90	11.3	1070	7000	10.5
Free State	12 982 520	3 796 784	129 077	0.99	3.4	832	6446	8.1
Gauteng	1 817 831	405 056	20 115	1.11	5.0	154	7656	1.5
KwaZulu-Natal	9 436 132	1 428 847	177 341	1.88	12.4	1518	8560	14.9
Mpumalanga	7 649 469	1 306 403	125 595	1.64	9.6	1245	9913	12.2
Northern Cape	37 288 940	272 079	144 579	0.39	53.1	1135	7850	11.1
Limpopo	12 575 390	1 251 682	218 302	1.74	17.4	1930	8841	18.9
North West	10 488 170	2 183 704	97 211	0.93	4.5	752	7736	7.4
Western Cape	12 946 220	1 947 345	269 476	2.08	13.8	1583	5874	15.5
National	**122 081 272**	**13 947 139**	**1 334 562**	**1.09**	**9.57**	**10 221**	**7659**	**100.0**

[a] According to SALC1314; [b] According to IAM Version 3

The largest proportion of water used for irrigation is in the Limpopo Province (18.9%), followed by the Western Cape (15.5%) and KwaZulu-Natal (14.9%). Gauteng (1.5%) contributes the least to overall water used for irrigation. Mpumalanga has the highest water use per hectare irrigated (9913 m^3/ha), while the water use per area unit is the lowest in the Western Cape (5874 m^3/ha).

It should be noted that crop cultivation is highly dynamic and heavily influenced by climatic and market conditions in a particular season. The estimation of 10 221 million m^3/yr for the 2014/15 season should be seen as a snapshot of the total consumptive water use: it is expected that this estimate will fluctuate from year to year. This estimate of total consumptive water use is not to be confused with the volume of irrigation applied, which would likely be higher than the 10 221 million m^3/yr estimate. Ideally, the water applied should not exceed consumptive use (i.e. 100% efficiency), but in practice maximum irrigation application efficiencies are typically only as high as 90% for drip irrigation (Brouwer et al. 1989). More work is needed to investigate the relationship between water applied and water consumed and to improve water use efficiencies and reduce non-beneficial, non-consumptive losses.

5.2 Water use by selected crop types

In order to determine the water use by selected crop types for the study period 1 August 2014 to 31 July 2015, maps showing the spatial distribution of these crops across SA were required. With no consolidated crop type map available at national level, the (limited) available local and provincial maps were sourced, collated and used. In a few instances (areas), new crop type maps were generated.

The crop type map for the Western Cape was obtained from the WCPDA. The dataset was created through an aerial survey carried out between 2010 and 2012 (released in 2013). This period did not correspond to the analysis period of this project and consequently only perennial and deciduous crops were used for the water use quantifications, since substantial changes (> 10%) in these crops were not expected. Maps showing the spatial distribution of sugarcane in Mpumalanga and KwaZulu-Natal were obtained from SASRI, although the exact map creation or representation dates are unknown. The assumption was made that the distribution of sugarcane fields will likely remain similar over time and were thus used as is. Detailed field boundaries and crop type information of the Douglas and surrounding regions in the Northern Cape were made available for use by GWK for 2014/15. Crop type maps for the two provinces contributing most to summer grains, namely the Free State and Mpumalanga, were generated by GeoTerraImage (GTI) for the use in this project. The GTI crop type maps were based on Landsat 8 imagery (30 m resolution) collected during the period July 2014 to June 2015. All available Landsat 8 imagery for this period was downloaded and processed to ensure a full coverage of satellite imagery representing the entire crop growth cycles of all grain crops. The Landsat 8 imagery was assessed province by province to select the optimal cloud free images for each individual province, while ensuring available imagery at regular intervals throughout the cropping season. More details about this dataset is provided in Appendix IV. Table 5.2 summarises the source of the collated crop type data used in the statistical analysis and Figure 5.1 shows the spatial distribution of selected fields of known crop types used to extract ET statistics.

Important notes

In the ET statistics, no distinction was made between single and double cropping systems – i.e. when one crop only was cultivated on a field during the 2014/15 season (single cropping), compared to more than one (dual cropping). Information on this was not captured in the crop type maps.

Areas cultivated under nets or in tunnels were excluded from the statistical analysis of ET.

Fields receiving low frequency irrigation applications were not distinguished from fields receiving high frequency irrigation applications.

The crop-specific ET statistics (number of samples/pixels, mean, median, maximum and standard deviations) were extracted using zonal (field specific) statistics. Outliers (ET values of above 1400 mm/yr) were excluded from the quantifications. The total area covered by the specific crop used in the analysis was also noted. Crops for which an insufficient number of samples were available were excluded from the analyses. The results are summarised in Table 5.3. The ET statistics are reported separately for summer and winter rainfall regions, where appropriate. A median value statistically represent the centre value of a frequency distribution and are considered more representative of a crop-specific ET than the mean value. The area considered to extract the ET statistics varied greatly between the different crop types considered, ranging between 1 558 pixels for wheat and 208 095 pixels for sugarcane, subsequently capturing a smaller and larger range in conditions respectively.

Table 5.2 Summary of crop type source information used for the ET zonal statistics data extraction

Crop type (Source)	Number of fields
Citrus (WCPDA)	5982
Grapes (not specified) (GWK)	146
Lucerne(WCPDA; GWK)	1075
Maize (GTI; GWK)	73037
Oil seeds (GTI; GWK; WCPDA)	11713
Other fruit (WCPDA)	1493
Other pastures & forages (GTI; GWK; WCPDA)	200301
Other small grains (GTI; GWK)	3363
Pome fruit (WCPDA)	16062
Potatoes (GWK)	32
Stone fruit (WCPDA)	11607
Sugarcane (SASRI)	209218
Table grapes (WCPDA)	5731
Vegetables (GTI; GWK)	30122
Wheat (GTI; WCPDA)	1577
Wine grapes (WCPDA)	41382

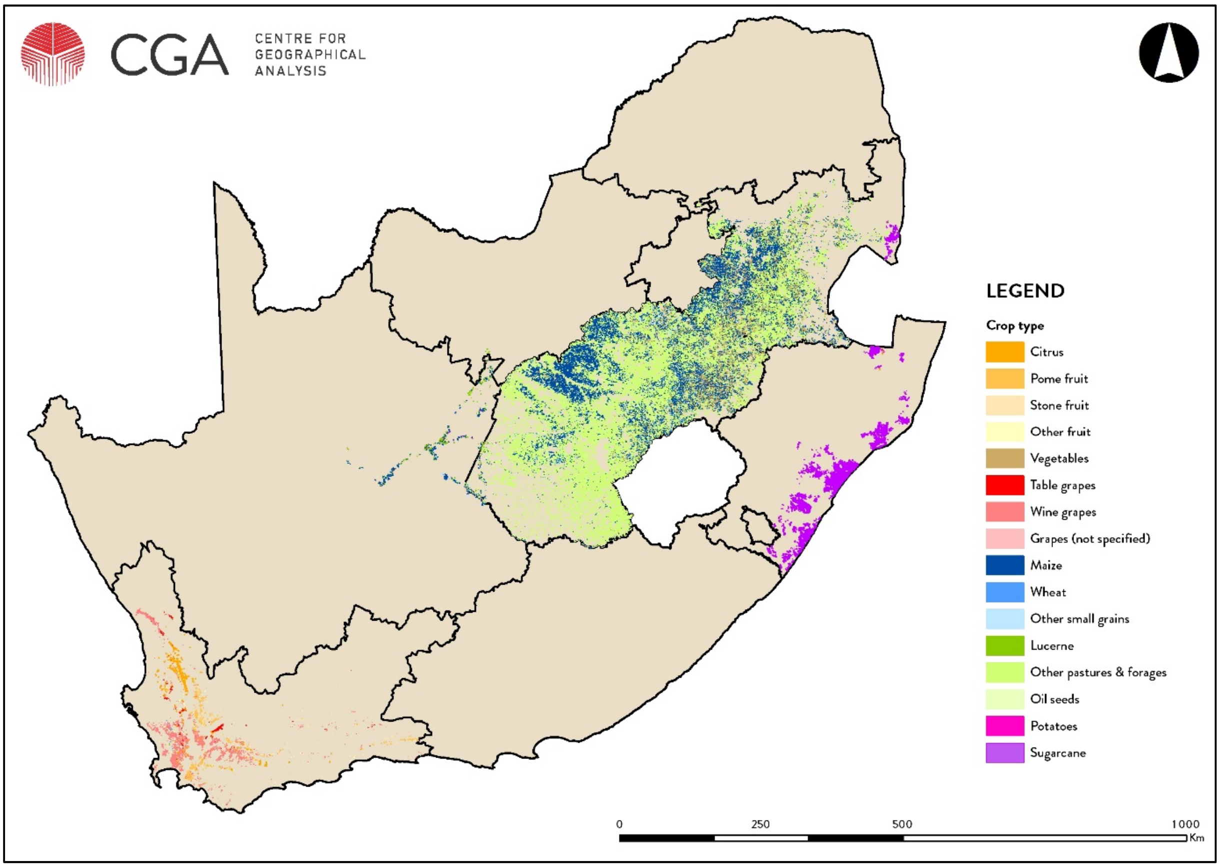


Figure 5.1 Spatial distribution of selected fields of known crop types used to extract ET statistics

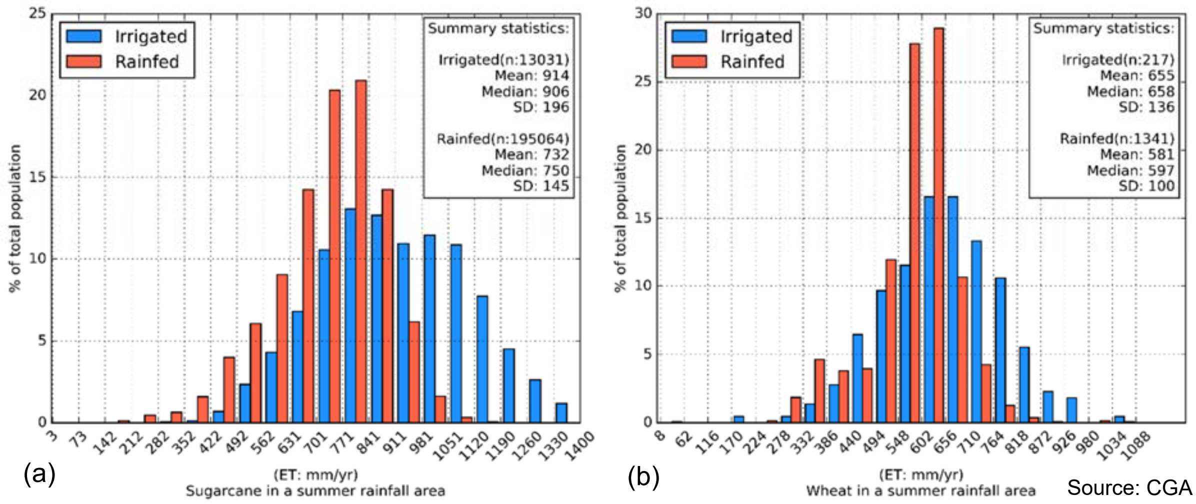
Table 5.3 Estimated water use (ET) statistics for selected crop types based on the available fields and extracted using zonal statistics

Crop type	Rainfall season	Group	# samples / pixels	Max ET (mm/yr)	Median ET (mm/yr)	Mean ET (mm/yr)	Standard deviation (mm/yr)	Area considered (ha)
Maize	Summer	All	72 969	1 385	615	618	113	1 771 083
		Irrigated	3 689	1 385	737	764	187	76 246
		Rainfed	69 280	1 378	611	610	102	1 694 837
Wheat	Summer	All	1 558	1 088	600	591	109	40 907
		Irrigated	217	1 088	658	655	136	4 038
		Rainfed	1 341	1 069	597	581	100	36 870
Other small grains	Summer	All	3 335	1 290	590	590	93	50 934
		Irrigated	184	1 129	660	663	189	4 050
		Rainfed	3 151	1 290	589	586	82	46 884
Vegetables	Summer	All	30 085	1 380	637	646	100	545 822
		Irrigated	1 445	1 380	771	789	180	18 843
		Rainfed	28 640	1 354	634	639	89	526 979
Grapes–Table	Winter	All	5 726	1 368	782	788	261	12 381
		Irrigated	5 638	1 368	786	791	260	12 192
Grapes–Wine	Winter	All	41 315	1 399	571	595	190	106 022
		Irrigated	39 937	1 399	574	598	190	103 010
		Rainfed	1 378	1 126	500	528	172	3 012
Grapes–Other	Summer	Irrigated	145	1 315	793	754	254	403
Fruit–Citrus	Winter	Irrigated	5 708	1 400	678	696	221	11 731
	Summer	Irrigated	164	1 396	911	925	206	403
Fruit–Stone	Winter	Irrigated	11 145	1 399	632	655	256	21 918
Fruit–Pome	Winter	Irrigated	15 702	1 398	833	828	237	31 322
Fruit–Other	Winter	Irrigated	1 425	1 331	553	572	210	3 002
Oil seeds	Summer	All	11 656	1 386	508	510	102	290 047
		Irrigated	589	1 386	619	628	173	8 257
		Rainfed	11 067	941	504	504	93	281 790
Lucerne	Summer	Irrigated	1 001	1 396	825	831	251	17 875
Other pastures & forages	Summer	All	199 861	1 397	539	537	123	2 157 027
		Irrigated	7 213	1 394	612	630	175	42 749
		Rainfed	192 648	1 397	536	534	119	2 114 279
Sugarcane	Summer	All	208 095	1 400	756	744	155	279 414
		Irrigated	13 031	1 400	906	914	196	55 929
		Rainfed	195 064	1 399	750	732	145	223 485

ET estimates of crops from fields with different crops cultivated during the 2014/15 period differed greatly. The highest median ETs were estimated for irrigated crops (911 mm/yr for *Fruit–Citrus* and 906 mm/yr for S*ugarcane*) and grown in a summer rainfall region (Figure 5.2, Table 5.3). Lowest ETs (based on median ET values) from irrigated fields were estimated for fields classified as *Fruit–Other* (553 mm/yr) and *Grapes–Wine* (574 mm/yr) (Figure 5.2). For the crops and areas considered, the highest ETs (based on median ETs) for rainfed fields were calculated for fields classified as *Sugarcane* (750 mm/yr) and the lowest for fields classified as *Grapes–Wine* (500 mm/yr) (Figure 5.2). Interesting to note is the small difference in median ETs between irrigated and rainfed fields classified as *Grapes–Wine*, but the large standard deviations in ET. Maximum ETs of irrigated fields were 1400 mm/yr for fields classified as *Fruit–Citrus* (winter rainfall) and *Sugarcane* (summer rainfall). The lowest maximum ETs were from rainfed fields, specifically classified as *Oil seeds* and *Wheat*, both cultivated in the summer rainfall season (941 and 1069 mm/yr respectively). For the crop types considered in this analysis, the standard deviation of ETs for irrigated crops ranged between 136 mm/yr (*Wheat*, summer rainfall) and 260 mm/yr (*Grapes–Table*, winter rainfall). For rainfed crops, the standard deviations in

ETs ranged between 82 (*Other small grains*, summer rainfall) and 172 mm/yr (*Grapes–Wine*, winter rainfall).

The frequency distributions (histograms) of annual ETs (in mm/yr) for all selected crop types for which ET statistics were extracted are provided in Appendix VI. A typical sugarcane crop grows for 12 to 18 months, therefore in our analysis over a 12 month period, higher ET estimates compared to that of a crop (e.g. wheat) with a shorter growing season is expected. Typically, a wheat season will extend to a maximum of six months, but wheat is often planted in dual crop rotations, which explains the high annual ET values obtained for this crop type considered in our analysis.



Source: CGA

Figure 5.2 ET histograms of rainfed and irrigated (a) sugarcane and (b) summer wheat

As expected, the ET values of fields cultivated under irrigation (Table 5.3) generally exceed those of fields with crops cultivated under rainfed (dryland) conditions. This is also illustrated in Figure 5.2, where a larger proportion of irrigated sugarcane and wheat fields have higher ET values compared to that of the dryland fields. The median ET[17] for both crops are also higher. In the case of wheat, the difference (61 mm) between the median ET of irrigated (658 mm) and rainfed (597 mm) wheat is marginal. Similar (small) differences between irrigated and rainfed consumptive water use were observed for other crops (e.g. maize, oil seeds, other small grains and vegetables).

The median values for irrigated sugarcane correspond to those of previous studies (Table 5.4), where values ranging from 996 and 1378 mm/yr were recorded. The lower median value of 906 mm/yr in Figure 5.2a is likely a result of the large sample representing fields that are cultivated under various conditions such as ratoon, irrigation system type, soils, climate and plant stress (e.g. pests, insufficient water, fertilising). The effect of mixed pixels and the influence of neighbouring land uses may also have contributed (see Section 5.3).

[17] Median ET values provide the better representation of the typical water use per crop type as it is less sensitive to outliers (compared to mean ET).

Table 5.4 Summary of annual and seasonal ET estimates of main crops produced in South Africa as found in literature

Crop type	Region	ET (mm/yr)	ETstdev (mm/yr)	ET (mm/growing season)	Method	Rainfed / Irrigated	Ref
Citrus	Winter	732–995			Meas, Mod	Irrig	Gush & Taylor 2014
Maize	Summer	692	118		SEBAL	Irrig	Jarmain et al. 2014
Pome fruit (apples)	Winter			746 +/-147 (Sep–Apr)	SEBAL	Irrig	Jarmain 2015
Pome fruit (apples)	Winter	952–966			Meas, Mod	Irrig	Gush & Taylor 2014
Pome fruit (pears)	Winter			710 +/-138 (Sep–Apr)	SEBAL	Irrig	Jarmain 2015
Stone fruit	Winter	771–821			Meas, Mod	Irrig	Gush & Taylor 2014
Sugarcane	Summer	1092	252		SEBAL	Irrig	Jarmain et al. 2014
Sugarcane	Summer	1016				Irrig	Bezuidenhout et al. 2006
Sugarcane	Summer	1050			SEBAL	Irrig	Hellegers et al. 2010
Sugarcane	Summer	988.76			SR	Irrig	Gokool et al. 2016
Sugarcane	Summer	1000–1378			Lysimeter	Irrig	Olivier et al. 2009
Sugarcane	Summer	996–1314			SWB	Irrig	Olivier et al. 2009
Table grapes	Winter			990 (Sep–Apr)	EC	Irrig	Jarmain 2016
Wine grapes	Winter			849, 756, 807 (Sep–Apr)	EC	Supp Irrig	Jarmain 2016
Wine grapes	Winter			937, 800, 617 (Sep–Apr)	EC	Irrig	Jarmain, 2016

NOTES: *Region* refers to summer or winter rainfall region, *ETstdev* refers to the standard deviation in ET, *season* refers to the growing season (typically 1 Sep. to 30 Apr.), *method* includes measurements (meas), *modelling* (mod) and *SEBAL* refer to the Surface Energy Balance Algorithm for Land model, *SR* to the Surface renewal method and *EC* to the eddy covariance method. *Irrig* refers to irrigated conditions.

The median ET of irrigated summer maize was calculated to be 737 mm/yr (SD=187 mm/yr) (Figure 5.3a). This is marginally higher than the 692 mm/yr (SD=118 mm/yr) calculated by Jarmain et al. (2014). The difference between the median ET of irrigated and rainfed summer maize is relatively large (126 mm/yr) compared to summer wheat, but this should be interpreted within the context of the substantially larger yields of irrigated maize considered in the statistical data analysis. The differences between irrigated and rainfed wine grapes are similarly small, which can be attributed to many rainfed vineyards occurring in high rainfall areas and often just receiving low frequency irrigation (Figure 5.3b).

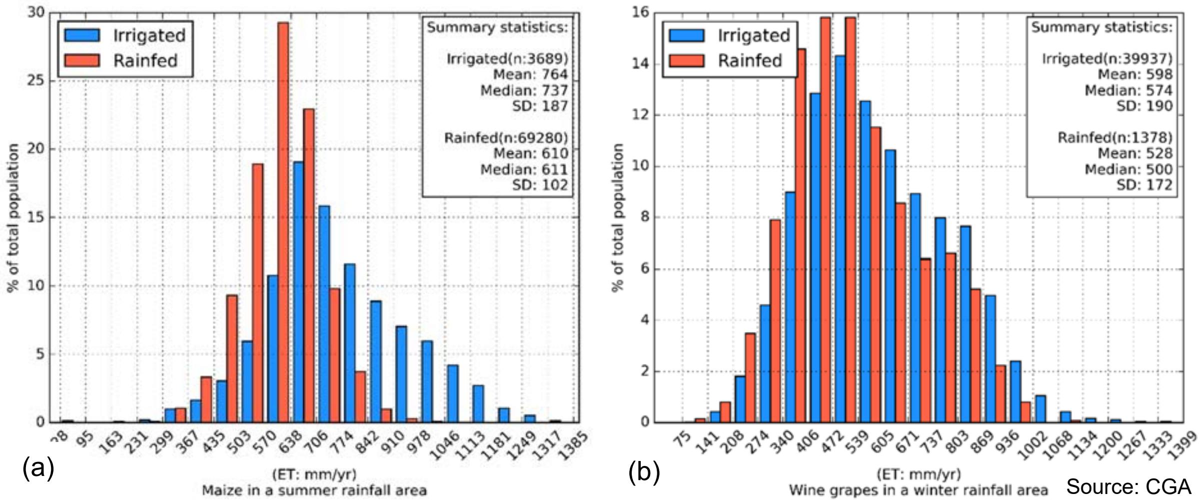


Figure 5.3 ET histograms of rainfed and irrigated (a) summer maize and (b) wine grapes in a winter rainfall area

In this study, the median ET values for irrigated table and wine grapes were estimated at 786 and 574 mm/yr respectively (Figure 5.4a and Figure 5.3b). Field estimates (for the growing season) from a specific field was higher at 990 mm/season for table grapes and 617–937 mm/season for wine grapes (Table 5.4), but within the ranges reported in this study. The higher ET rates for table grapes compared to wine grapes is likely due to the to higher foliage cover (leaf area) of table grapes and higher crop water requirements. For the latter a trellising system is used, where vines are trained and pruned to form a complete canopy cover (roof effect) to protect the grapes, while vines for wine are trained on a vertical trellis system to get as much exposure to sunlight as possible. The median ET of 678 mm/yr for citrus fruit (Figure 5.4b) was slightly lower than the measurements of Taylor & Gush (2014) (Table 5.4), which recorded annual ET values of between 732 and 995 mm/yr.

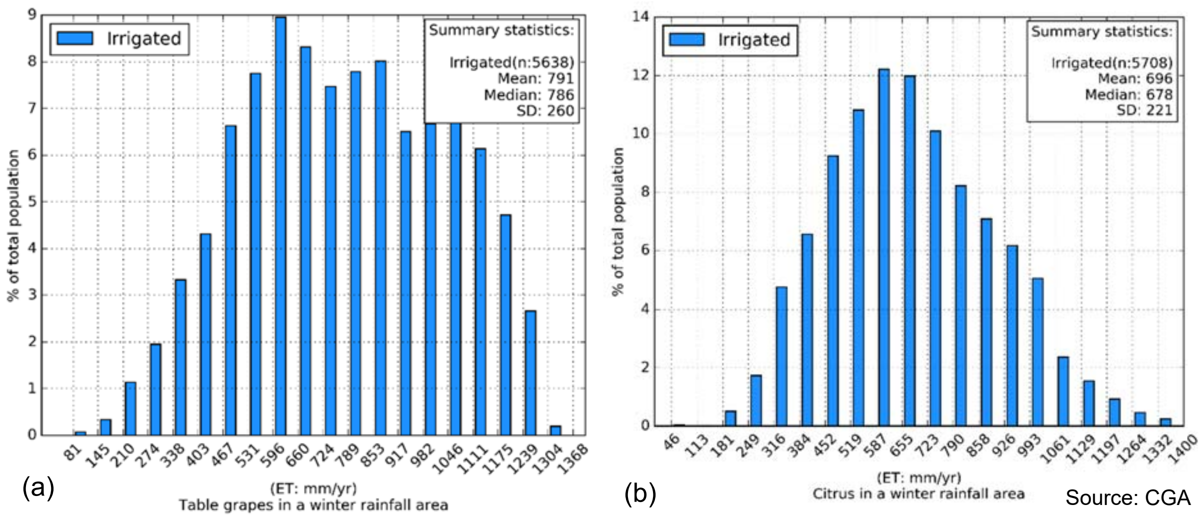
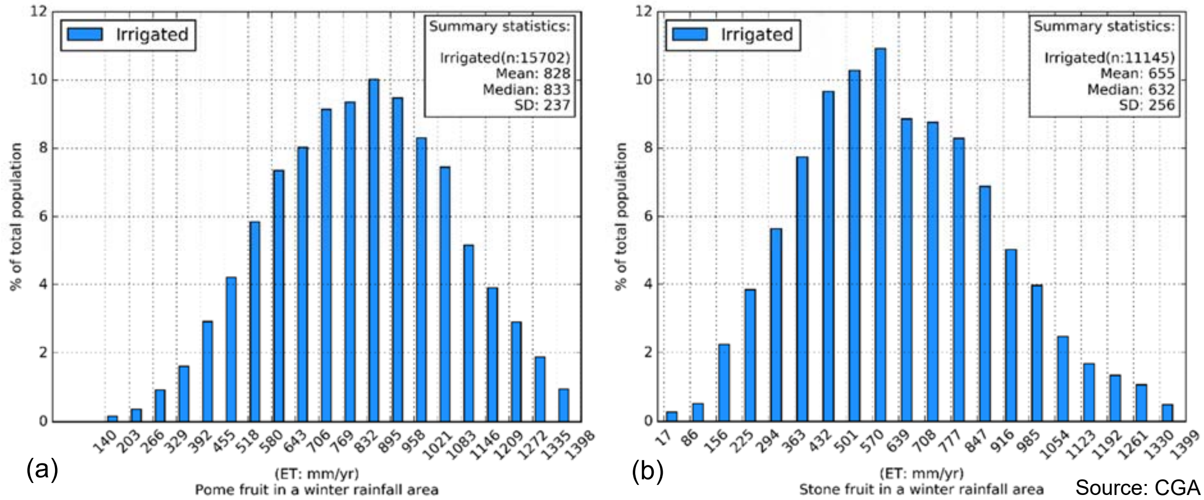


Figure 5.4 Evapotranspiration histograms of irrigated (a) table grapes and (b) citrus fruit in a winter rainfall region

For pome fruits (apples and pears) , the median ET of 833 mm/yr (Figure 5.5a) is lower than the 952 to 966 mm/yr measured by Taylor & Gush (2014). Their measurements of stone fruit (771–821 mm/yr) are also higher than the 632 mm/yr median ET in Figure 5.5b.



Source: CGA

Figure 5.5 Evapotranspiration histograms of irrigated (a) pome and (b) stone fruit in a winter rainfall region

Generally, the median ET values in Table 5.3 were lower compared to many of the field measured estimates, which is to be expected with the former considering numerous fields and the latter typically representing optimal conditions. The values in Table 5.3 reflect the varied cultivation conditions represented by the large number of samples used in this study. For rainfed annual crops, the ranges represent climate (specifically water availability), production targets, cultivar and rootstock types and soils. For other crops age, irrigation system type, production classes, cultivars, rootstocks, soils and climate can have a significant effect on the ET quantifications.

The mixed-pixel effect of adjacent land covers with lower ET values included in the estimates may also have contributed to this (more about this in the next section). Considering all of this, the ET estimates per crop type (using the 250 m ETLook dataset) relate remarkably well to field measurements.

5.3 Sensitivity analysis

A sensitivity analysis was carried out to assess the implications of using relatively low (250 m) resolution imagery for the water use quantifications. Given that many irrigated fields are smaller than 250 m x 250 m (or 6.25 ha), the concern was that the surrounding land use/cover will affect the water use quantifications at field level or on a whole. For instance, a neighbouring water body (e.g. river or dam) might cause an overestimation of the water use in an irrigated field (water bodies have very high ET values due to evaporation). This “mixed-pixel” effect can potentially have a substantial impact on quantification, especially when accumulated over large areas.

In RS, mixed pixels occur when a pixel is not representative of a single homogeneous land cover category (Campbell 2006). For example, a single pixel of the ET dataset (which covers an area of 6.25 ha) is often representative of multiple land cover classes. Figure 5.6 compares the annual cumulative ET values (mm/yr) of an area north of Citrusdal, next to the Olifants River, to a high resolution colour satellite image of the same area (but of a different year). The area shown in Figure 5.6 includes various land covers, including natural vegetation, bare ground, built-up areas, fallow fields, citrus orchards and waterbodies. It is clear that waterbodies have the highest ET values (dark green) (consisting of the evaporation of water and transpiration of riparian vegetation), while dry bare soil and built-up areas generally have low ET values (dark orange). The difference between the ET values of citrus orchards (green) and natural vegetation (yellow-orange) is clearly visible.

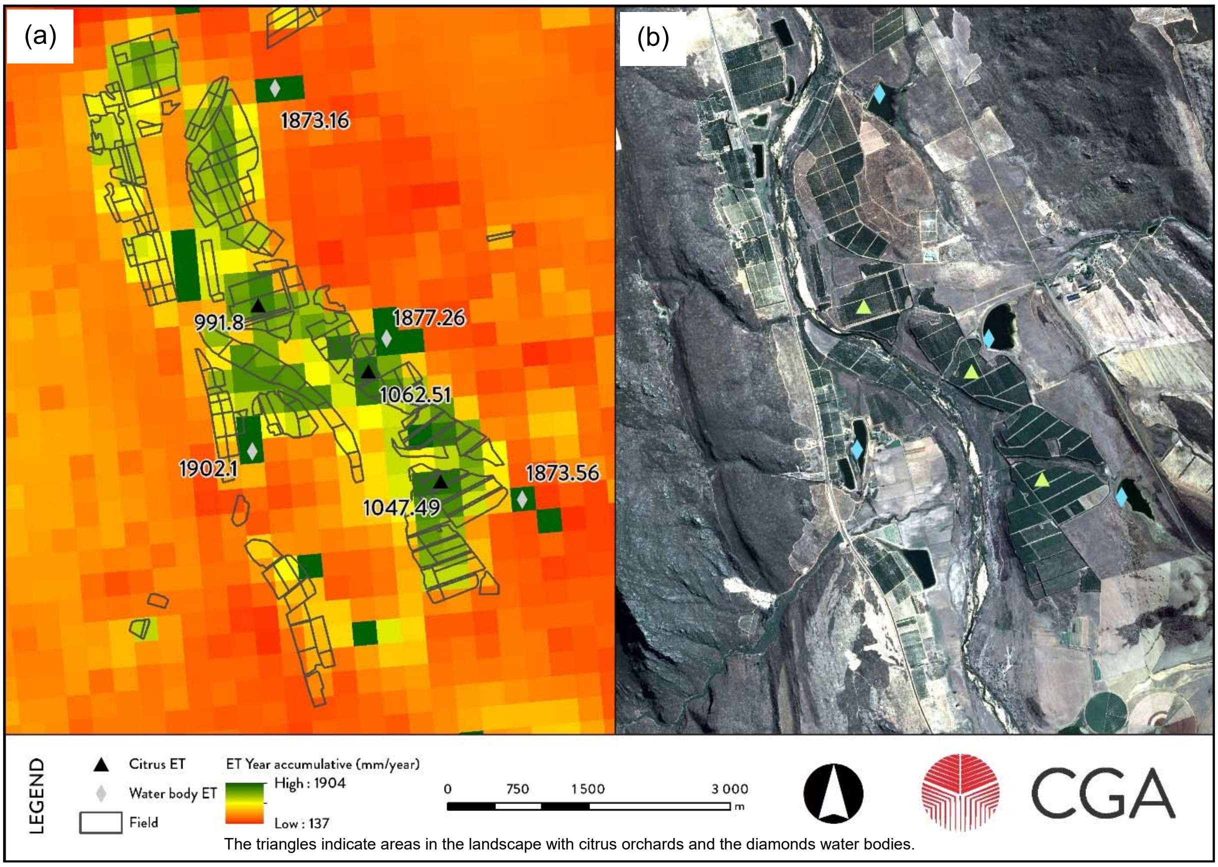


Figure 5.6 Comparison of (a) 250 m resolution ET data for an area north of Citrusdal, with (b) a 0.5 m resolution colour satellite image (of different date).

In Figure 5.6, the mixed-pixel effect causes pixels on the edges of citrus orchards (roads or bare soil) to have lower ET values compared to those that represent a complete orchard (i.e. are fully surrounded by orchards). Conversely, when a pixel is located on the edge of an actively and fast transpiring orchard or an evaporating waterbody, the ET estimates for that pixel will be higher. This is often the case where crops are situated next to a river with open water and riparian vegetation (Figure 5.7) or a dam (Figure 5.8). Wet soils on the fringe of the dams show similar high ET values (consisting of evaporation only) (Figure 5.8).

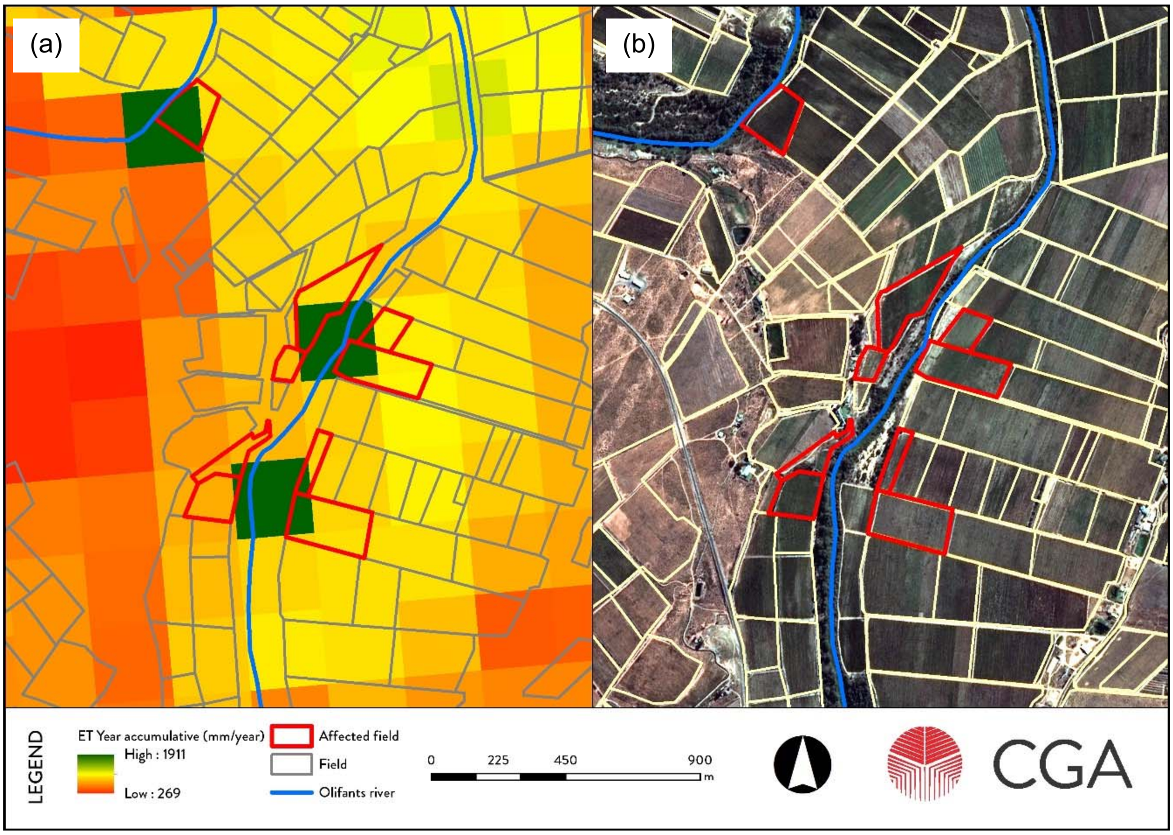


Figure 5.7 Example of mixed pixels in waterbodies and crops next to the Olifants River near Vredendal, Western Cape, shown in (a) the 250 m ET data and (b) the 0.5 m satellite image

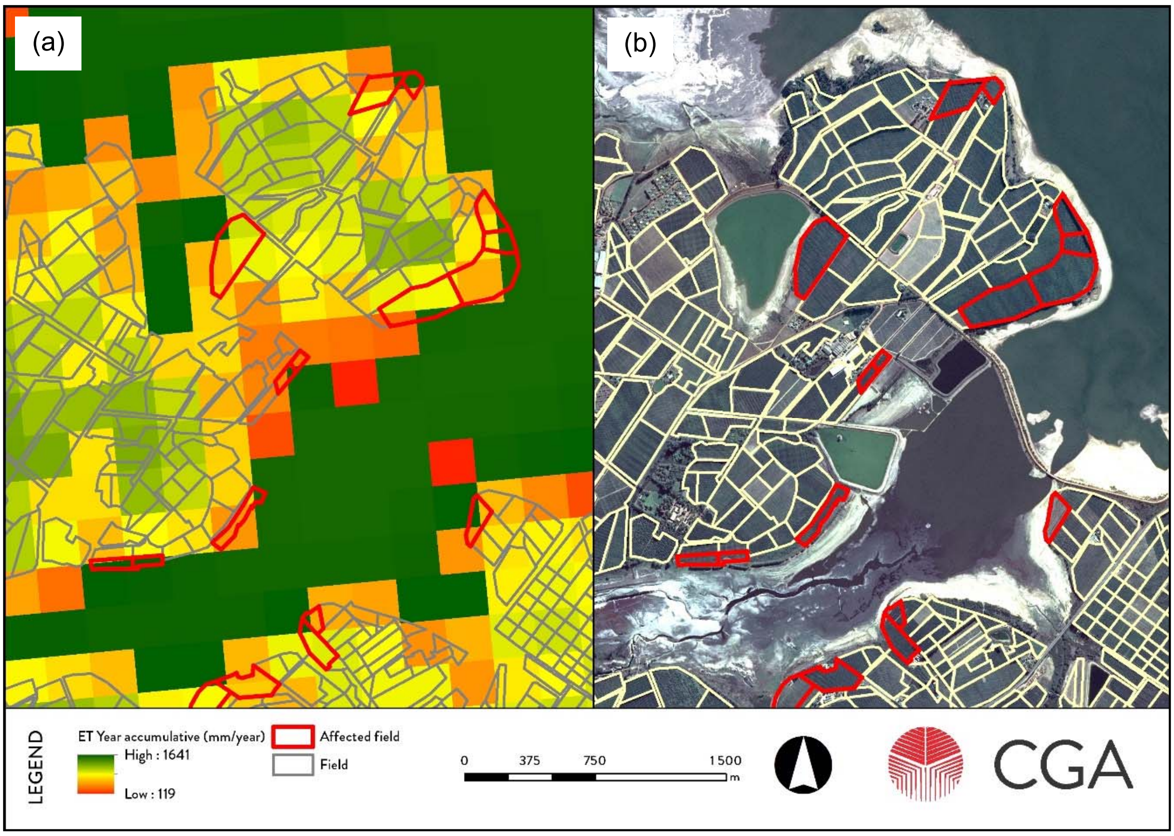


Figure 5.8 Example of mixed pixels in waterbodies and crops next to the Theewaterskloof Dam near Grabouw, Western Cape, in (a) the 250 m ET data and (b) a 0.5 m satellite image

Given that ET estimates from waterbodies typically have much higher ET values than irrigated areas (consisting of open water evaporation and transpiration by riparian vegetation), the focus of the sensitivity analysis was placed on determining the impact of the waterbody mixed pixels (WBMPs) on cumulative water use estimations for irrigated agriculture. First, mean ET values were extracted for irrigated fields. The mean ET values were then aggregated to a regional and national scale and the total water use estimated. In the second step, the influence of WBMPs on ET estimates was determined by systematically eliminating WBMPs from the ET dataset and then recalculating the national water use (ET) for irrigated fields. The differences in ET of these estimates (before, and after eliminating WBMPs) were then compared to get a sense of the overall impact of mixed pixels.

Different WBMPs elimination scenarios were carried out to investigate their influence on total water use estimates for irrigated agriculture. Two datasets were interchangeably used to eliminate WBMPs. This first dataset consisted of a waterbody mask generated from the SALC1314. Here, all waterbodies classified as permanent or seasonal were extracted from the dataset (Dataset 1). However, based on visual inspections of the resulting water mask, not all WBMPs were eliminated. A second dataset was consequently created in an attempt to flag additional WBMPs, or WBMPs missed when creating the first water mask. This was done by comparing each 250 m pixel’s ET value to those of its immediate neighbouring pixels. If the pixel value was significantly higher than any of its surrounding pixels, the pixel was flagged as being a potential WBMP (Dataset 2). The following WBMP exclusion scenarios were subsequently applied in the sensitivity analysis:

- **Scenario 1:** Remove pixels containing permanent water according to SALC1314 (Dataset 1) AND flagged pixels (Dataset 2).
- **Scenario 2:** Remove pixels containing permanent AND seasonal water (Dataset 1) AND flagged pixels (Dataset 2).
- **Scenario 3:** Remove only flagged pixels (Dataset 2).
- **Scenario 4:** Remove pixels containing permanent water (Dataset 1) OR flagged pixels (Dataset 2).
- **Scenario 5:** Remove pixels containing permanent AND seasonal water (Dataset 1) OR flagged pixels.

Table 5.5 summarises the relative changes in cumulative water use of all irrigated fields for each of these WBMP exclusion scenarios.

Table 5.5 Relative changes in irrigated area water use (ET) estimates under different waterbody mixed-pixel exclusion scenarios based on Version 3 of the IAM

Scenario	# of pixels excluded	Total water use by irrigated agriculture (Million m^3/yr)	Total water use % decrease (mm^3/yr) from original
Original	0	10 221	0.00
Scenario 1	69 496	10 192	0.28
Scenario 2	69 542	10 192	0.28
Scenario 3	70 151	10 188	0.32
Scenario 4	210 457	10 169	0.51
Scenario 5	261 926	10 159	0.61

From Table 5.5 it is clear that the elimination of WBMPs did not have a substantial impact on overall water use estimations. In the extreme scenario (Scenario 5), the overall water use estimation was only 0.61% lower than when no WBMPs were excluded. It should be noted that Scenario 5 is likely an exaggeration of the expected WBMPs. Scenario 3 (excluding only flagged pixels) was likely the more realistic approach and estimate. This suggests that the low resolution of the ET dataset did not have a dramatic effect on the overall water use estimate of irrigated agriculture in SA.

While WBMPs artificially increase the water use estimations of irrigated fields, it is similarly likely that other land covers (e.g. bare areas, rainfed crops) at the edges of irrigated areas reduce ET values (and water use estimations) of irrigated agriculture. Although the differences between the ETs of irrigated crops and other land covers are not as dramatic (compared to ETs of waterbodies), the number of pixels involved is higher. This means that such land covers (in combination) would have a similar, but inverse effect on water use estimates. One can consequently argue that the increases caused by waterbodies adjacent to agricultural fields would be negated by the reductions caused by other land uses/covers, and that water use estimates without any elimination of pixels will provide a good compromise. Nevertheless, the variations in Table 5.5 provide a good indication of the confidence level of the overall water use estimations. In other words, the margin of error of the overall estimations is likely within a 0.61% range (above and below the estimations when no mixed pixels are eliminated) and should be interpreted as such.

Based on the results of the WBMP sensitivity analysis, it was concluded that estimating irrigated agricultural water use or ET without eliminating any mixed pixels and as presented in Sections 5.1 and 5.2, was an acceptable approach to follow. Hence, the estimated total consumptive water use (ET) from irrigated agriculture in SA of **10 221 million m^3/yr** for the evaluation period (1 August 2014 to 31 July 2015), based on an irrigated area of **1 334 562 ha**, was left unaltered.

6 DEMONSTRATION OF WATER ACCOUNTING FOR DECISION SUPPORT

In the preceding chapters it was showed how EO can be used to map irrigated agriculture (Chapter 4) and determine the water use thereof (Chapter 5). When this data is considered within the context of water availability in a catchment it becomes an invaluable source of information that can be used to improve water management. Water accounting provides a framework through which this data can be analysed and interpreted to support water-related decision-making. Within this study, the water accounting plus (WA+) methodology is demonstrated for seven selected catchments in SA.

6.1 Catchment selection

South Africa has 22 major drainage regions, which include 148 secondary catchments (Table 6.1). A spatial overlay analysis was performed to select suitable secondary catchments for the WA+ demonstration, using a number of criteria. This process helped to identify secondary catchments where water has a large economical, sociological, environmental and/or political impact and where sound water management is essential.

Table 6.1 Primary catchments of SA with their respective number of secondary catchments

	Name	No. of secondary Catchments			Name	No. of secondary catchments
A	Limpopo	9		M	Swartkops	3
B	Olifants (E)	9		N	Sundays	4
C	Vaal	9		P	Bushmans	4
D	Orange	8		Q	Great Fish	9
E	Olifants (W)	4		R	Keiskamma	5
F	Buffels	6		S	Great Kei	7
G	Great Berg	5		T	Mzimvubu	9
H	Breë	9		U	uMngeni	8
J	Gourits	9		V	Thukela	7
K	Coastal Rivers	9		W	Phonoglo	7
L	Gamtoos	9		X	Crocodile	4

For the spatial overlay analysis, a shapefile delineating all secondary catchments was populated with information on irrigated agriculture (total area and proportion), rainfed agriculture (total area and proportion) and estimated population count and density for the year 2015 (Table 6.2). The areas for rainfed and irrigated agriculture were based on the IAM and land use classification generated in this project. The IAM Version 2 was used in the WA+ demonstration. Population data were obtained from CIESIN (2016) at a spatial resolution of 1 km^2.

Table 6.2 Information captured per secondary catchment and used to select catchments for the WA+ demonstration

Irrigated agriculture	Rainfed agriculture	Population
1 Area irrigated agriculture [ha]	3 Area rainfed agriculture [ha]	5 Population count
2 Proportion irrigated agriculture [%]	4 Proportion rainfed agriculture [%]	6 Maximum Population density [km^{-2}]

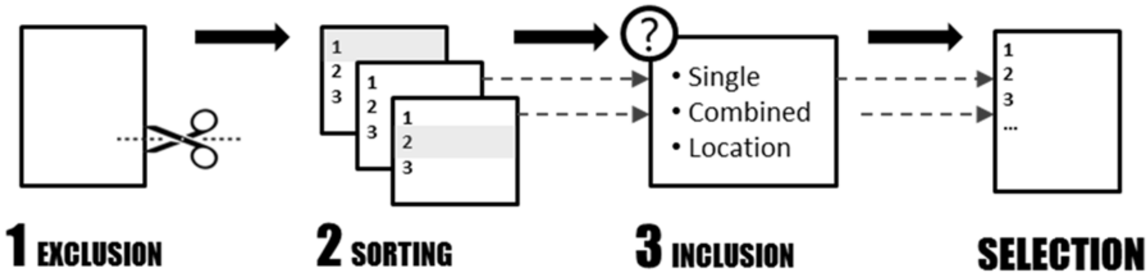


Figure 6.1 A representation of the WA+ catchment selection process, consisting of three main steps

The process of selecting suitable secondary catchments comprised three main steps: 1) exclusion; 2) sorting/prioritising; and 3) inclusion (Figure 6.1).

1) The exclusion process consisted of three steps:

   a) *Exclude catchments without agriculture.* Since WA+ determines the water use of modified landscapes and shows the amount of utilisable water left to enhance land productivity, it is especially relevant for areas with irrigated agriculture. Since irrigated agriculture is the focus of this project, secondary catchments without agricultural areas were excluded from our research.

   b) *Exclude catchments where total irrigated area is less than 10 000 ha, or cover less than 10% of the total surface area of the sub-catchment.* One possible application of WA+ is determining the amount of water left for expanding irrigated agriculture. An expansion in irrigated agriculture will mostly likely occur in secondary catchments where irrigated agriculture is already present (i.e. irrigation infrastructure already exits). Hence, secondary catchments that already contain irrigated agriculture are preferred for demonstrating WA+. To prevent the exclusion of small, secondary catchments, this step not only considers the actual area (10 000 ha), but also the proportion of irrigated area within the catchment (10%).

   c) Exclude catchments that have at least one 1 km^2 pixel with a population density higher than 10 000 people/km^2. This step considers the maximum population density within a secondary catchment. The WA+ process evaluates opportunities to expand (irrigated) agriculture, which will mostly likely happen in rural areas. Population counts are considered since it is a good indication of the likelihood of job creation because of expanding (irrigated) agriculture. Highly urbanised regions were excluded from consideration as it is assumed that the opportunities for the expansion of irrigated areas will be less in these areas.

Based on these three exclusion criteria, 100 catchments were excluded, leaving 48 potential candidates for demonstrating WA+. Figure 6.2 shows the excluded catchments (grey) as well as the remaining catchments for consideration for the WA+ demonstration.

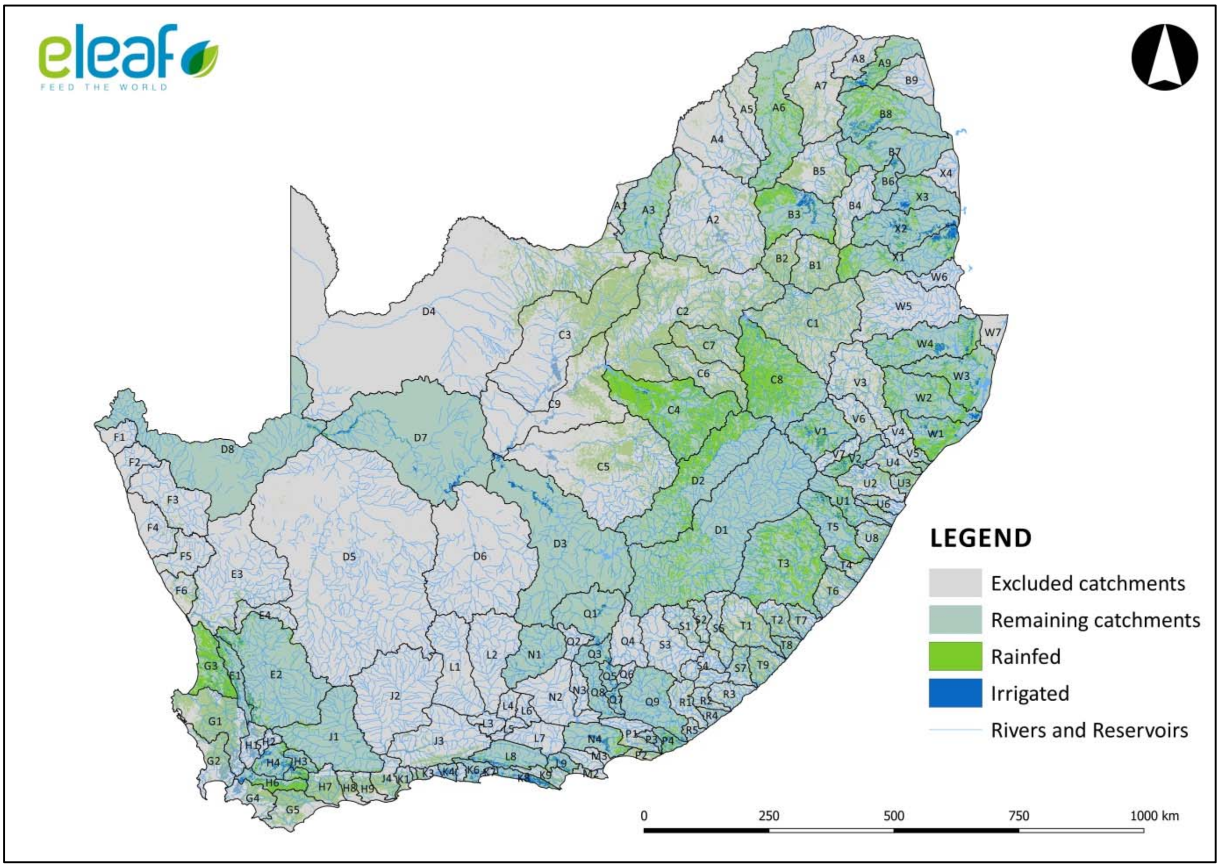


Figure 6.2 A spatial representation of the 48 suitable secondary catchments for demonstration of water accounting (shown in light blue) following the first exclusion step

2) The next step in this catchment selection process was to sort the catchments according to favourable characteristics. Three lists were created containing:

   a) *The twenty catchments with the highest irrigated area proportion*: In catchments with a large proportion of irrigated agriculture, the water cycle is strongly influenced by manmade interventions. This is represented as managed water use in WA+. In these areas, WA+ can provide valuable insight into water consumption and the amount of water that is still available for expansion of the irrigated area (List 2a).

   b) *The twenty catchments with the highest population count*: Sound water management is very relevant in densely populated areas. Good water management has a positive effect on food security, availability of (clean) drinking water and disaster risk reduction. In addition, efficient use of water can have a positive effect on job opportunities. For example, an increase in the efficiency of water use could increase the possibility of larger areas of irrigated agriculture (List 2b).

   c) *The five secondary catchments with the highest proportion of rainfed agriculture:* In secondary catchments with a high proportion of rainfed agriculture, the landscape is highly influenced by human behaviour. This is represented as modified land use in WA+. Since WA+ was designed to highlight water problems and the potential for improvement by human intervention, it will be interesting to demonstrate this in predominantly modified catchments (List 2c).

3) Based on the results from Step 2, the third or inclusion step only selected secondary catchments that were highly ranked on the three created lists. The inclusion proceeded in a categorical manner to allow for representation of catchments with different characteristics. The selection was based on the following queries:

a) Selection of potential impact based on a single category.

- The *most intensively irrigated sub-catchment* was K8. This catchment is located along the coast. There seems to be no room for expansion of irrigated agriculture, based on close examination of true colour satellite imagery. The existing agriculture is already irrigated and as such it is not interesting for demonstration of WA+. Subsequently, the 2nd catchment on the list was selected, namely H4 – Breede, as it contains substantial irrigated and rainfed crops.

- The *most densely populated sub-catchment*, with the exception of those with large urban centres, was D2. This catchment is partly located in Lesotho, which makes it unsuitable as this project only focuses on SA and has data available only for SA. This was also the case in the second catchment on the list (D1). Hence, the third catchment on the list was selected, which is T3 - Mzimvubu.

- Catchment G3 - Verlorenvlei has the *highest proportion of modified land use* for agriculture and was consequently selected.

b) Selection based on potential impact constructed from a combination of categories. The outcomes of two lists were combined to represent regions where improved water management may have a large impact.

- Catchments found in Lists 2a and 2c represent the regions with the highest proportion of agriculture, indicating a strong human influence on water consumption in these catchments. H5 emerges as an interesting candidate. H4 (also located in the Breede Rivier catchment) was selected in Step 3a. Hence, demonstrating the WA+ of H4 and H5 together provides insight into the effect of upstream water use on downstream users.

- Secondary catchments found in List 2a and 2b represent areas where proper water management is essential for support of a large local population. Three catchments meet these conditions, namely B3, X1 and X2. Being from the same catchment, X2 - Crocodile was selected as it has a larger irrigated area than X1. Although B3 was initially selected as well, this catchment was exchanged for B8, Letaba, upon request and after interaction with local authorities.

c) Selection based on sub-catchment location.

- All catchments with the highest proportion of irrigated agriculture along a state border were ranked. Along a multinational border, water available for downstream usage is an important consideration associated with large potential political pressures. This selection criterion, like Step 3b, highlighted catchment X1 and X2. Hence, no new selection was made based on this criterion.

- All catchments with the highest proportion of irrigated agriculture located along the coastline were ranked. There are no downstream users of water dependent on these catchments as they directly discharge into the ocean. Subsequently, based on Google Maps imagery and the IAM generated in this project, the room for potential expansion of (irrigated) agriculture was inspected for the highest-ranking catchments. P4 - Kowie was selected as it has a large proportion of rainfed and irrigated agriculture, where rainfed cropland can be converted into irrigated cropland if water is available.

d) Selection after interaction with local authorities.

- The Letaba catchment (B8) was selected on request by local authorities (the Letaba water user association (WUA) and Dr. Eddie Riddell from SANParks). B8 is one of the highest populated catchments in SA. According to local authorities, the water resources are highly over-allocated, with extensive water demands from various sectors. Proper management of water is therefore essential to make ends meet. The Letaba was also included in the reconciliation studies undertaken by DWA (2013).

Based on the exclusion, sorting and inclusion process, seven secondary catchments located across SA were selected to demonstrate the WA+ process. Figure 6.3 shows the location of the selected secondary catchments.

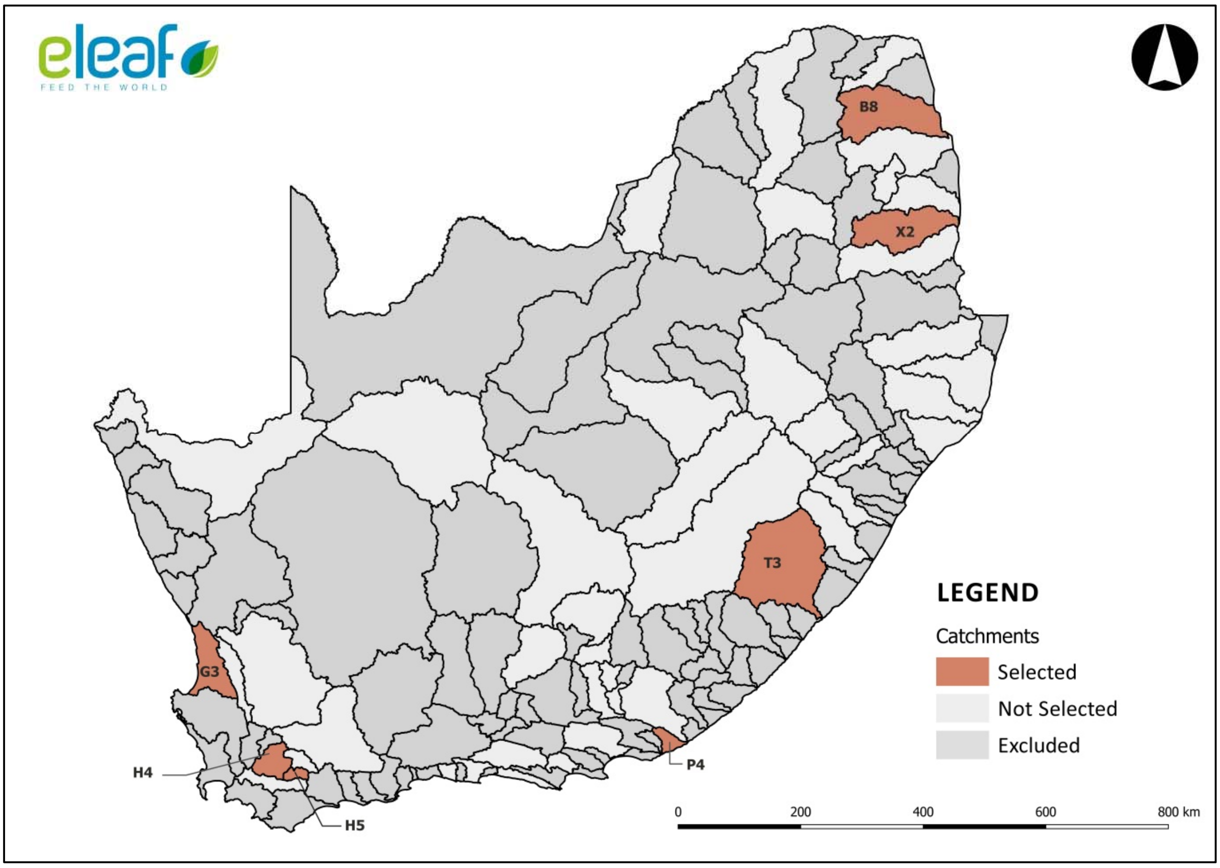


Figure 6.3 Location of the final selection of seven secondary catchments for WA demonstration, including the B8, P4, G3, H4, H5, T3 and X2 catchments

6.2 Data collection and preparation

Table 6.3 lists the various sources of available data that were used in the WA+ calculations. This includes RS and GIS-based sources, ground measurements and information obtained from literature.

Table 6.3 Overview of datasets used in the WA+ calculations

Dataset	Description	WA+ Sheet
RS and GIS		
ETLook Data Products	Raster data on actual transpiration, transpiration deficit, soil evaporation, interception evaporation, actual evapotranspiration, and actual biomass production have been produced by ETLook. The data covers SA at 250 m resolution and is available on a monthly basis.	1 to 4
Irrigated Area Map	The IAM distinguishes irrigated and rainfed agriculture in SA at field level. It was created through a machine learning approach based on ETLook data and NDVI time series of Landsat 8. The August 2016 version of the IAM was used in the WA+ calculations.	1 to 4
Incremental ET	The incremental ET is the additional water consumption (evapotranspiration) by irrigated croplands due to supplementary water availability from irrigation (Eekelen et al. 2015). It is calculated through comparison of ET of an irrigated pixel with the ET calculated on surrounding rainfed pixels. The difference in ET is ascribed to be due to the addition of water by irrigation: the incremental ET. This calculation is done on a pixel-by-pixel basis for all pixels classified as irrigated within the IAM.	
GSMaP Precipitation	GPM-GSMaP Ver.6 is the latest algorithm developed by the GSMaP project. Hourly rainfall data based on this algorithm were available at 11 km resolution for SA.	1 to 4
SALC1314 Land Cover Map	An updated national land cover map based on 2013–2014 Landsat 8 data, created by GeoTerraImage, was used. The classification distinguishes between a wide range of land use and vegetation classes, including bushland, cultivated land and build up categories.	1 to 4
WR 2012 Resource Centre	WR 2012 built on the WR 2005 study. It is the most recent water resource study available for SA and took place between 2012–2016. The website portal provides all data used for modelling in shapefile and map format. Many of these datasets were useful for this WA+ demonstration.	1
CIESIN 2016 Population data	Gridded Population of the World (GPW v4) provides population count and density on a 1 km^2 grid. The 2015 estimates were used. Data were produced by NASA SEDAC, hosted by Columbia University.	4
Ground Measurements		
ARC Weather Stations	Data from 73 ARC meteorological ground stations were used in the WA+ demonstration. An interpolated rainfall map was created in combination with the NOAA station data.	1
NOAA Weather Stations	Data from 166 NOAA meteorological ground stations were used in the WA+ demonstration. An interpolated rainfall map was created with ARC station data.	1
DWA Dam Levels	Historical and real-time data on water levels of major dams in SA are available from www.dwa.gov.za and http://niwis.dwa.gov.za/niwis2/ and were used.	1, 4
WCPDA Dam Levels	Historical and real-time data on major dams in the Western Cape are available at elsenburg.com and were used.	1, 4
DWA River Flow	Data from gauges measuring streamflow and river discharge, listed per catchment and indicating start and end date of measurement, are available from www.dwa.gov.za and were used.	1, 4
National Ground Water Archive	A web portal providing access to a large database of historical water levels measured at these stations, sorted by province, is available from different providers at http://www3.dwa.gov.za/NGANet/ and was used.	1,4
Literature		
Various sources	Information from literature was used to attain input on domestic and industrial water use, the ecological reserve, possible ground water use and other water resource-related information. Among others, a range of reports from DWA, DAFF, WRC were examined for suitable information.	1,4

6.3 Implementation of WA+

The WA+ framework was implemented for the seven selected sub-catchments of SA and the water accounts illustrated for the period 1 August 2014 to 31 July 2015. The WA+ framework consists of multiple accounting sheets, but this study focussed on and demonstrated Sheets 1 to 4, which forms the backbone of WA+. The WA+ methodology was applied to all seven secondary catchments at an annual time step. The raster data products used were resampled to 250 m resolution. Each sheet was completed as thoroughly as possible. However, due to a lack of source data, especially for Sheet 4, this could not always be done. The following steps were followed in preparation of each sheet:

Sheet 1 Water Resources:

- The SALC1314 land cover map, a shapefile delineating the protected areas of South Africa, a shapefile delineating reservoirs and the IAM produced during this project were used to distinguish protected (PLU), utilised (ULU) and modified (MLU) land uses, as well as managed water use areas (MWU). This categorisation was used to define the water consumption through ET per land use type (i.e. the depletion of water from the catchment).
- The mean values for a number of variables were calculated per land use class, including actual ET (separated for a precipitation based and irrigation based component) and precipitation. All values were extracted in mm.
- The resulting mean values were converted into m^3 by considering the area (in ha) and used in combination with the surface areas per land use class to complete WA+ Sheet 1.
- Other inputs required for Sheet 1 included surface water in- and outflow, domestic and industrial water use, reserved outflow, storage changes and ground water in- and outflow. These inputs were obtained from literature and general information from the Department of Water and Sanitation. This included discharge measurements from flow stations and information on dam levels.

Sheet 2 Water Consumption:

- The land use classes defined for Sheet 1 (PLU, ULU, MLU and MWU) were subsequently subdivided into subcategories for Sheet 2. These subcategories are specific for each land use type. For instance, subclass 'forest' occurs in PLU and ULU, but not in the other two classes. Subclass 'rainfed crops' occurs only in MLU. Sometimes productive land use types, like forestry or agriculture, are located in a PLU area. In this case, the land use is defined as 'Other' and the area remains classified as PLU. Each combination of land use and subclass type was assigned a unique class number.
- Similar to the process described for Sheet 1, the mean values for a number of variables were calculated for each of these subcategories. The following datasets were used as input: evaporation, interception, transpiration and evapotranspiration (all in mm).
- The resulting mean values were then converted to m^3 (taking the area into account) and used in combination with the surface areas per land use class to populate WA+ Sheet 2.

Sheet 3 Water Productivity:

- Sheet 3 estimates ET, biomass and water productivity for agricultural services. This sheet focuses on productive land cover, like common production fields, pivots, orchards, vineyards, plantations and areas of subsistence farming. These areas were selected from the SALC1314 land cover map and subsequently intersected with the irrigated and rainfed agricultural areas map created in this project. As a result, the irrigated and rainfed part of various productive land use classes were separately classified.

- Similar to the method used in earlier sheets, mean values were computed per class using zonal statistics by overlaying the class dataset with the input datasets. Because no crop yield information was available, biomass was used as an indicator of plant production. The unit of biomass was converted to tons and ET was converted to m^3 (considering the area).
- Water productivity is defined as the amount of water consumed (in m^3) to produce biomass (in kg). High values therefore indicate higher productivity (more crop per drop). The resulting unit is kg/m^3.

Sheet 4 Water Withdrawals:

- Sheet 4 investigates water withdrawals in more detail. In this demonstration, water demand was estimated using ETpot as surrogate, while water consumption was equated to ETact.
- Domestic and industrial water use estimates were sourced from literature.

6.4 Results and discussion

6.4.1 Breede Rivier (H4)

Catchment H4 covers approximately 2 600 km^2 and is located in the Western Cape (Figure 6.4). The main settlement in this catchment is the town of Robertson, which is governed by the Langeberg Local Municipality. The catchment is primarily fed by sub-catchments H1 and H2. A tributary coming from H3 enters H4 almost at the outlet of the catchment, where after it becomes H5 (also covered in this WA+ demonstration). All secondary catchments mentioned have extensive irrigated areas, with the result that water availability in H4 is strongly influenced by upstream usage.

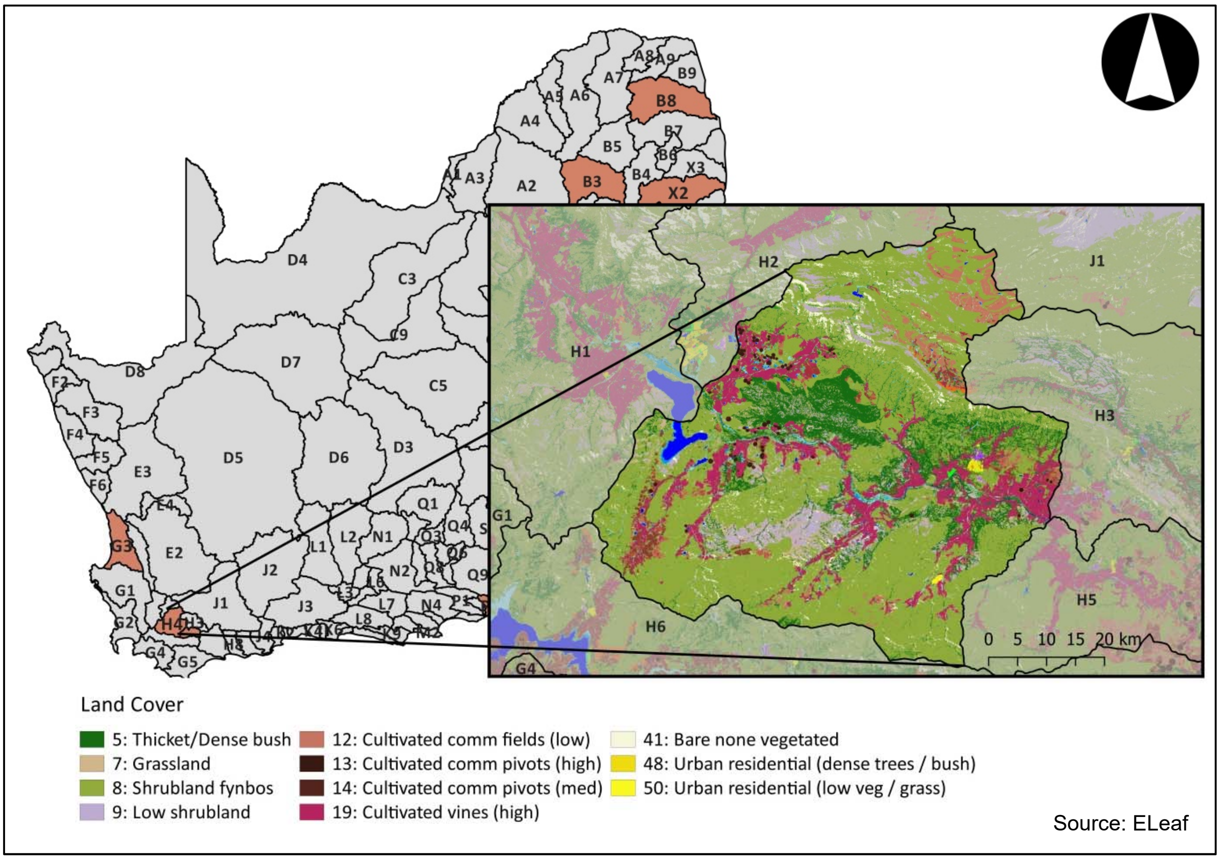


Figure 6.4 Location of secondary catchment H4 – Breede and land cover/use (insert) in this catchment and based on SALC1314

Important hydrological features are the Brandvlei and Kwaggaskloof dams situated in the western part of the catchment. These dams supply water to irrigated farming downstream. The water supplied is mostly used for the cultivation of wine grapes (Figure 6.4). Additionally, there are some centre pivot irrigation systems in the area. Almost all agricultural fields in this area are irrigated (Figure 6.5). The mountainous parts of this sub-catchment are mostly protected as a designated Mountain Catchment Area.

H4 was selected for this WA+ demonstration since it has the highest proportion of irrigated agriculture in a catchment within SA, which is clearly visible in Figure 6.5.

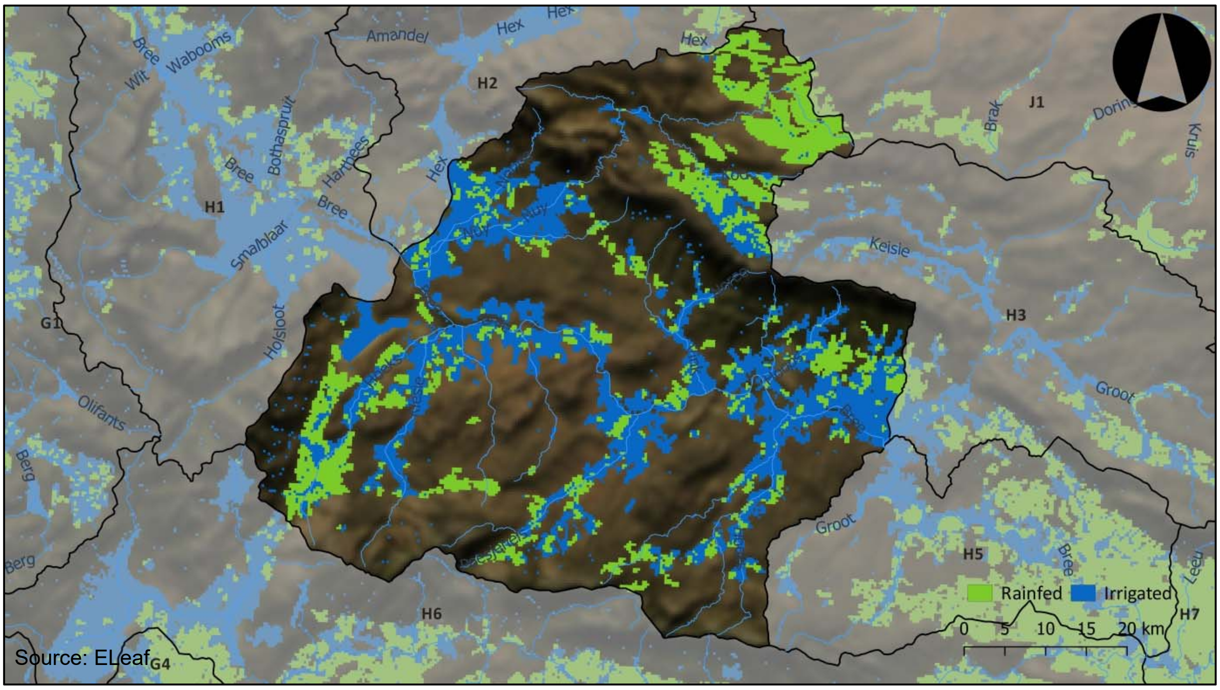


Figure 6.5 The extent of rainfed (green) and irrigated agricultural areas (blue) within secondary catchment H4

WA+ Sheet 1: Resources H4 – Breede

The PLU-class represent 772 km^2 of the catchment, while the ULU, MLU and MWU classes cover 1 380 km^2, 169 km^2 and 280 km^2 respectively. The resulting Sheet 1 for catchment H4 is displayed in Figure 6.6.

Precipitation estimates obtained from local weather stations and GSMaP satellite data range between 598 and 838 million m^3 of water. In an analysis conducted, both sources underestimated precipitation in the mountainous areas. The estimated annual precipitation varied between 200 and 350 mm for the period 1 August 2014 to 31 July 2015 per pixel in this catchment area based on the mentioned sources. DWA (2012a) quotes precipitation amounts in the mountains around Franschhoek, which is on the western side of this sub-catchment, of up to 3000 mm. The precipitation amount obtained from GSMaP and the interpolated station measurement data are therefore likely (substantially) lower than the actual precipitation.

Although there are currently no useful estimates of groundwater abstractions for the area available, the DWA aquifer classification map (DWA 2012a) shows that water in the Breede River catchment is mainly sourced from surface water resources. IDP 2017, the Integrated Development Plan of Langeberg municipality, mentions that municipal water comes directly from the Breede River. According to DWA (2012a) groundwater contributes 107 million m^3 of water to the annual water resources of the total Breede region, compared to 873 million m^3 from surface water. Most groundwater extractions likely occur in areas further away from the river. Given that the agricultural fields in catchment H4 are located directly along the Breede River, groundwater extractions and contributions were deemed negligible in this study.

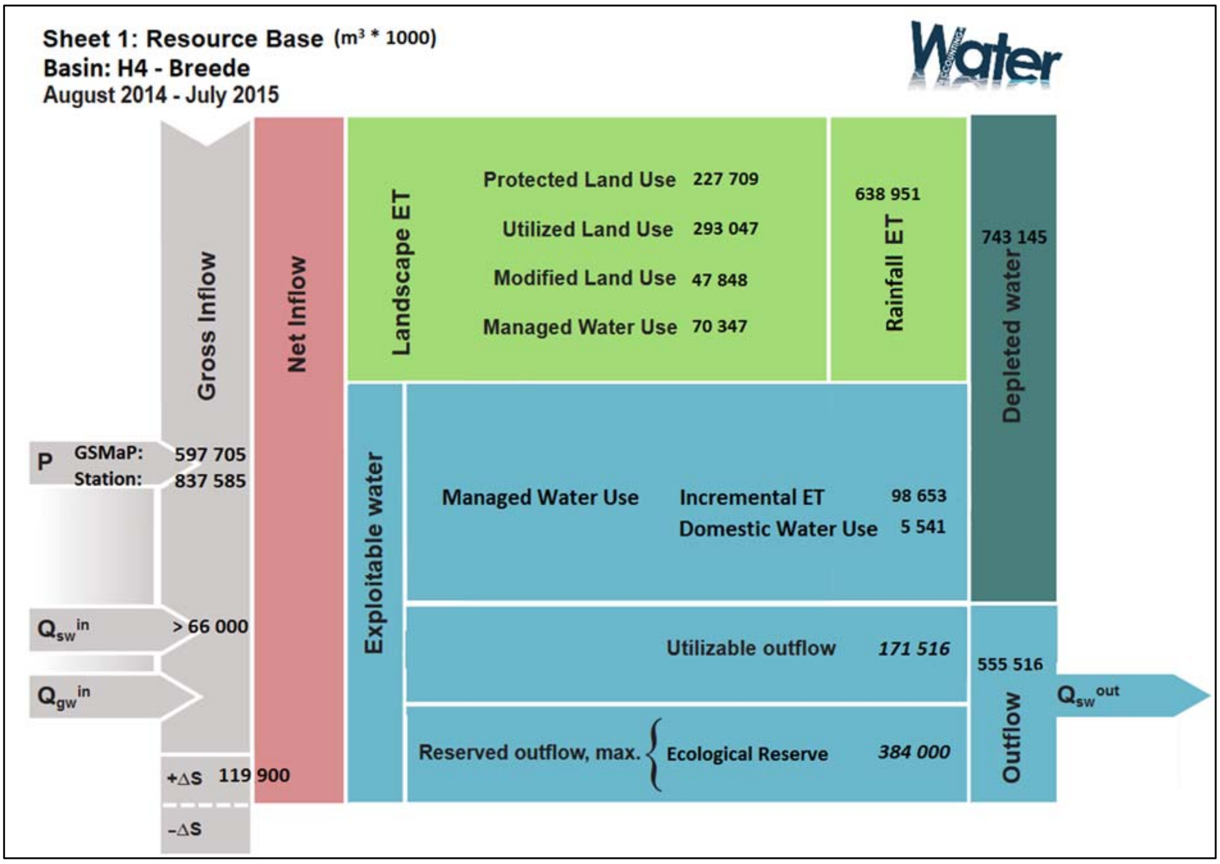


Figure 6.6 WA+ Sheet 1: Resources in H4 – Breede, showing volumes of water in thousands of m^3 (m^3 * 1000)

There are significant storage dams in the area, including the Brandvlei and Kwaggaskloof dams. Storage levels during the monitoring period were obtained[18], indicating ~120 million m^3 of water was sourced from these dams during the monitoring period. The amount of dam water used is derived from the percentage storage change as a fraction of the full storage capacity (FSC) of each dam in the area (Table 6.4).

Table 6.4 Dam and storage levels between 1 August 2014 and 31 July 2015 within the H4 catchment in thousand m^3

Dam name	River	FSC (Million m^3)	Storage August 2014 (%)	Storage July 2015 (%)	Storage Change (Million m^3)
Brandvlei Dam	Lower Brandvlei River	286.1	72.8	46.5	75.1
Keerom Dam	Nuy River	9.8	98.3	100.5	-0.2
Klipberg Dam	Konings River	2.0	96.3	100.1	-0.1
Kwaggaskloof Dam	Doorn River	169.5	72.2	45.6	45.1
Total		467.4			119.9

http://niwis.dwa.gov.za/niwis2/

Catchments upstream from H4 include H1 and H2. The only working streamflow station available close to the catchment inlet was H2H006, located at the end of H2 (Figure 6.7). Here, 66 million m^3 of water was measured flowing into catchment H4 during the study period (Table 6.5). This is taken as the minimum inflow into the catchment, as additional surface water will be coming from catchment H1. Surface water outflow was estimated from monthly discharge volumes obtained from DWS stations

[18] http://niwis.dwa.gov.za/niwis2/

H5H004 and H3H011. There was no station at the outlet of H4, but H5H004 is directly downstream of H4, and by subtracting the amount measured at H3H011, a good estimate can be obtained for the discharge of H4. Discharge from H4 was estimated to be 556 million m^3 for the monitoring period. The ecological reserve was estimated at 384 million m^3, as stated by a report describing the water sector in SA for the year 2000 (DWA 2012a).

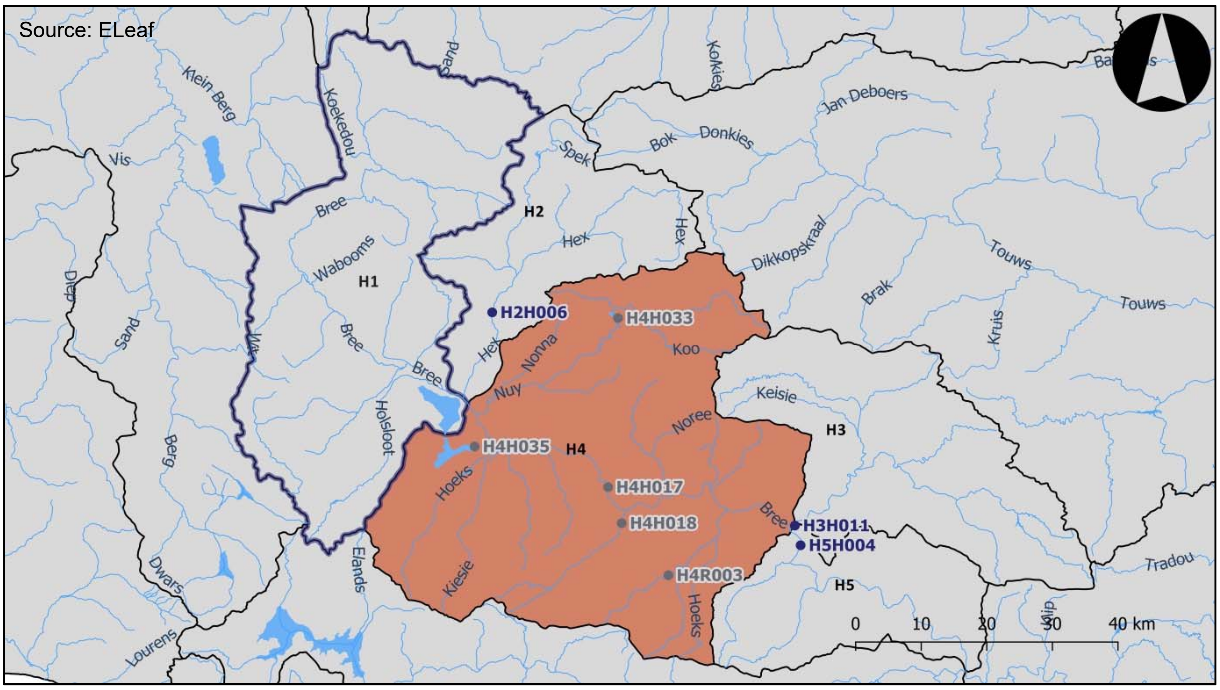


Figure 6.7 Locations of operating DWA water (streamflow) monitoring stations. Specifically, H4H004 and H7H006 were used to determine discharge from H4, which was used in this component of work.

Table 6.5 Monthly river flow data of stations H4H006 (inflow) and H5H004 and H3H011 (outflow) in million m^3 from DWA

IN	2014					2015							
station	Aug	Sept	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Annual
H2H006	26.1	16	5.6	2.84	1.58	1.06	0.784	0.799	0.715	0.775	3.6	6.05	65.903
OUT	2014					2015							
station	Aug	Sept	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Annual
H5H004	232	121	26.2	10.7	6.61	3.67	2.64	4.01	4.79	5.58	77.5	86.8	581.5
H3H011	2.31	2	2.04	1.5	0.932	0.734	0.625	0.863	1.17	1.11	7.02	5.68	25.98
DIFF	229.69	119	24.16	9.2	5.678	2.936	2.015	3.147	3.62	4.47	70.48	81.12	555.51

The estimated residential water demand was based on information from DWA (2012a), which recorded the domestic water volume demand for the entire Breede catchment at close to 49 million m^3. According to the same report, there were almost no industrial water requirements in this catchment. This information was combined with the CIESIN 2016 gridded population raster data to calculate the average water demand per person for the entire Breede catchment. The residential water demand for sub-catchment H5 was subsequently estimated using the population estimate, resulting in an estimated 5.5 million m^3 of domestic water use in H4.

WA+ Sheet 2: Consumption H4 – Breede

The completed Sheet 2 is shown in Figure 6.8. According to this assessment, most water is consumed via PLU and ULU, mostly through natural vegetation in the mountainous areas. There is also significant water consumption through ET by irrigated crops at close to 150 million m^3. Water from both precipitation and irrigation were consumed in these areas. Evaporation losses in irrigated croplands were notably low (around 4%). This might be related to efficient irrigation practices, which concentrates the application of water to the root zone e.g. via drip irrigation. Grape vines, the predominant irrigated crop in the area, have relatively open canopies and rain falls mainly during periods of low LAI, therefore lower interception evaporation losses are expected. High evaporation losses (approximately 12%) were recorded, especially under shrubland in the ULU class. This is likely due to the large proportion of bare soil between shrubs. The average non-beneficial use of water through evaporation, i.e. water that is used without being beneficial to any plant growth, was estimated to be 14% for this secondary catchment. High ET values were estimated for areas along the stream channels, where most irrigated croplands (and invasive alien plants) are located. This is clearly visible on the ETact map displayed in Figure 6.9.

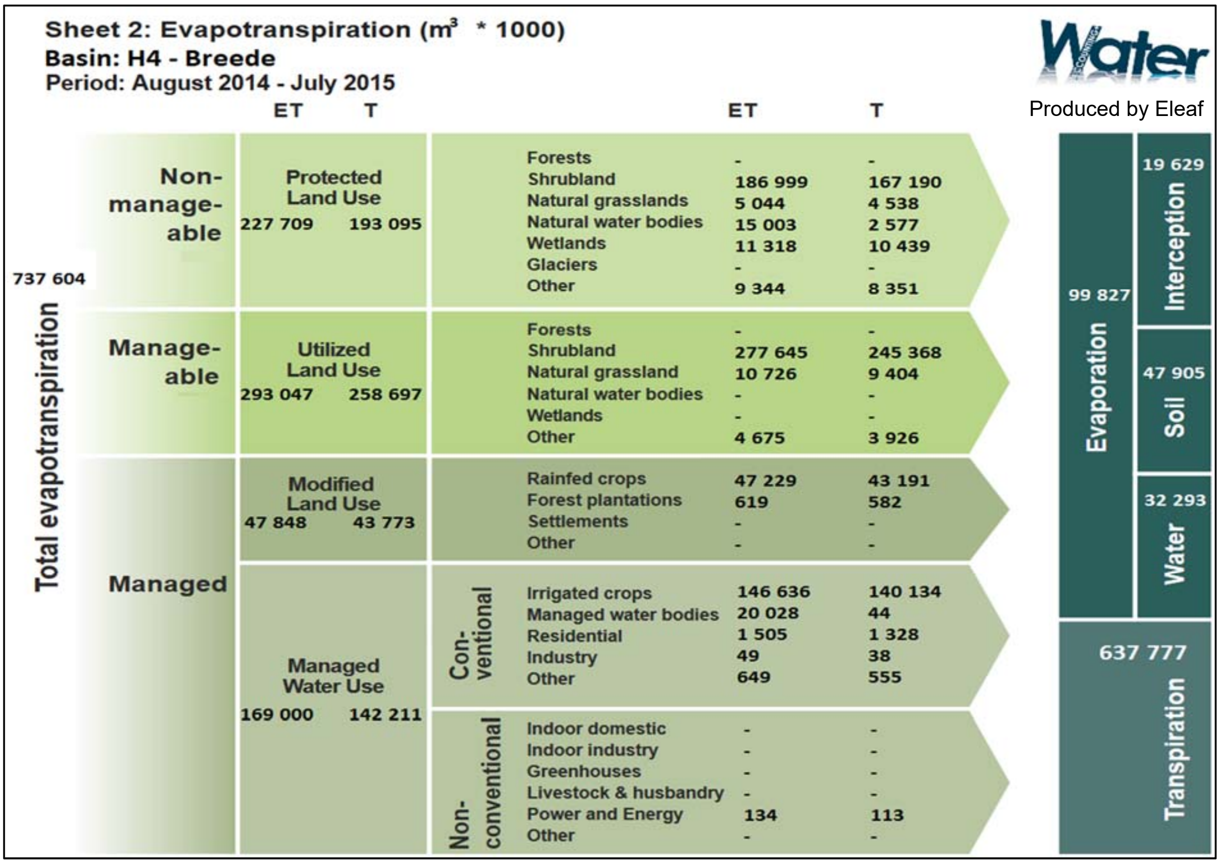


Figure 6.8 WA+ Sheet 2: Evapotranspiration in H4 – Breede in thousand m³

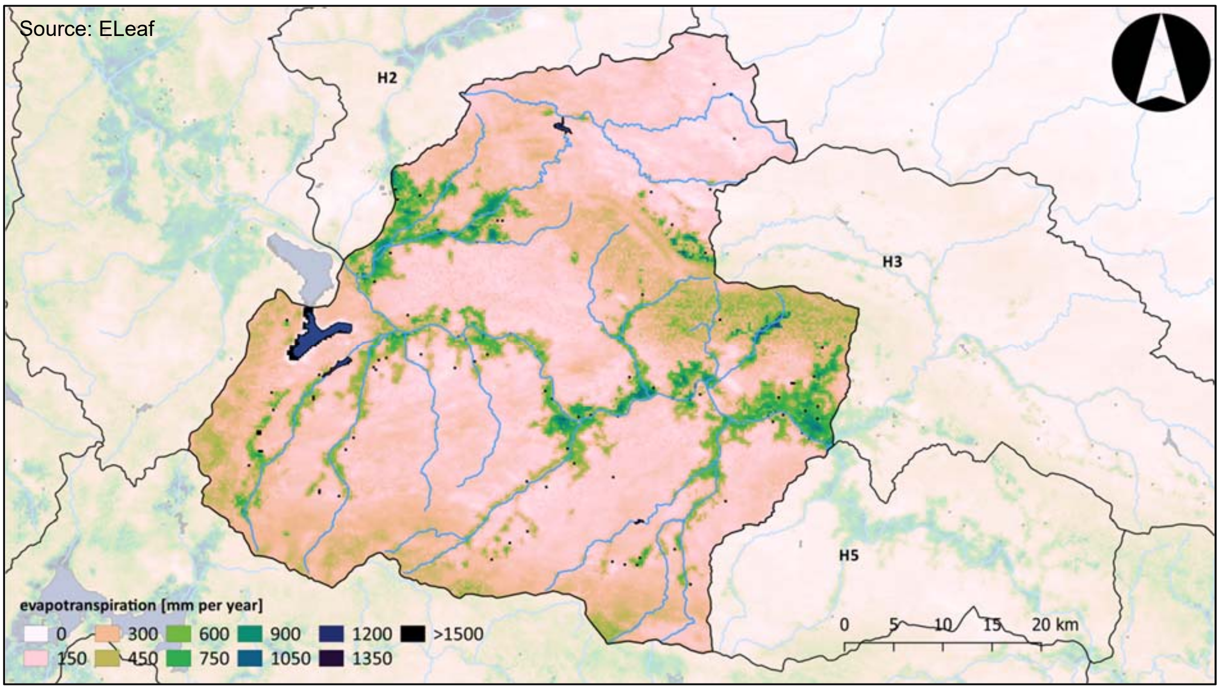


Figure 6.9 Annual ET (mm/yr) estimates for the H4 – Breede secondary catchment, displayed. Blue areas indicate the highest values.

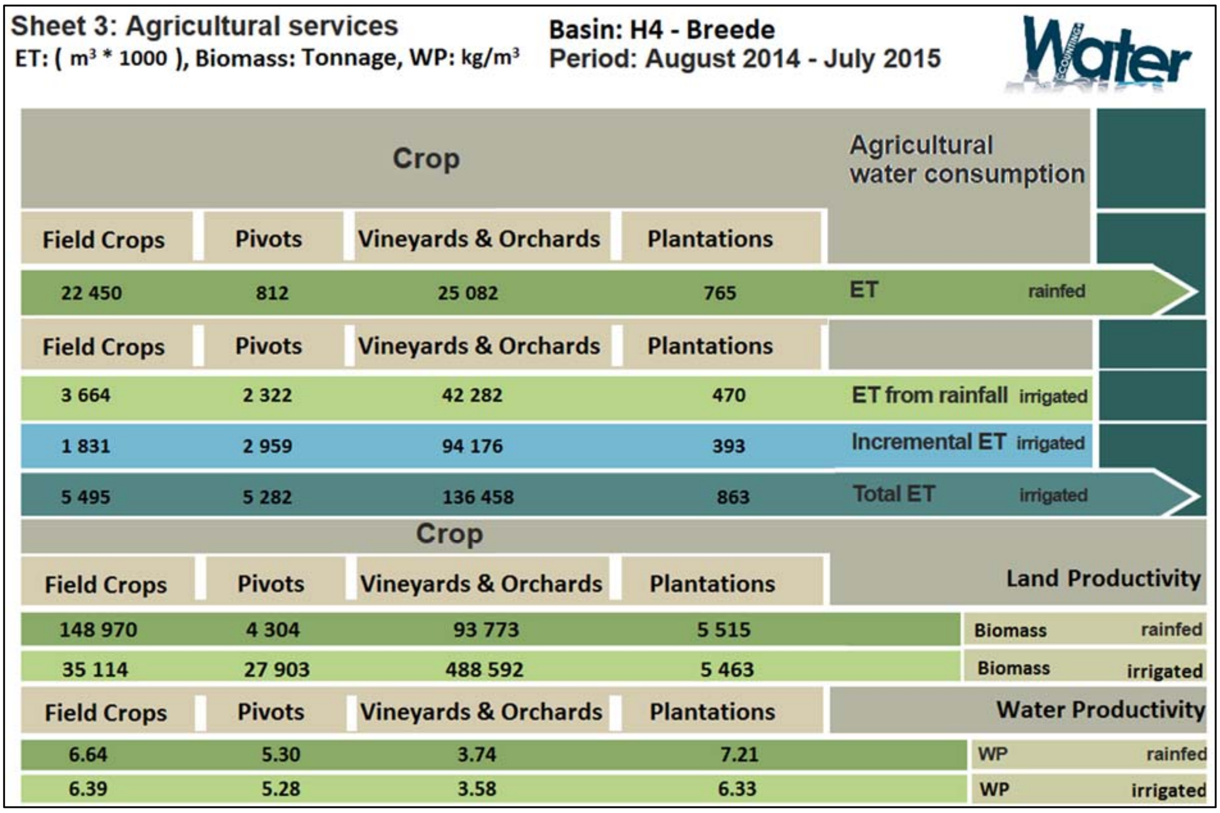
WA+ Sheet 3: Productivity H4 – Breede

Table 6.6 shows that field crops form a large part of rainfed agriculture in this area, whereas vineyards and orchards are the dominant irrigated crop type.

Table 6.6 Area of Rainfed and Irrigated Agriculture per service class in ha based on the 250 m resolution maps used in this analysis. Pivots listed under Rainfed area (ha) refer to crops cultivated on pivot circles/fields, but without irrigation actively applied.

	Area Rainfed (ha)	Area Irrigated (ha)
Field Crops	12 350	1 869
Pivots	206	1 325
Vineyards & Orchards	4 613	22 381
Plantations	175	181

Figure 6.10 presents the outcome of Sheet 3. The more efficient water users in terms of produced water use in this region were plantations and field crops. There is, however, a limited area under forest plantations within this catchment, which is reflected in the low total produced biomass. Vineyards and orchards are the least productive in terms of biomass production compared to water consumption (ET). Important to note is that the average productivity values reflected considers young to full bearing vineyards and orchards. The lower water productivity might also be due to climatic conditions in the summer. In summer, air temperature is high and relative humidity low, resulting in a strong gradient between inner-leaf water content and outer-leave humidity. This causes high rates of transpiration from vineyards and orchards while they are stressed for production of biomass by harsh growing conditions. Since irrigated vineyards (and orchards) dominate the area, this crop class is also responsible for the highest water consumption.



Produced by Eleaf

Figure 6.10 WA+ Sheet 3: Agricultural Services reflected in land and water productivity for the H4 – Breede catchment

WA+ Sheet 4: Withdrawals – H4 Breede

The WA+ Sheet 4 for H4 is shown in Figure 6.11. Sheet 4 shows the potential of this catchment to provide sufficient water to the different land use types present. The results show that there is a water deficit of about 14% for irrigated agriculture, with 147 million m^3 consumed through ET where the potential ET (or demand) was 171 million m^3. This could imply that the irrigation applied was insufficient for certain periods of the growing period, leading to an ET deficit. Water stress (deficits) also occur in most of the natural land use classes.

As mentioned in the description for WA+ Sheet 1, the residential demand estimate is based on DWA 2012b. This report recorded the domestic water volume demand for the entire Breede catchment. This information was combined with the CIESIN 2016 gridded population raster data to calculate the average water demand per person for the entire catchment.

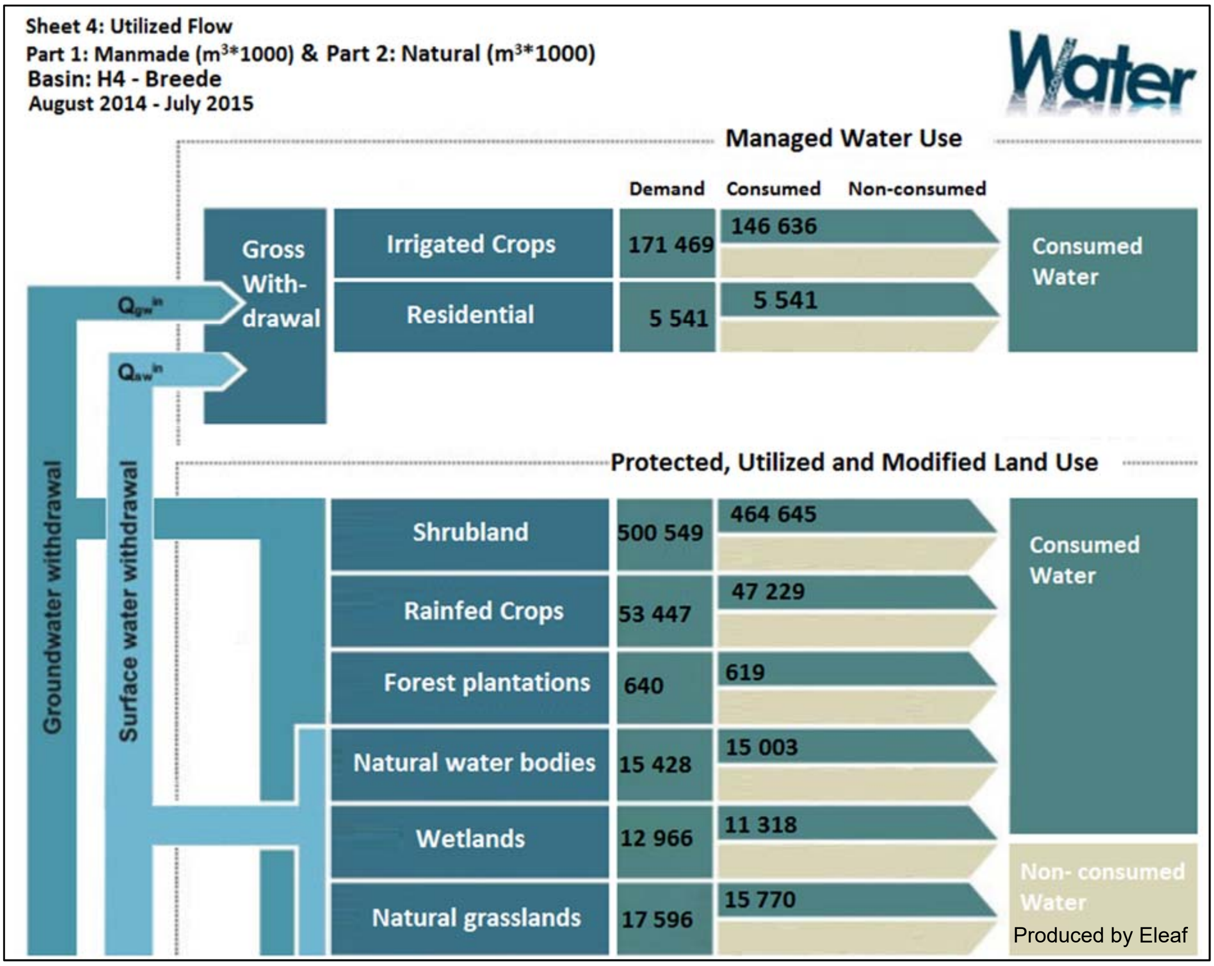


Figure 6.11 WA+ Sheet 4: Water withdrawals in H4 – Breede

The water available from return flows can potentially be used for other purposes. An estimation of return flows was made by DWA (2012a) for the entire catchment (Table 6.7), but no return flow information is available for sub-catchment H4 and hence no estimate of return flows could be included into Sheet 4.

Table 6.7 Useable return flows for the Breede-Gouritz catchment in million m^3 after DWA 2012b

Region	Yield (1:50 Year)				
	Natural Resources		Usable Return Flows		
	Surface Water	Ground Water	Irrigation	Urban	Bulk Industry
Gouritz	263	64	7	11	6
Breede	873	107	110		
Breede-Gouritz	1 136	171	117	11	6

Concluding remarks: H4 - Breede

Based on Sheet 1, one can conclude that there is potential for additional storage of water following the winter rainfall period as there was an (additional) utilisable outflow of 172 million m^3 from this catchment during the assessment period. The utilisable outflow is calculated as the difference between the ecological reserve and the discharge measured at the catchment outlet. The need for additional irrigation water is apparent from Sheet 4, showing the relatively high ET demand compared to ET consumption (demand exceeds supply by 14%) of water by irrigated agricultural crops. The complete water consumption by irrigated crops is approximately 147 million m^3 for the monitoring period. This ET deficit could therefore likely be supplemented by the potential water storage proposed above. Before extending storage capacity the downstream effect should be investigated. This could be done by the application of WA+ on a primary catchment rather than a secondary catchment scale, as has been done in this study.

6.4.2 Breede Rivier (H5)

H5 is a relatively small catchment of approximately 712 km^2 and is located in the Western Cape. The main settlement in this catchment is the town of Bonnievale, which is also governed by the Langeberg Local Municipality. The catchment lies downstream of the secondary catchment H4 and is additionally fed by H1, H2 and H3. All sub-catchments feeding into H5 have large areas of irrigated agriculture, which means that water availability in H5 is strongly influenced by upstream usage and users.

H5 itself has a strong focus on wine grape production, especially along the Breede River (Figure 6.12). Centre pivot irrigation is found further downstream. In H5 there is also a significant proportion of rainfed agriculture (Figure 6.13), primarily consisting of winter wheat fields. The mountainous areas in this sub-catchment are mostly protected areas.

H5 was selected for this WA+ demonstration on the grounds that it has one of the highest proportions of modified land use for rainfed and irrigated agriculture in SA.

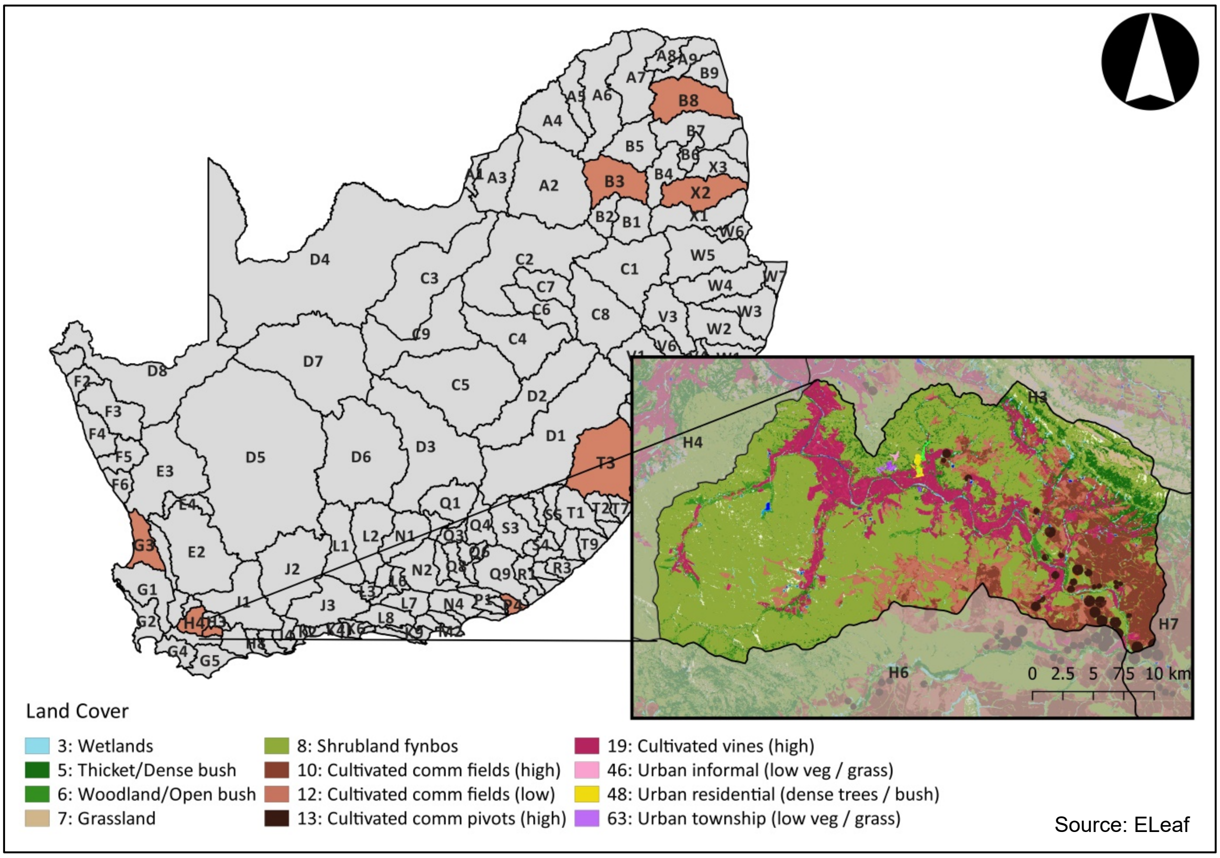


Figure 6.12 Location of secondary catchment H5 – Breede and land use based on SALC1314

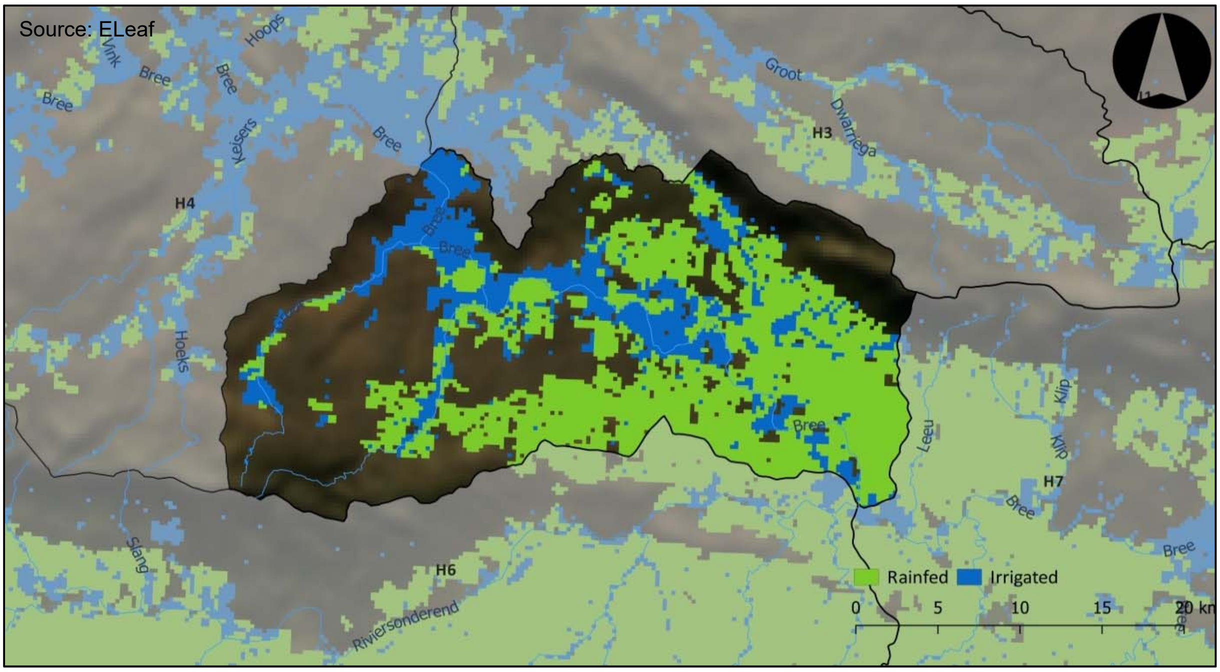


Figure 6.13 Secondary catchment H5, showing non-agricultural areas (brown), rainfed (green) and irrigated agricultural areas (blue)

WA+ Sheet 1: Resources H5 – Breede

The PLU-class represents 126 km^2 of the catchment, while the ULU, MLU and MWU classes cover 354 km^2, 162 km^2, and 70 km^2 respectively. The resulting Sheet 1 for catchment H5 is displayed in Figure 6.14.

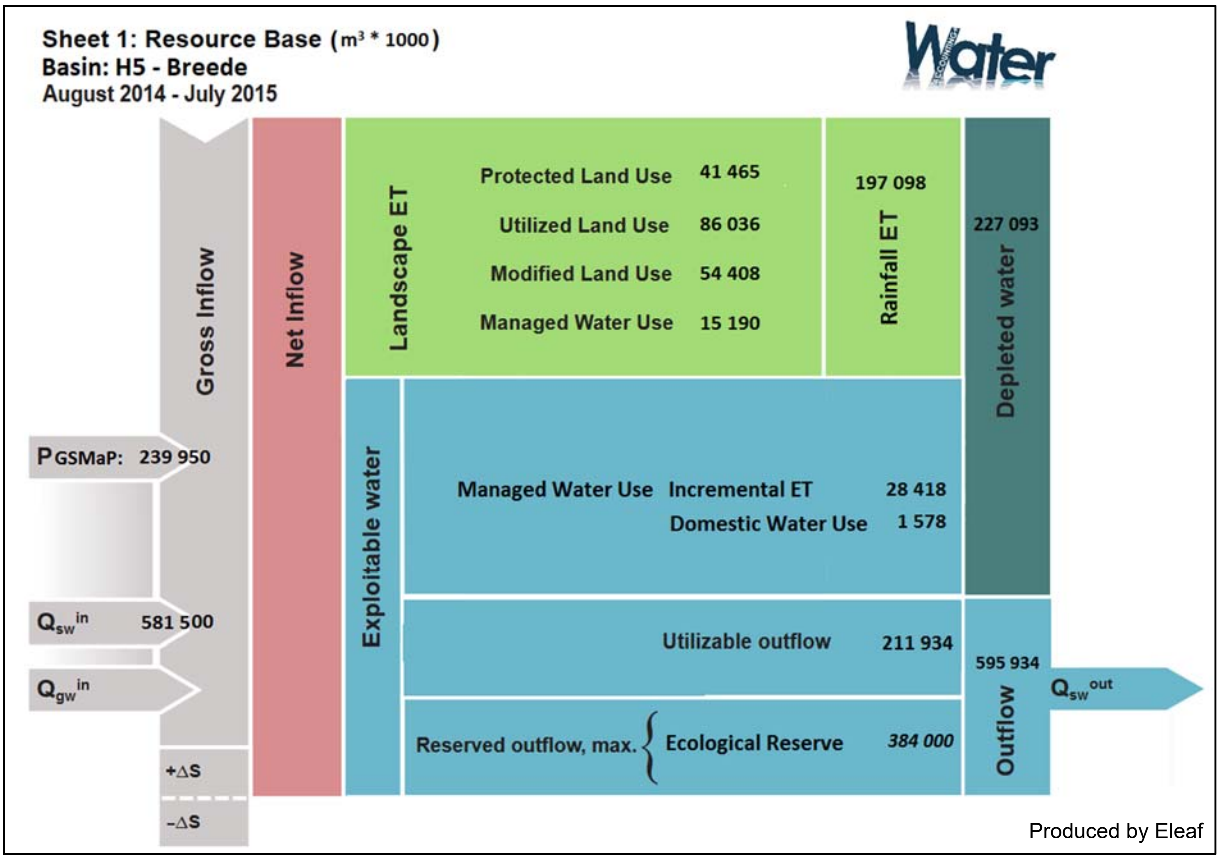


Figure 6.14 WA+ Sheet 1: Resources in H5 – Breede

Exactly the same assumption regarding groundwater extractions was made for the H5 catchment as for the H4 catchment, namely that groundwater extractions were deemed negligible (see Section 6.4.1).

Surface water inflow was estimated from monthly discharge volumes, obtained from the DWS station H5H004. This station is located a short distance downstream of the inlet of the sub-catchment and is consequently a good indicator of inflow (Figure 6.15). The discharge measurements from H5H004 are shown in Figure 6.16 and listed in Table 6.8. There are many private-owned farm dams in the catchment, but no large state dams. However, no information on the potential and actual amount of water captured in farm dams were available. As such, the variable storage change (ΔS) was not taken into account for this demonstration.

H7H006 is the first downstream river discharge station after sub-catchment H5, but two other tributaries feed into it. Hence, it is not a good representation of the water leaving the catchment via the Breede Rivier. The discharge measured at this station is shown in Table 6.8. There is no functioning flow measurement station directly at the outlet of this catchment. Hence, the outflow is estimated based on the other inputs to the sheet (gross input of water minus depleted water) at 596 million m^3 of water. The ecological reserve is estimated at 384 million m^3, based on a report of the water sector in SA for the year 2000 (DWA 2012b).

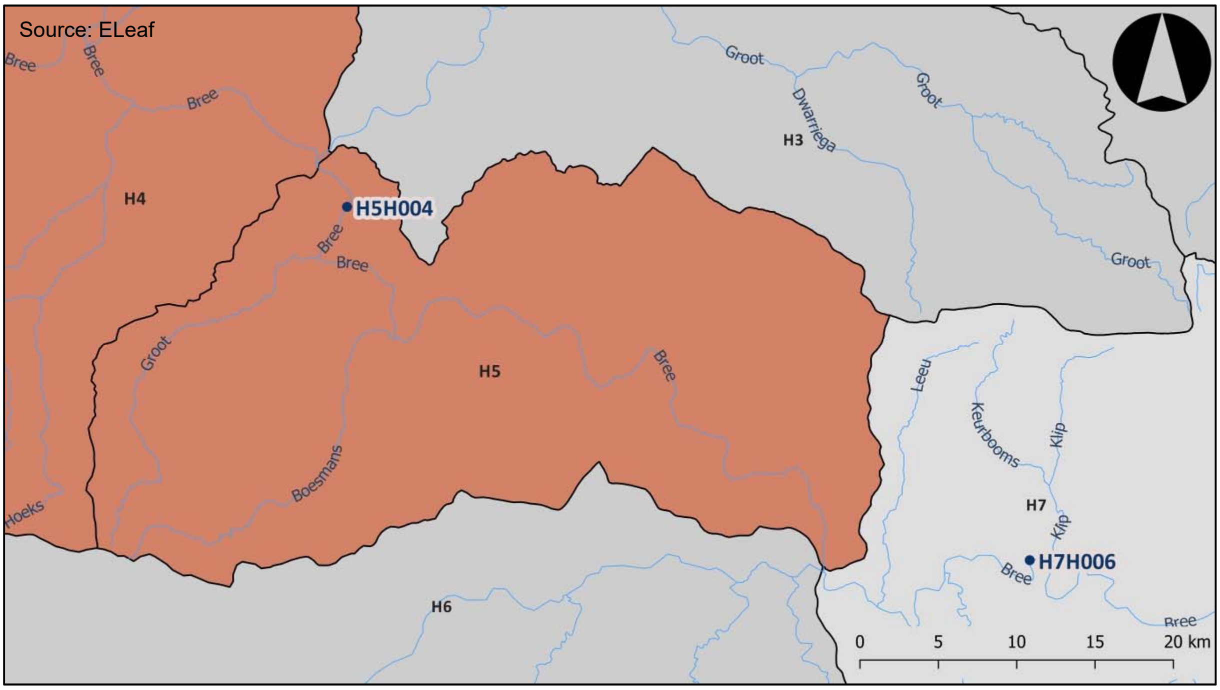


Figure 6.15 Locations of operating DWA water stations H5H004 and H7H006

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Data are continuously updated and reviewed.
Format of the data is as follows :(I4,X,I4,13(X,A6,A1,A1) where:
    I4 = CCYY
     X = /
    I4 = CCYY
    13(X,A6,A1,A1) = 12 Monthly volumes in million cubic metres from Oct to Sep.
                     Value 13 is the yearly total.
                     X  = Space
                     A6 = 999999
                     A1 = &/+/E/*/m/M or space(& = Good monthly reading)
                                              (+ = Above rating)
                                              (E = Estimated Data)
                                              (* = Calculated estimate)
                                              (m = Greater than)
                                              (M = Less than)
                     A1 = # or space (# = record incomplete or does not exist)

MONTHLY VOLUMES H5H004
Variable 100.00 Surface Water Level
I4,X,I4,13(X,A6,A1,A1)
AAAAAAAAAAAA
2013/2014        #        #        #        #        #        #        #        #        #        #     232      121      #
2014/2015   26.2     10.7     6.61     3.67     2.64     4.01     4.79     5.58     77.5     86.8          #        #      #
ZZZZZZZZZZ
```

Figure 6.16 Original monthly river flow data of station H5H004, acquired from DWA

Table 6.8 Monthly river flow data of stations H5H004 and H7H006 in million m^3, acquired from DWA

	2014					2015							
station	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Annual
H5H004	232	121	26.2	10.7	6.61	3.67	2.64	4.01	4.79	5.58	77.5	86.8	581.5
H7H006	291	189	47.2	21.6	16.3	4.99	4.36	10.4	13.5	7.3	120	152	877.65

From Figure 6.14 it is clear that most water is consumed by the ULU, with this class covering more than half of the catchment area. Although the MWU covers less than half the area covered by the MLU, the water loss through ET of the MWU is 80% of the water loss in MLU class. Both Figure 6.14 and Table

6.8 show that there is more outflow of water at the outlet of the catchment than what the ecological reserve requires. This could mostly be attributed to high discharges in August and September 2014, as well as June and July 2015 (Table 6.8). These high discharges were measured both at the entry point of the catchment and downstream of the outlet. This suggests that additional water available during wintertime can be stored and utilised for irrigation during the summer season. Currently, there are no (significant) storage dams in the catchment.

WA+ Sheet 2: Consumption H5 – Breede

The completed Sheet 2 is shown in Figure 6.17. High evaporation losses (approximately 13%) were recorded, especially under "manageable" shrubland. This is likely due to the large proportion of bare soil between fynbos shrubs. Under denser vegetation cover, such as rainfed crops or grasslands, the evaporation losses are lower (8–9%). The lowest relative evaporation losses were recorded for irrigated areas. The average loss of water through evaporation, i.e. water that is lost without being beneficial to any plant growth, was estimated at slightly over 10% for this secondary catchment. The largest ET rates were found along the main river, as can been seen in Figure 6.18. This is where substantial areas under irrigated vineyards and riparian vegetation (including invasive alien plants) are likely situated.

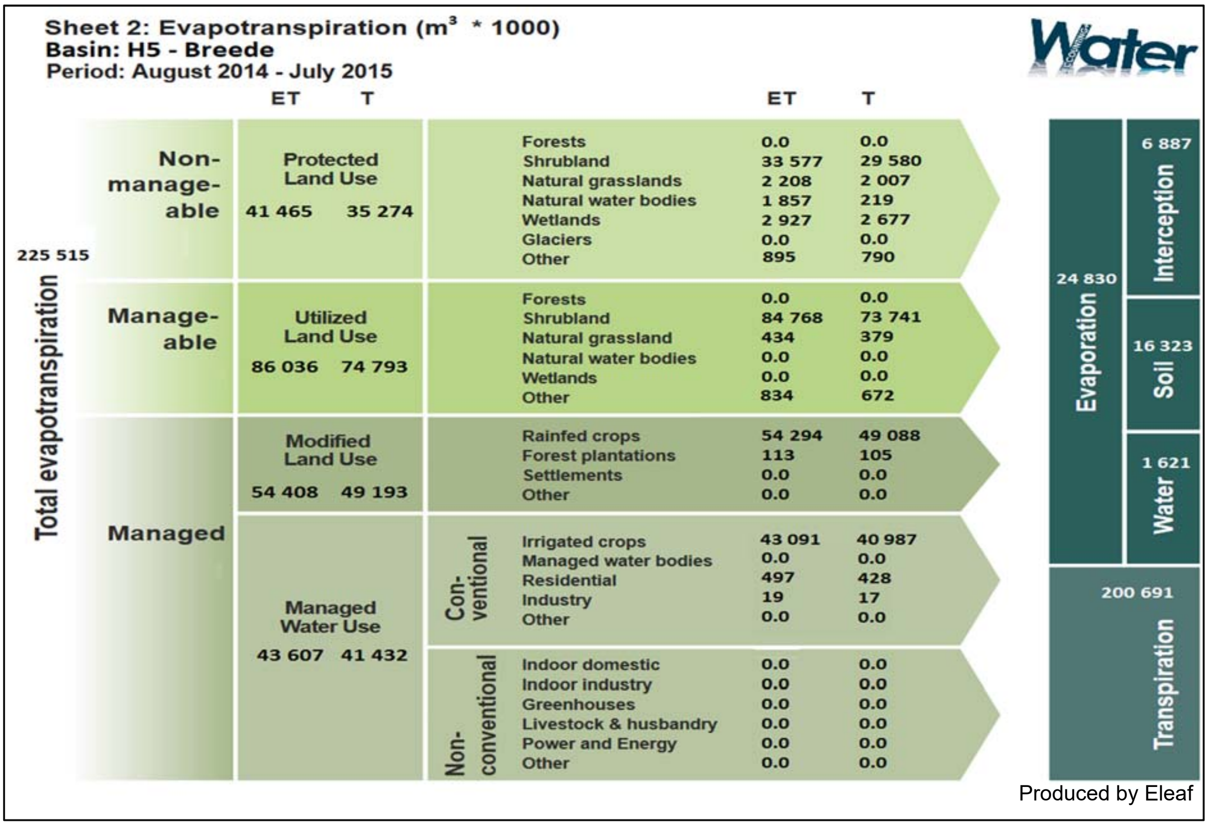

Figure 6.17 WA+ Sheet 2: Evapotranspiration in H5 – Breede

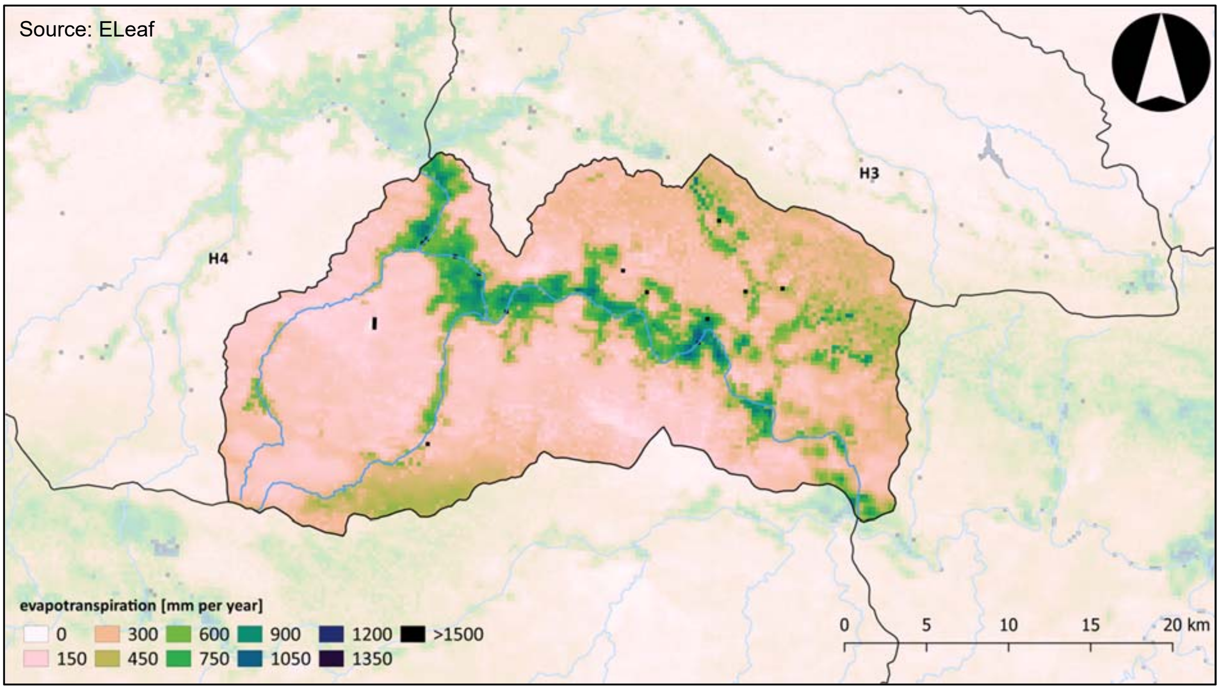

Figure 6.18 Annual evapotranspiration in the H5 – Breede catchment

WA+ Sheet 3: Productivity H5 – Breede

Table 6.9 shows that most field crops in H5 are rainfed, while orchards and vineyards comprise most of the irrigated area.

Table 6.9 Area of Rainfed and Irrigated Agriculture per service class in ha based on the 250m resolution maps used in this analysis

	Area Rainfed (ha)	Area Irrigated (ha)
Field Crops	12 600	419
Pivots	500	569
Vineyards & Orchards	3 119	5 750
Plantations	25	50

The relatively large area of vineyards & orchards classified as rainfed is inconsistent with local knowledge. This misclassification was caused by the generalised nature of the DAFF field boundary dataset used as input to the IAM. Some irrigated vineyards and orchards along the Breede River were grouped into large polygons that include other non-agricultural land uses and were thus erroneously classified as rainfed (because of the overall low ET within the polygons). Table 6.9 illustrates the impact of such errors on local applications. Such errors can be avoided by improving the quality of the field boundary database of South Africa (see APPENDIX V).

Figure 6.19 presents the outcome of Sheet 3, based on data generated in this project. Water productivity of field crops was highest (6.31 kg/m^3) in irrigated areas, while being lower (5.74 kg/m^3) in rainfed fields. Plantations also had a high average water productivity. The water productivity of vineyards and orchards produced under rainfed and irrigated conditions were comparable to but notably lower than that of other agricultural services. In this catchment, most water was used (consumed) by irrigated vineyards and orchards, followed by rainfed field crops. Interestingly to note is that the area covered by orchards and vineyards was actually less than half of the area covered by field crops.

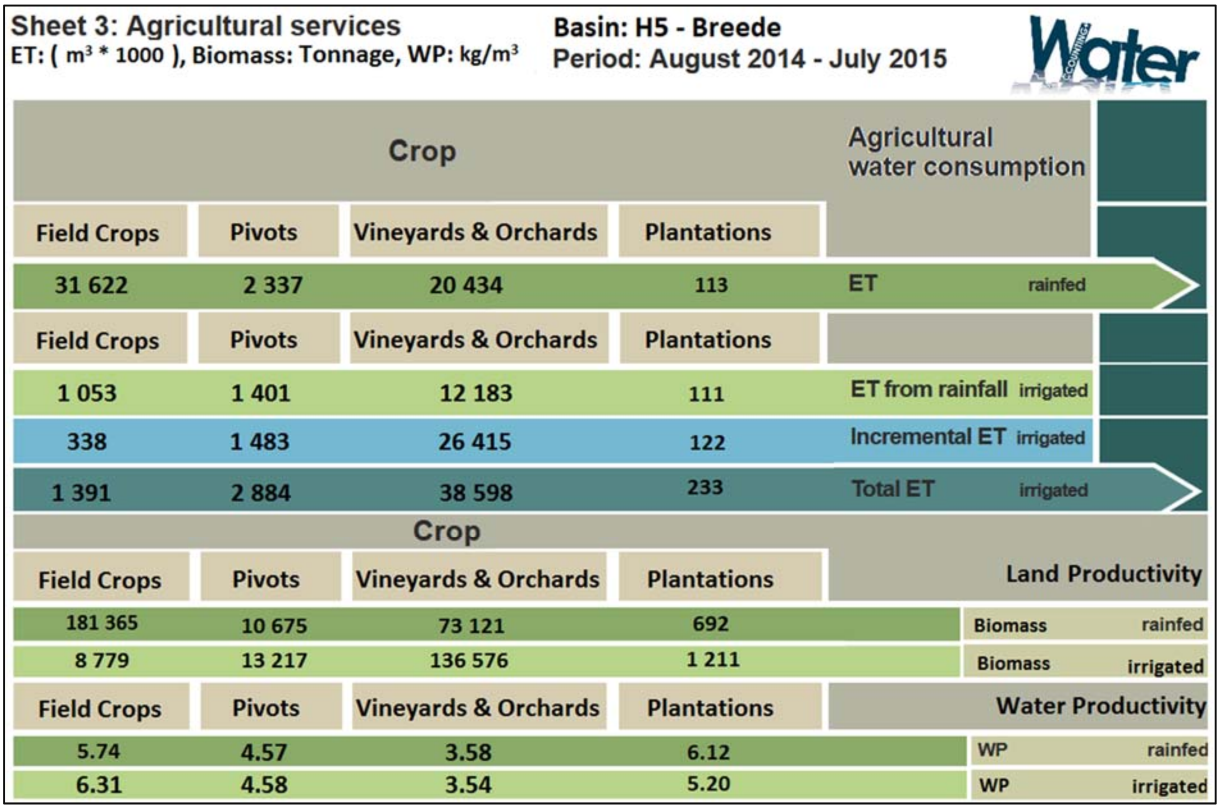

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Figure 6.19 WA+ Sheet 3: Agricultural Services in H5 – Breede

<u>WA+ Sheet 4: Withdrawals H5 – Breede</u>

The results of Sheet 4 for the secondary catchment H5 are shown in Figure 6.20. The results show that there is an ET deficit of about 12% for irrigated agriculture (when taking into account actual water used and water demand based on potential ET). This might indicate a need for expansion of water storage for irrigation purposes. Additionally, stress caused by extreme weather conditions might also influence the significant average ET deficit. Water stress (deficits) also occur in most of the natural land use classes. The residential demand was estimated in the same way as was done for catchment H4 (see Section 6.4.1), using data from DWA (2012b) and CIESIN (2016).

An estimation of return flows was made by DWA (2012b) for the entire Breede River catchment (Table 6.4), but no return flow information could be found for sub-catchment H5. Hence, no information on return flows in entered in Sheet 4.

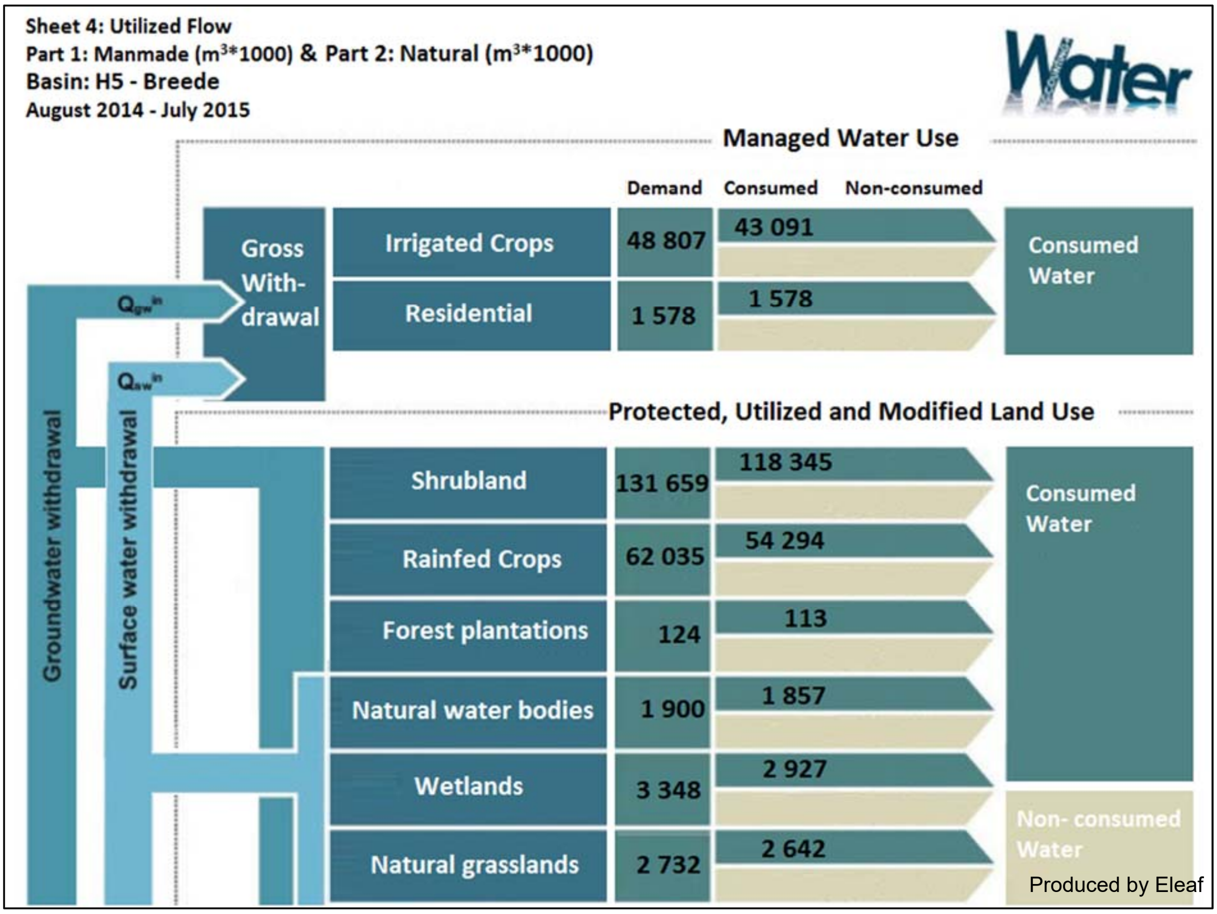

Figure 6.20 WA+ Sheet 4: Water withdrawals in H5 – Breede

Concluding remarks: H5 – Breede

Based on the WA+ framework, there seems to be potential for additional storage of water during the winter rainfall period. Sheet 1 shows an additional utilisable outflow of 212 million m^3 in this catchment in addition to the ecological reserve. The utilisable outflow was calculated as the difference between the ecological reserve and the (estimated) discharge at the outlet of this catchment. The need for additional irrigation water seems apparent, based on the relatively high demand compared to consumption (demand exceeds supply by 12%) of water in irrigated agriculture shown in Sheet 4. This could also indicate sub-optimal irrigation system design or irrigation scheduling. Heat waves in summer might also influence this estimated shortage, as crops will not transpire optimally under extreme weather conditions. More local research is needed to further interpret these results. The water consumption by irrigated crops is close to 43 million m^3, based on the monitoring period.

6.4.3 Verlorenvlei (G3)

Verlorenvlei is located in the northern part of the Western Cape. This sub-catchment covers approximately 5 160 km^2. The more prominent towns are located along the coast, including Lambert's Bay and Elands Bay. There is a large fresh water lake at the ocean's border where a small estuary connects the lake to the ocean.

Apart from some patches of fynbos, almost all land in this catchment is used for agricultural purposes (Figure 6.21). There is a larger number of centre pivot irrigation systems, mostly used in a crop rotation system for the cultivation of vegetables, particularly potatoes. Figure 6.22 shows that close to 95% of the agricultural land in this catchment had not been irrigated during the monitoring period of this project. There are no tributaries feeding into this secondary catchment, although there are multiple channels running through the sub-catchment into the ocean.

G3 was selected for this WA+ demonstration as it has the highest proportion of modified land use for rainfed agriculture in SA.

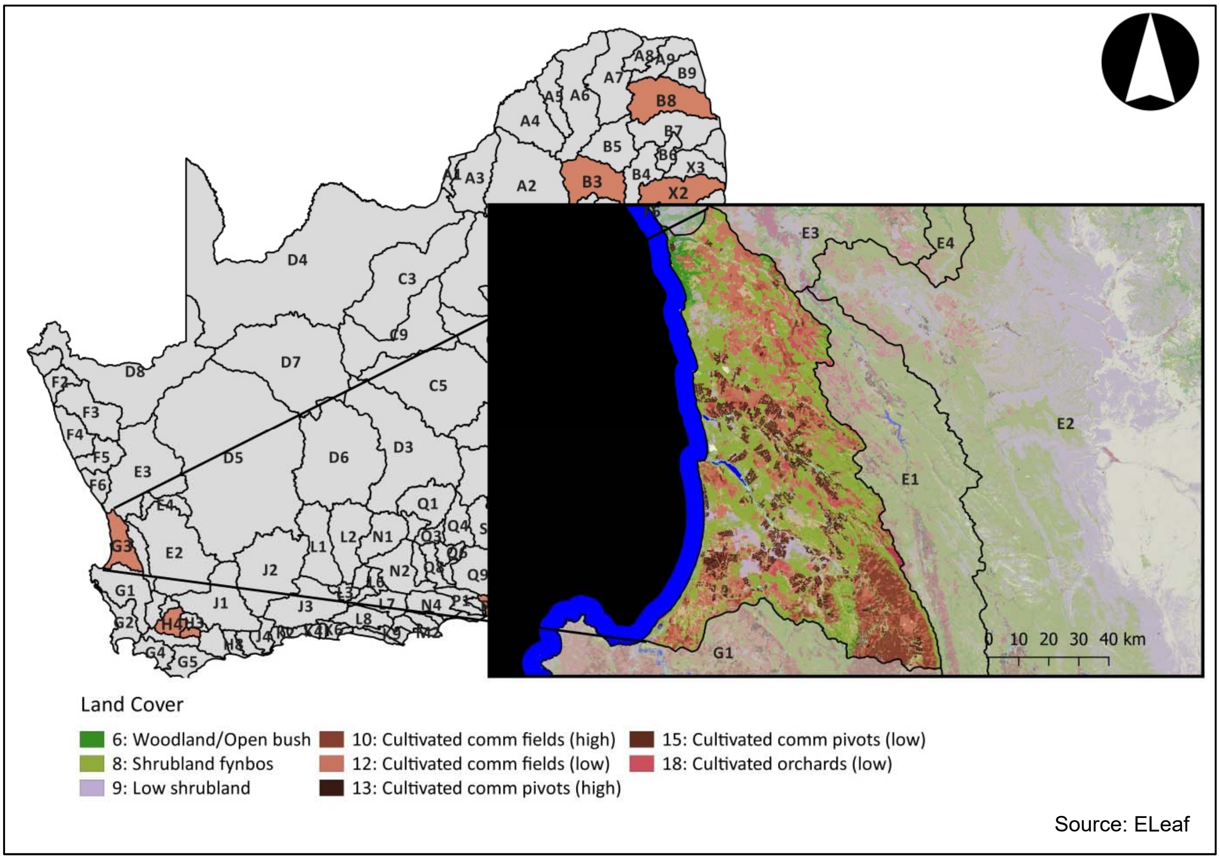

Figure 6.21 Location of secondary catchment G3 – Verlorenvlei and land use based on SALC1314

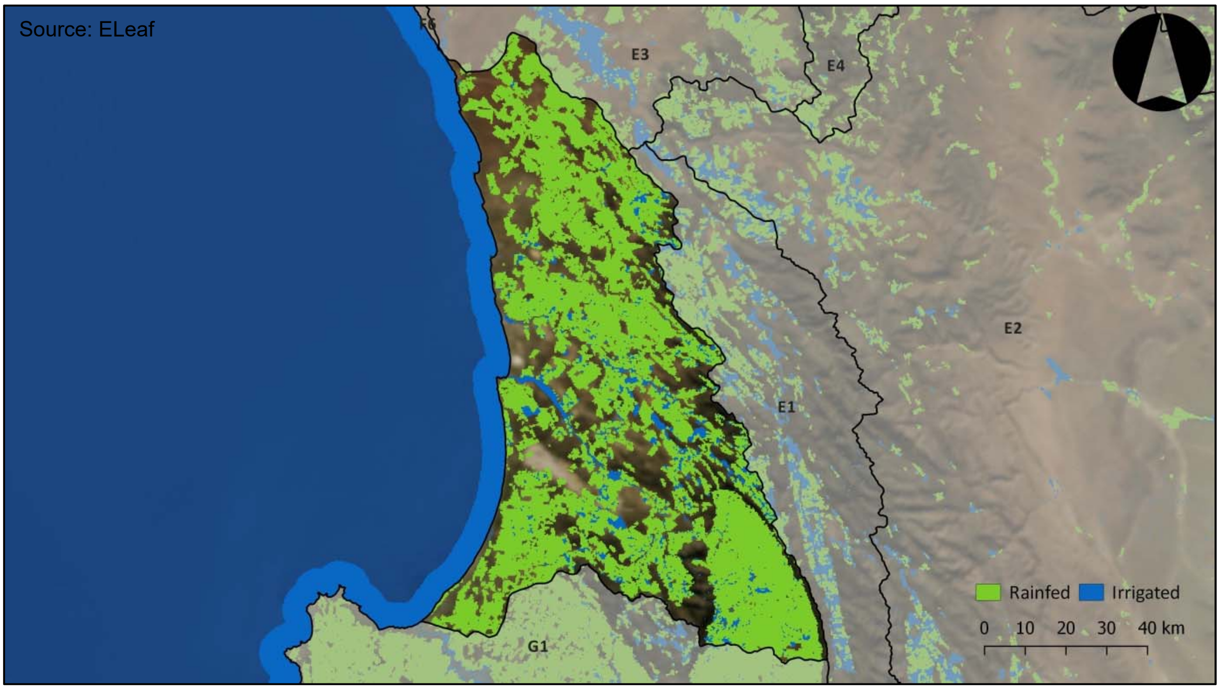

Figure 6.22 Secondary catchment G3, showing non-agricultural areas (brown), rainfed (green) and irrigated agricultural areas (blue)

WA+ Sheet 1: Resources G3 – Verlorenvlei

The PLU-class represent 173 km^2 of the catchment, while the ULU, MLU and MWU classes cover 2 822 km^2, 2 042 km^2 and 125 km^2 respectively. The resulting Sheet 1 for catchment G3 is displayed in Figure 6.23.

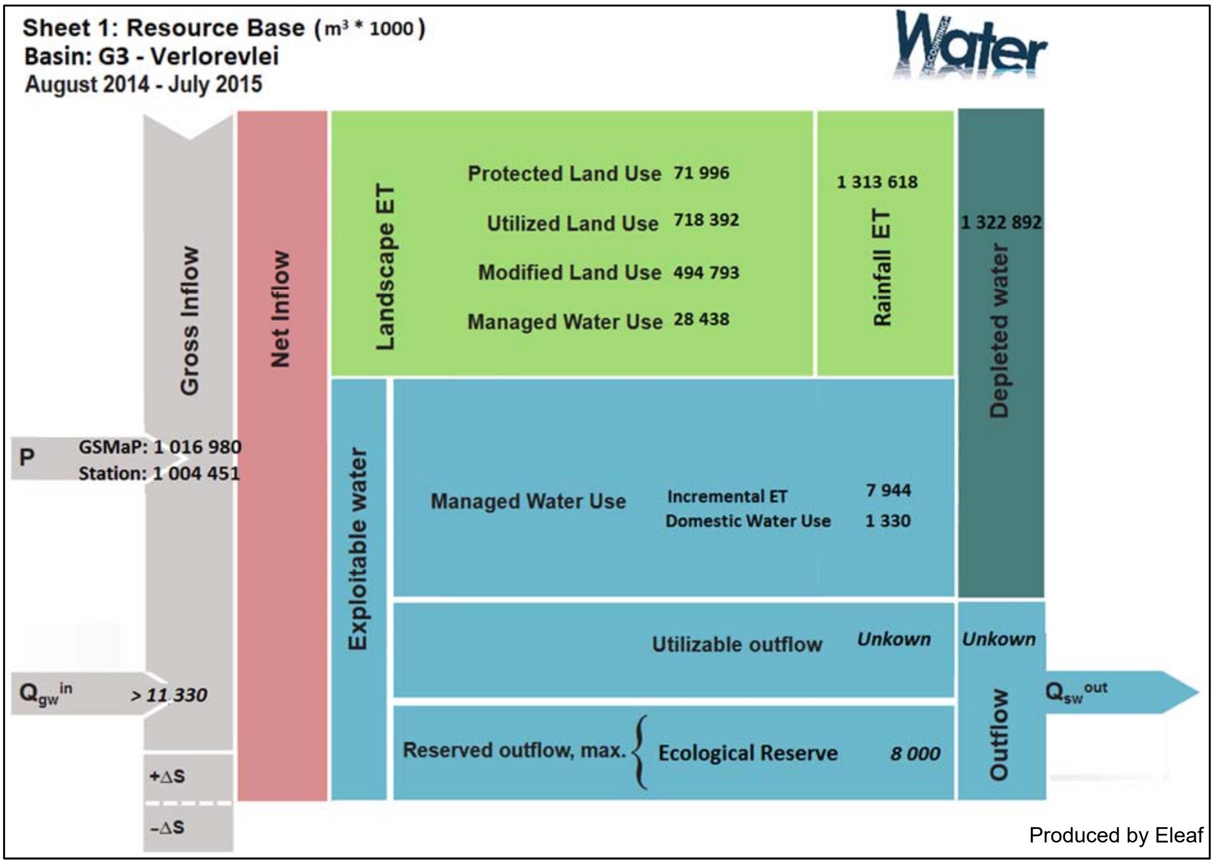

Figure 6.23 WA+ Sheet 1: Resources in G3 – Verlorenvlei

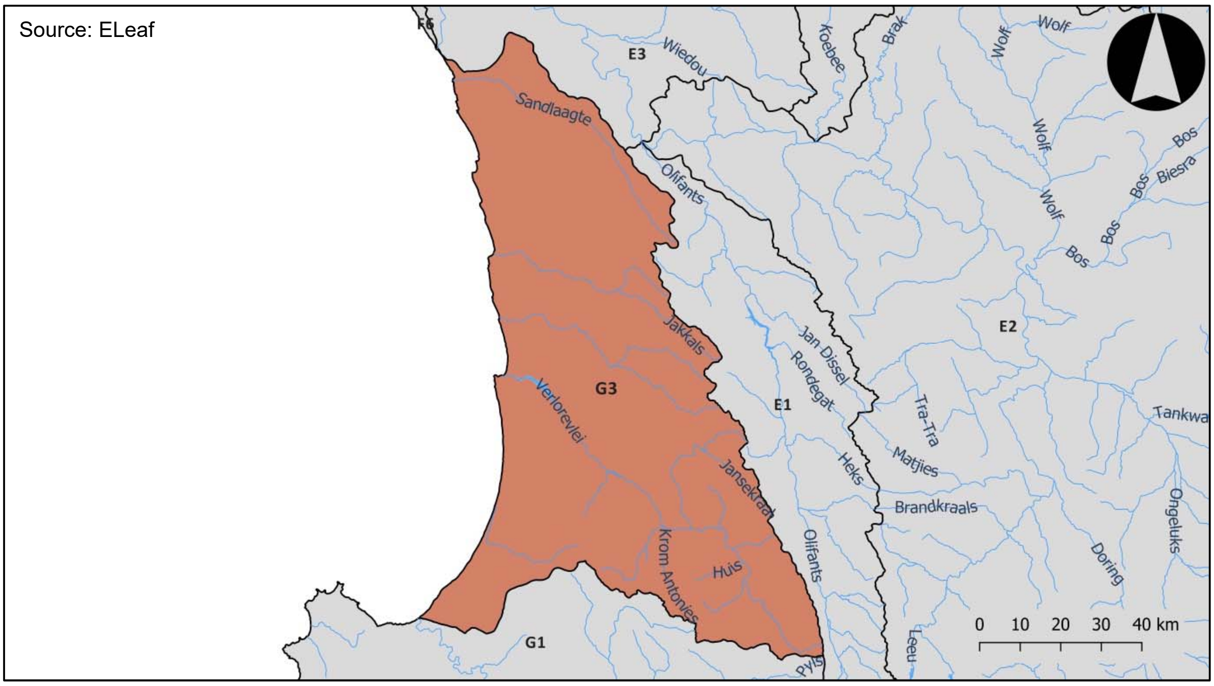

Figure 6.24 No operating DWA streamflow stations within the Verlorenvlei area

In the G3 secondary catchment, the ULU and MLU are the biggest consumers of water. Most of the water utilised likely comes from rainfall. There are no large storage dams in the Verlorenvlei area and no operating stations from DWA in the Verlorenvlei area from which discharge information could be obtained (Figure 6.24). This means the outflow of the various watercourses into the ocean is unknown. Simultaneously, the sub-catchment is a closed system. There is no river flowing into the catchment. As such, rainfall and groundwater are the only sources of water. The ecological reserve is estimated at 8 million m^3, as stated by a report from Blackhurst et al. (2002b) on the Olifants/Doring Water Management Area. According to the same report, there is between 1.3 and 1.5 million m^3 of water required for domestic consumption.

The DWA aquifer classification map shows that significant abstraction of groundwater takes place in this area (DWA 2012a). This was confirmed by CSIR (2009) in a study on estuary management. The four quaternary catchments G30B, G30C, G30D and G30E together account for approximately 10 million m^3 of groundwater abstracted. These quaternary catchments cover the bulk of irrigated agriculture identified during the irrigated area mapping process within this project. Additionally, according to the Groundwater Strategy (DWA 2010), there is significant extraction of groundwater for municipal use in the coastal region near Lambert's Bay and Elands Bay. Assuming municipal water use is purely based on groundwater and taking into account the earlier mentioned 10 million m^3 of water use in irrigated agriculture, it is estimated the total groundwater use is *at least* 11.3 million m^3/yr. The total potential (water) yield within the entire Olifants-Doring area, of which the Verlorenvlei catchment is part, is 157.5 million m^3/yr according to DWA (2010).

From Figure 6.23 it is clear that the estimated amount of water going into the catchment (extracted groundwater (Q_{gw}) plus precipitation (P)) is significantly less than the depleted water. This does not include outflow yet, as there are no measurements available from the different waterways. This dissimilarity is likely due to the underestimation of the rainfall amounts. Based on GSMaP rainfall data, there should be approximately 1 000 million m^3 of water available through precipitation. Interpolation of stations measurements from ARC and NOAA lead to a similar estimation. However, it seems likely that precipitation is significantly underestimated on higher altitudes, especially within the upstream areas. According to the NDVI maps generated in this project, the mountainous areas are also the most vegetated areas, suggesting high water consumption and water availability.

In Figure 6.25 the annual precipitation obtained from GSMaP (August 2014 to July 2015) is compared to the mean annual rainfall as depicted in CSIR (2009). Especially notable is the variation in Figure 6.25a, which can be linked to local topography. This variation is not visible in Figure 6.25b showing the same area. Unfortunately, there is no station data from NOAA or ARC from the high-lying areas, therefore the source of the difference in precipitation could not be investigated.

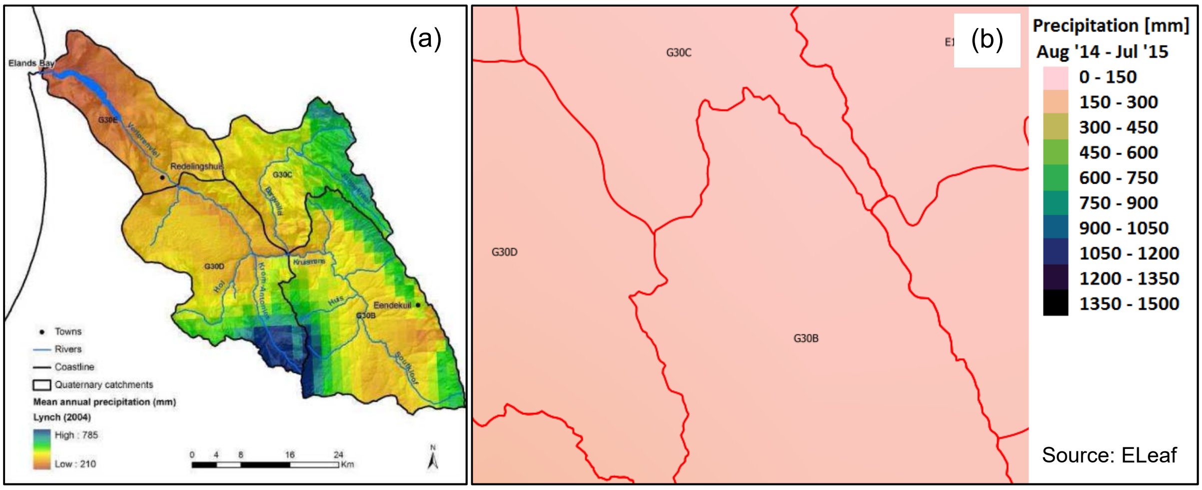

Figure 6.25 The mean annual precipitation estimates for the G3 secondary catchment (a) obtained from CSIR (2009) and (b) estimated precipitation obtained from GSMaP for the same area.

<u>WA+ Sheet 2: Consumption G3 – Verlorenvlei</u>

The completed Sheet 2 is shown in Figure 6.26, with the corresponding annual ET map shown in Figure 6.27. In catchment G3, most water is consumed by the ULU, particularly grass- and shrubland. Shrubland is mostly located on the sloping areas in this sub-catchment. There are significant areas of rainfed croplands, consuming 494 million m^3 of water through ET. Apparent are the large evaporation losses on this land use type (close to 18%). The rainfed fields are likely barren for a significant period of the year, which might cause higher evaporation due to a large, exposed soil surface. Additionally, not all areas identified as rainfed cropland were productive during the monitoring period. This is likely linked to crop rotation of potato farming. The evaporation losses from irrigated cropland are lower at around 14%.

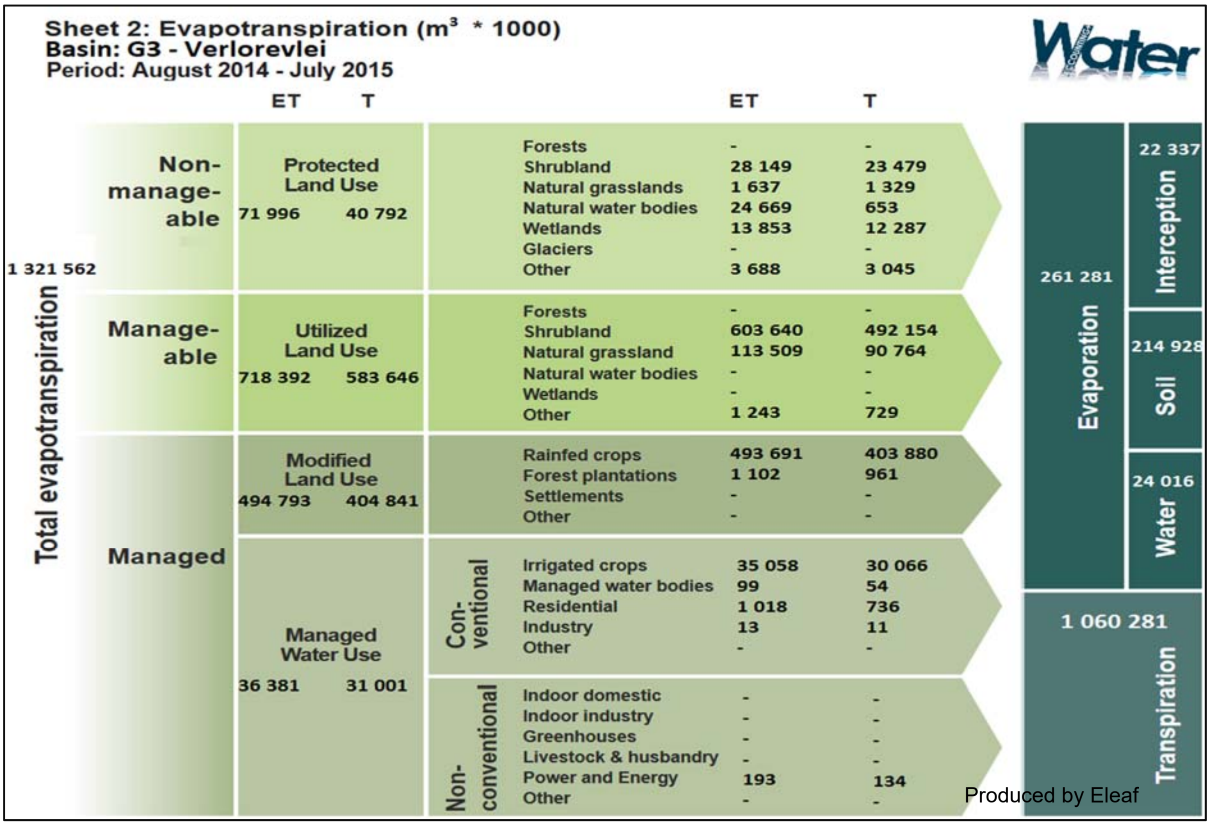

Figure 6.26 WA+ Sheet 2: Evapotranspiration in G3 – Verlorenvlei

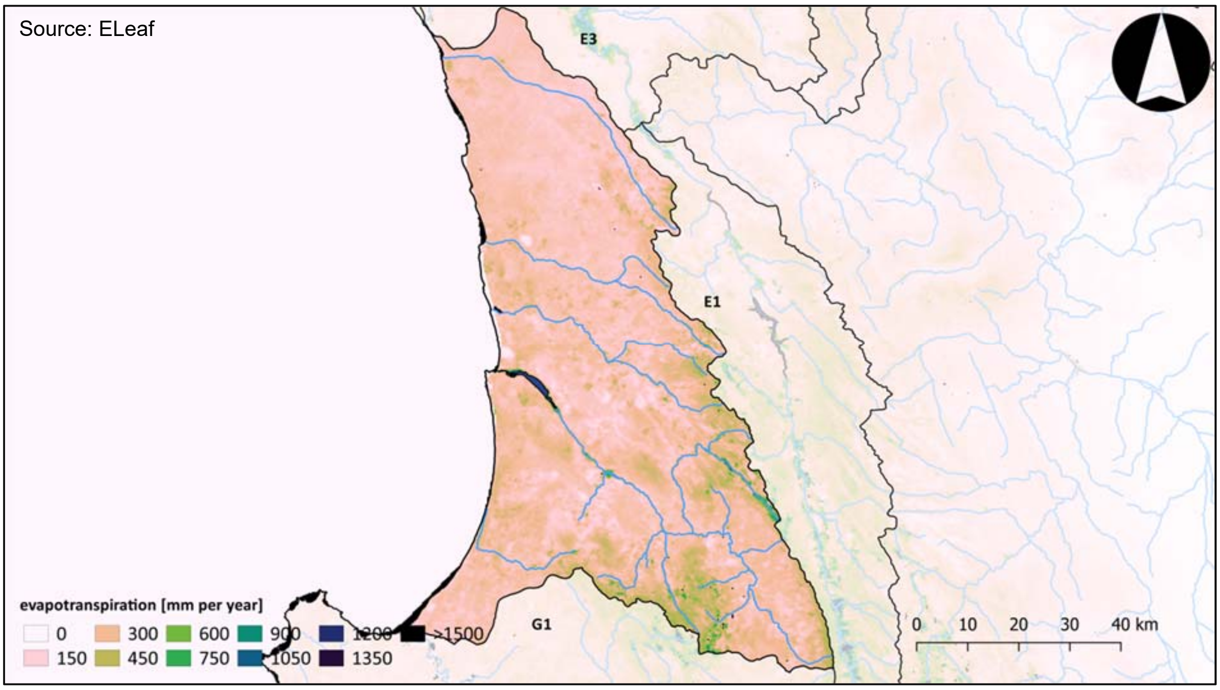

Figure 6.27 Annual ET for the G3 – Verlorenvlei secondary catchment in mm/yr

WA+ Sheet 3: Productivity G3 – Verlorenvlei

Table 6.10 shows extensive areas under rainfed field crops, exceeding 150 000 ha in this sub-catchment. There are also large areas with centre pivot irrigation. Vineyards are also found in the region.

Table 6.10 Area of Rainfed and Irrigated Agriculture per service class in ha based on the 250 m resolution maps used in this analysis

	Area Rainfed (ha)	Area Irrigated (ha)
Field Crops	159 994	4 825
Pivots	34 125	4 113
Vineyards & Orchards	11 050	2 850
Plantations	363	19

Figure 6.28 presents the outcome of Sheet 3. The large areas of rainfed cropland are reflected in the high total water consumption (375 million m^3) and biomass produced (1.7 million tons). Additionally, there are large areas classified as cultivation under centre pivot irrigation. These are mainly used for production of vegetables. However, it is known that only a fraction of the pivots are utilised annually for irrigated crop cultivation, due to crop rotations, which is reflected in the relatively low area total water consumption and biomass production as well as the area irrigated (Table 6.10).

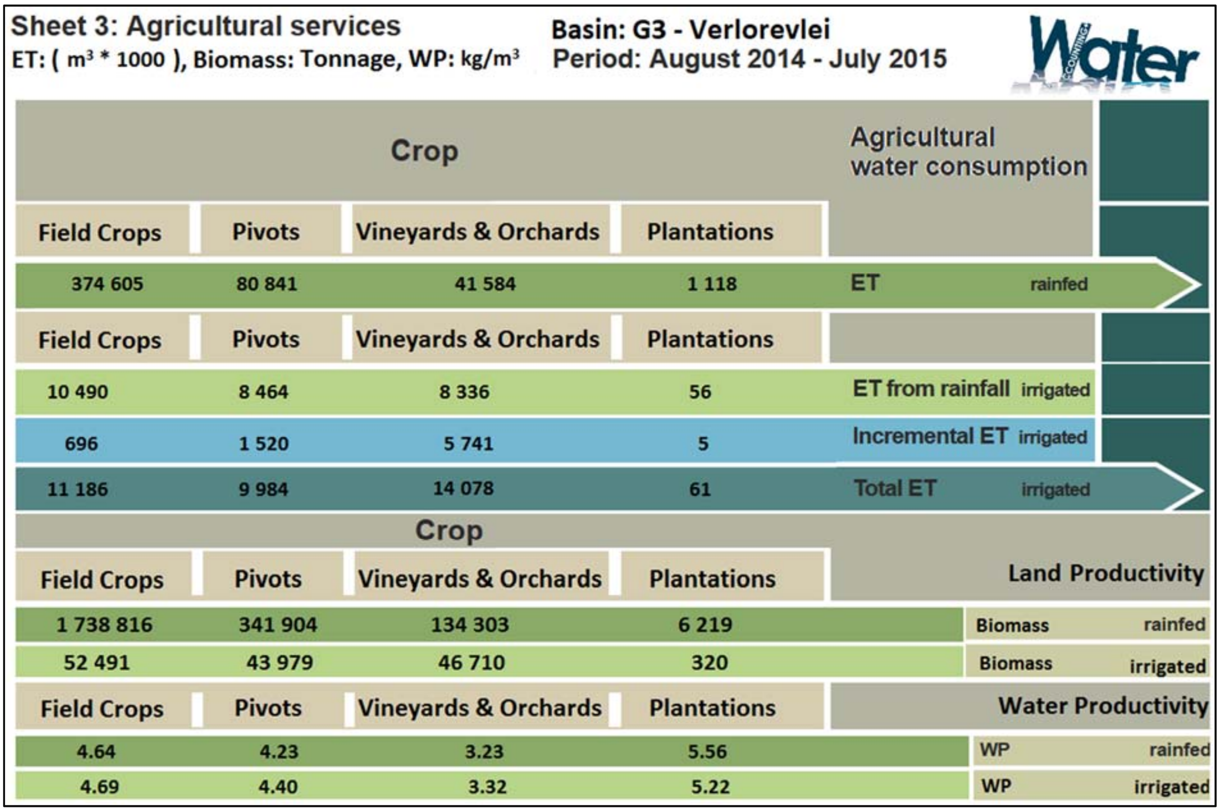

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Figure 6.28 WA+ Sheet 3: Agricultural Services in G3 – Verlorenvlei

WA+ Sheet 4: Withdrawals G3 – Verlorenvlei

The WA+ Sheet 4 for G3 is shown in Figure 6.29. This sheet shows that there is a water consumption deficit of about 12% for irrigated agriculture in this catchment. Water stress or deficits also occur for all of the natural land use classes, e.g. for rainfed croplands the ET deficit accounts to 13.5%, which is comparable to the ET deficit for irrigated agriculture.

The residential demand is estimated at 1.3 to 1.5 million m^3 of water (based on Blackhurst et al. (2002b). The capacity for domestic use in 1995 was 1.33 million m^3 of water per year. More recent numbers could not be found. The total return flows (non-consumed water) in the catchment, as estimated by DWA 2002, were 0.2 million m^3/yr, which is all lost to sea.

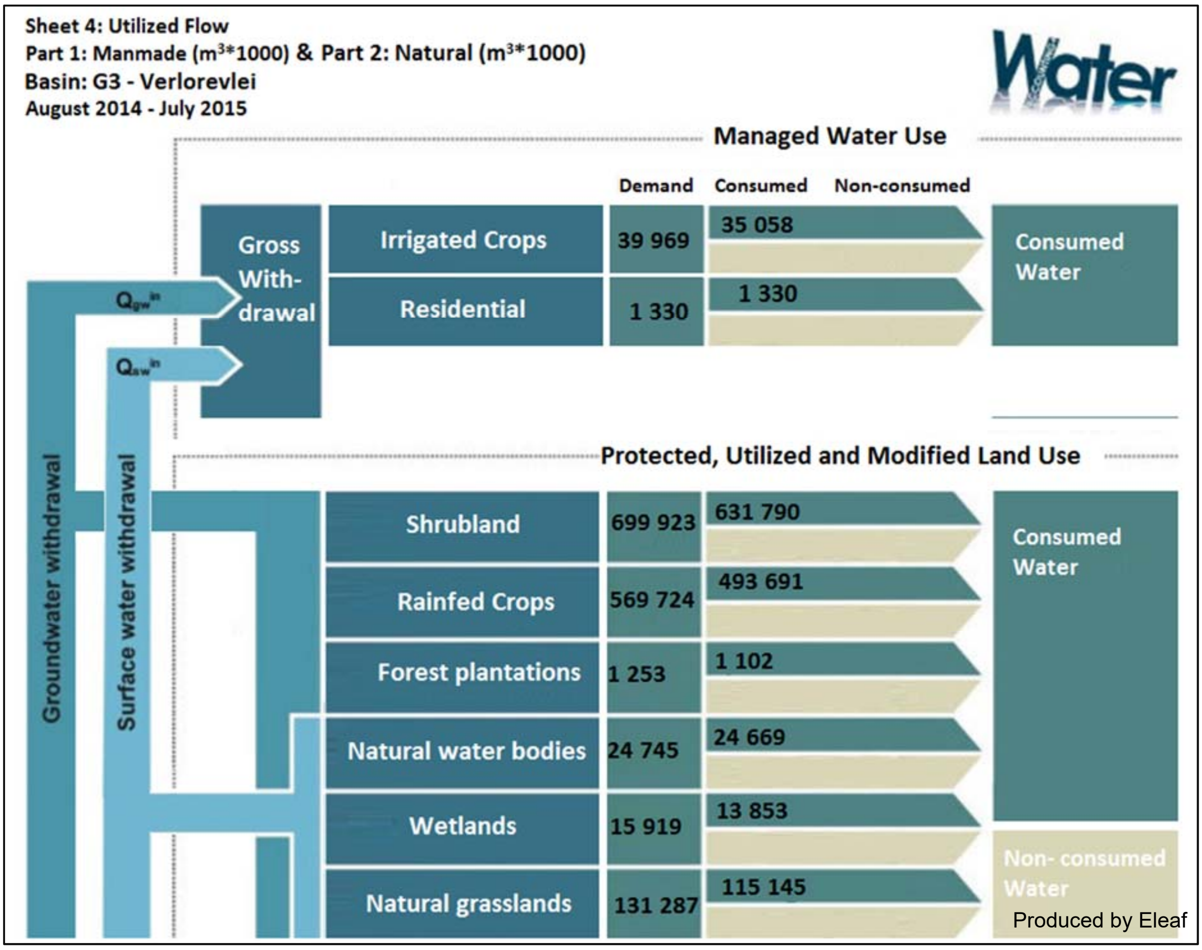


Figure 6.29 WA+ Sheet 4: Water withdrawals in G3 – Verlorenvlei

Concluding remarks: G3 – Verlorenvlei

The satellite-based precipitation information for the Verlorenvlei secondary catchment seems to be of low quality. Without any discharge measurement stations in the area, no conclusions on water availability from surface water resources could be drawn. The dependency of this secondary catchment on groundwater, both for domestic and agricultural use, appears to be substantial. Based on literature sources, the use of groundwater could potentially be expanded; however, this should be investigated with care.

6.4.4 Mzimvubu (T3)

The majority of T3 is located in the Eastern Cape; however, the eastern part of this secondary catchment is located in KwaZulu-Natal. This sub-catchment covers approximately 19 800 km^2. T3 is located directly south of Lesotho. The majority of the streams into this catchment originate in the Drakensberg mountains. As the sub-catchment borders both mountains and sea, there is a large elevation difference between the source and outlet of various streams.

The natural vegetation in this area is mostly grassland, but patches of bushland and thicket are located around the river channels in the southern part of the catchment (Figure 6.30). A significant portion of this catchment is used for subsistence farming, while there are a few small nature reserves in the region. Some forest plantations and commercial rainfed cropland also occur. Figure 6.31 shows that the majority of the agricultural land in this catchment was classified as rainfed for the monitoring period of this project.

T3 was selected for this WA+ demonstration as it is one of the most densely populated areas in SA, while a major city centre is absent. According to the Irrigation Strategy for South Africa, published by the DAFF in 2015 (DAFF 2015), expansion of the irrigated area by utilising water from the Umzimvubu Dam is likely.

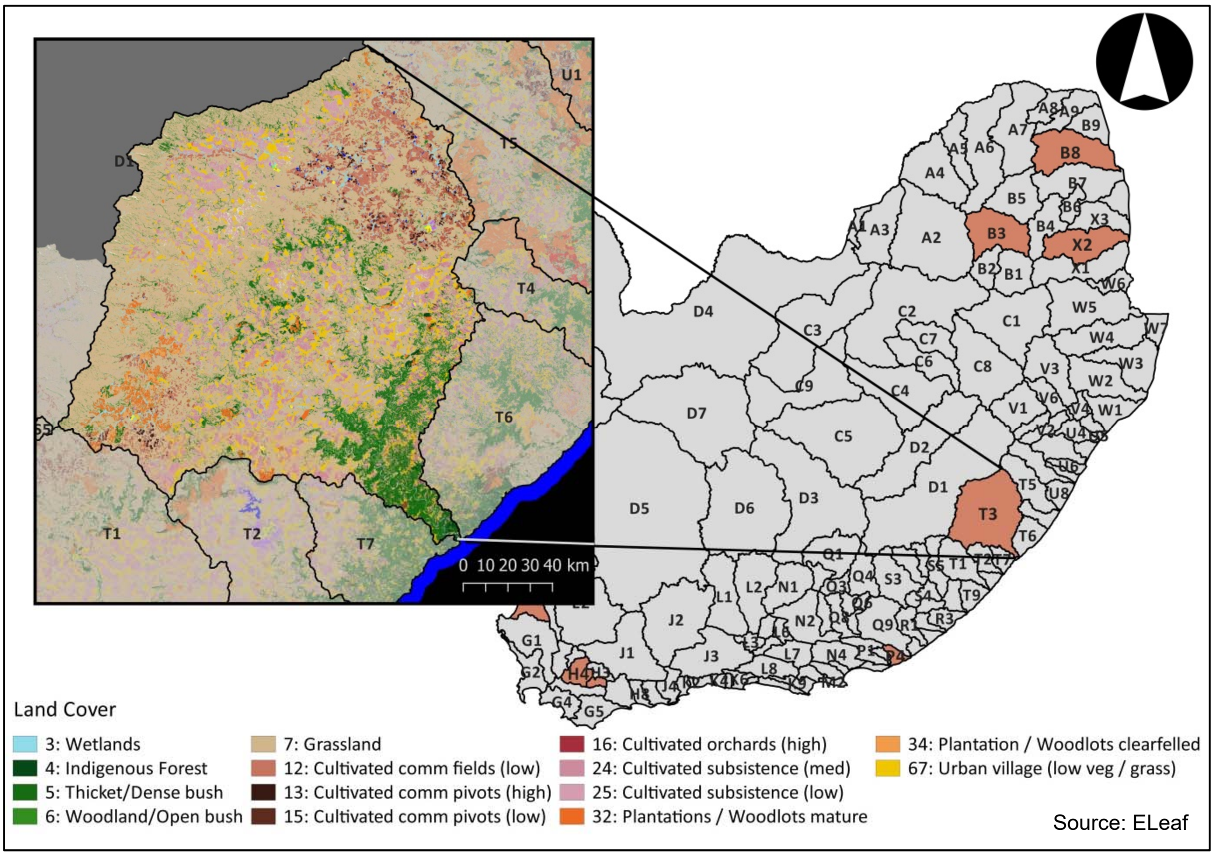


Figure 6.30 Location of secondary catchment T3 – Mzimvubu and land use based on SALC1314

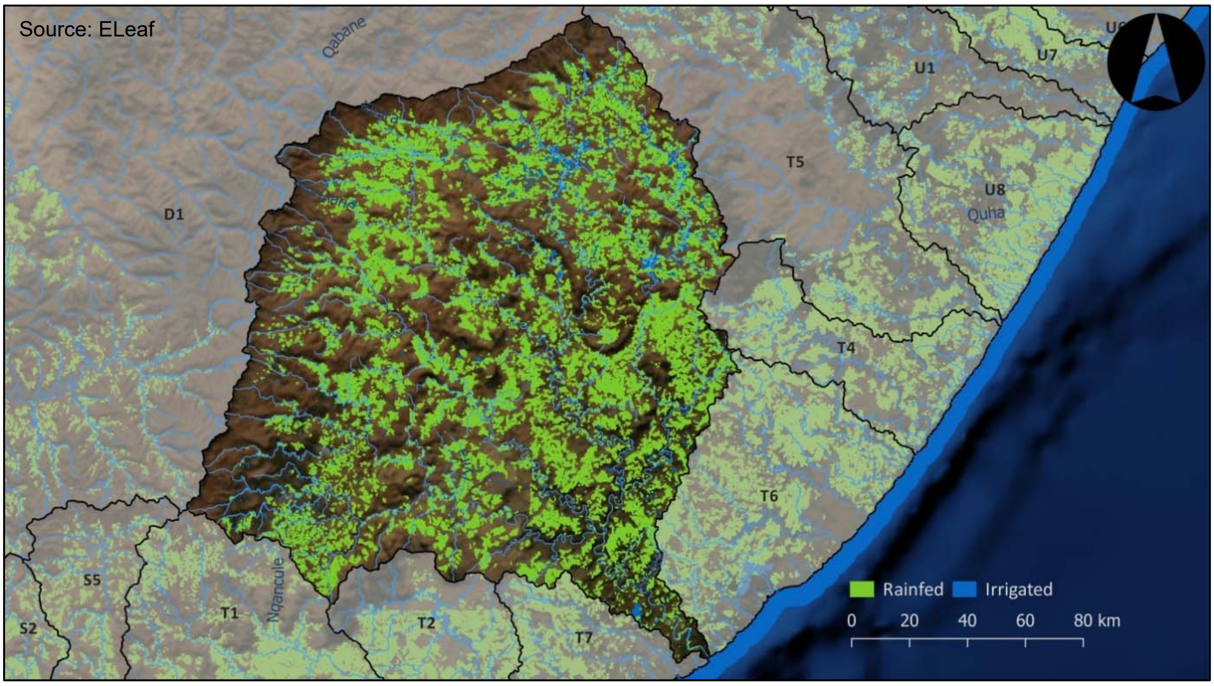


Figure 6.31 Secondary catchment T3, showing non-agricultural areas (brown), rainfed (green) and irrigated agricultural areas (blue)

WA+ Sheet 1: Resources – T3 Mzimvubu

The PLU-class represents 859 km^2 of the catchment, while the ULU, MLU and MWU classes cover 13 900 km^2, 3 582 km^2 and 1 460 km^2 respectively. Sheet 1 for catchment T3 is displayed in Figure 6.32.

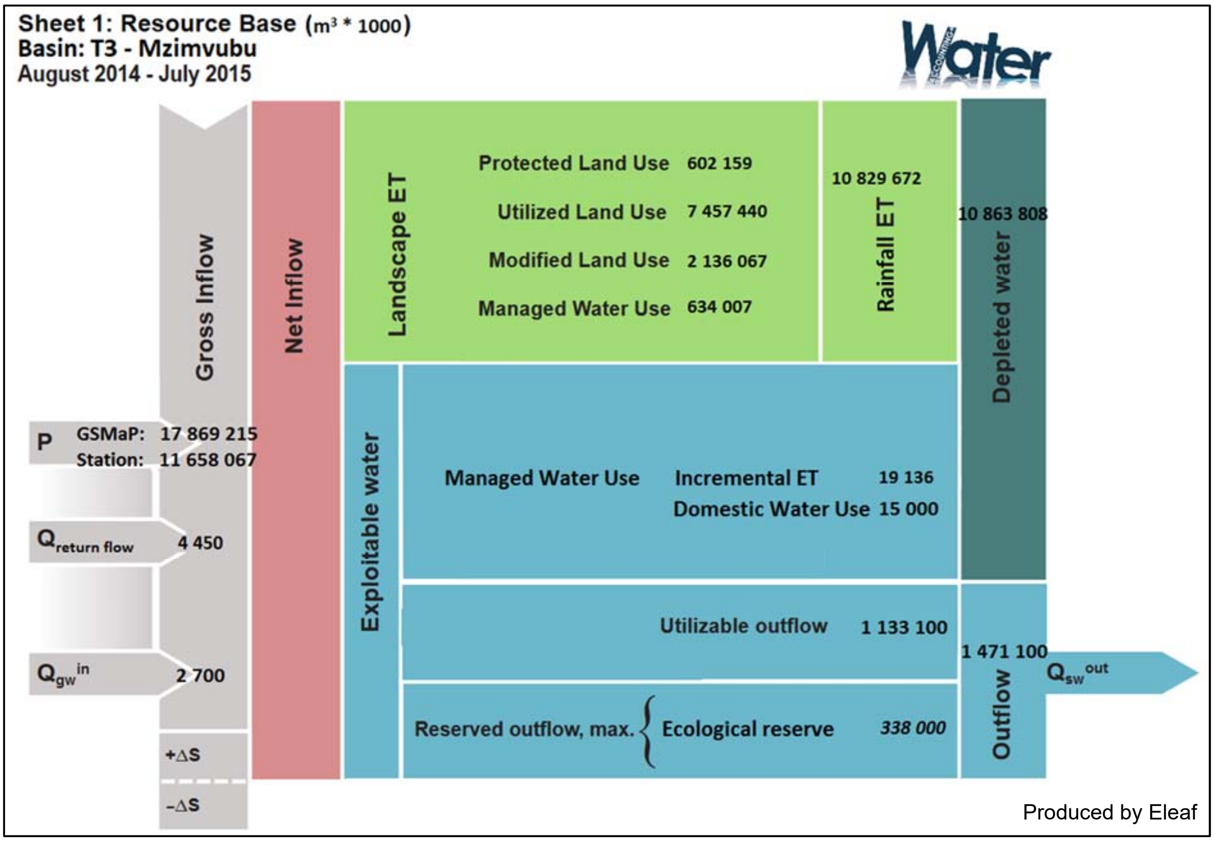


Figure 6.32 WA+ Sheet 1: Resources in T3 – Mzimvubu

The water resources from the Mzimvubu catchment originates mainly from precipitation. Precipitation estimates have been obtained from local weather stations and GSMaP satellite data. These estimates range between 11 658 and 17 869 million m^3 of water during the monitoring period. There are no major water storage facilities in this catchment. There is also very limited use of groundwater resources since surface water is abundant (Basson & Rossouw 2002). In 1995, the groundwater use was estimated at 2.7 million m^3 for the full Mzimvubu catchment (Blackhurst et al. 2002a). Return flows were estimated at close to 4.5 million m^3 by Blackhurst et al. (2002a) for this catchment.

There is no surface water inflow since Mzimvubu is a closed catchment. Outflow estimates were obtained from DWA station T3H020, which is located relatively close to the outlet of the catchment (Figure 6.33). According to this station, the outflow of the Mzimvubu River was 1 471 million m^3 of water between August 2014 and July 2015. This is far more than contained in the ecological reserve, which was estimated at 338 million m^3 of water per year (Basson & Rossouw 2002). This indicates there is potentially room for additional developments. This explains why Mzimvubu has been selected as one of the potential areas for expansion of irrigated agriculture in SA (DAFF 2015).

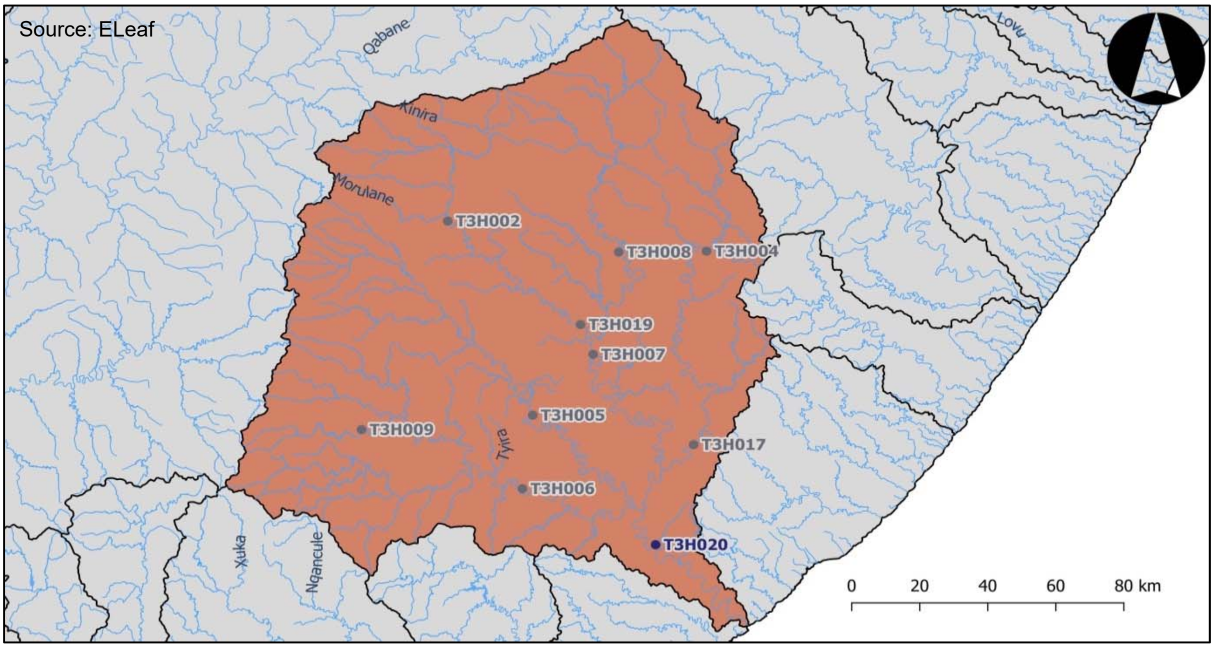


Figure 6.33 Location of operating DWA water stations in Mzimvubu.

Table 6.11 Monthly river flow data of station T3H020 in million m^3

	2014					2015							
station	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Annual
T3H020	23.4	14.2	26.3	80.9	285	414	276	148	121	34.9	19.9	27.5	1471.1

From Figure 6.32 it is clear that most water is consumed by ULU, mainly from extensive areas under grass- and shrubland. There is almost no irrigated agriculture in this area, and therefore relatively little MWU for agricultural purposes. The domestic water use in the catchment is approximately 15 million m^3 and there is almost no industrial use (Basson & Rossouw 2002).

WA+ Sheet 2: Consumption – T3 Mzimvubu

The completed Sheet 2 is shown in Figure 6.34. Mzimvubu consists of an extensive natural grassland area, which is reflected in the annual water consumption through ET for this land use class, represented in both PLU and ULU, of approximately 6 315 million m^3 for the monitoring period. Another large consumer of water was natural shrubland. In terms of agriculture, almost all crops within the Mzimvubu catchment were cultivated under rainfed conditions. Rainfed crops consumed approximately 1 824 million m^3 of water compared to 72 million m^3 of water by irrigated agriculture. Notable is the large amount of ET in residential areas due to large vegetated agricultural areas in-between houses. An aerial photograph shows a typical residential area in Mzimvubu in Figure 6.36.

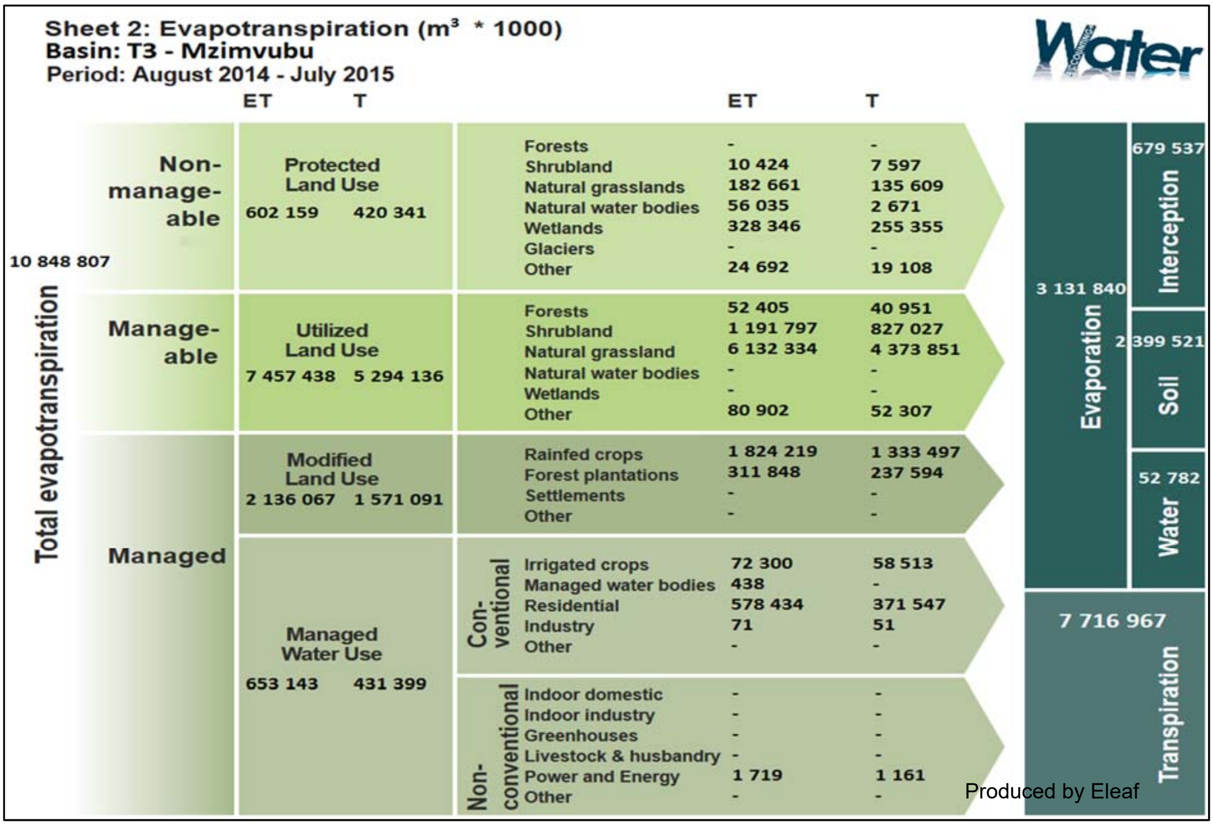


Figure 6.34 WA+ Sheet 2: Evapotranspiration in T3 – Mzimvubu

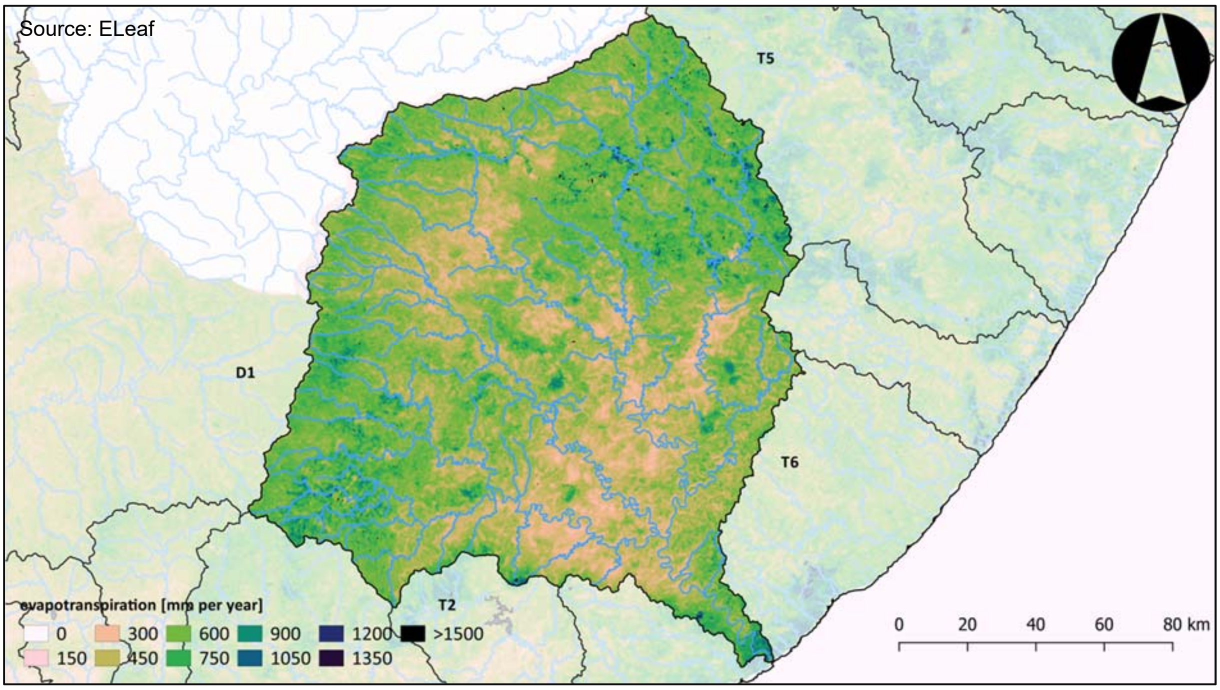


Figure 6.35 Annual ET from secondary catchment T3 – Mzimvubu in mm/yr

Figure 6.36 An aerial view of a typical residential area in Mzimvubu, showing large vegetated patches located in-between houses

WA+ Sheet 3: Productivity – T3 Mzimvubu

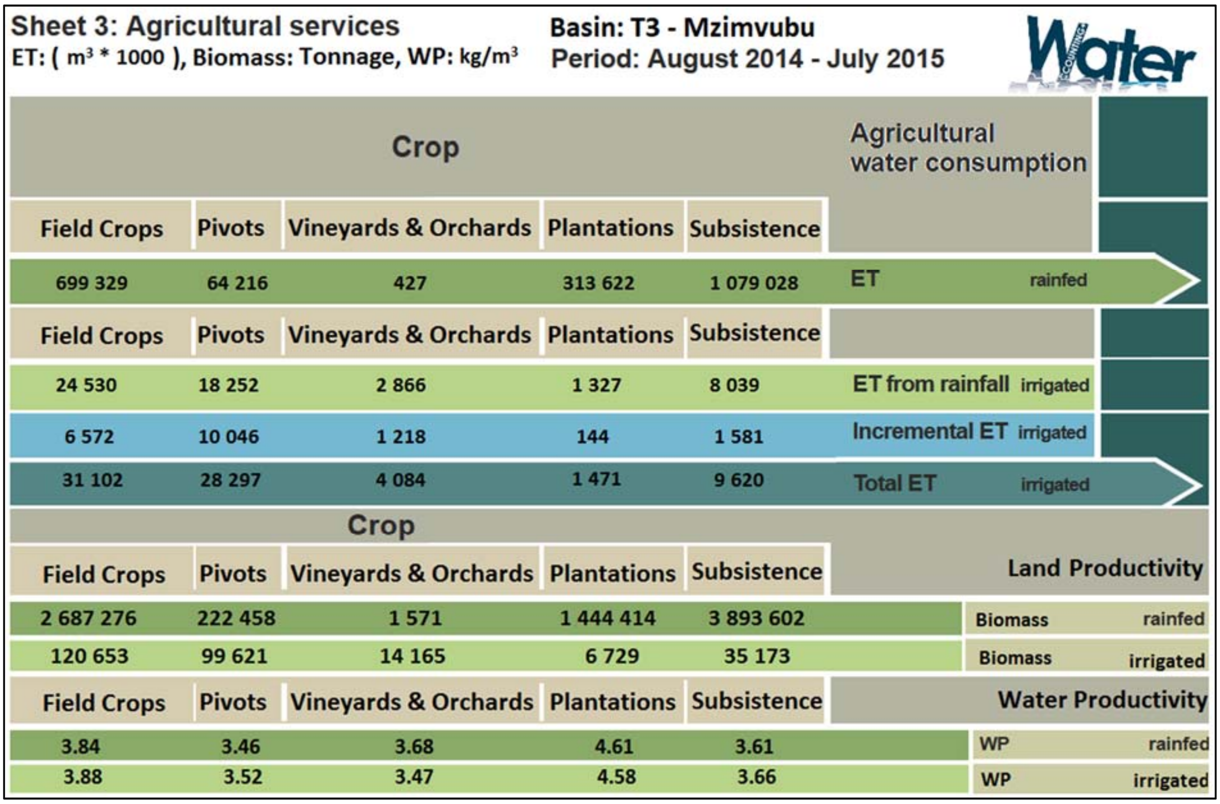
Table 6.12 shows that almost all crop cultivation, both regular or subsistence farming, in this area is rainfed. The area under rainfed subsistence farming is almost twice as large as regular rainfed fields. There are a number of centre pivots, but almost no irrigated fruit farming. There are also large areas of forestry.

Table 6.12 Area of Rainfed and Irrigated Agriculture per service class in ha based on the 250 m resolution maps used in this analysis

	Area Rainfed (ha)	Area Irrigated (ha)
Field Crops	106 113	4 094
Pivots	8 256	2 994
Vineyards & Orchards	56	406
Subsistence	201 875	1 581
Sugarcane	12	0
Plantations	44 963	219

Figure 6.37 presents the outcome of Sheet 3. Notably, on an annual average basis, the water productivity of fields under subsistence farming and regular fields were similar. Plantations are the most effective water users in terms of biomass production, with centre pivots showing the lowest water productivities. In this area, the water efficiency of irrigated field crops were lower than rainfed crops.

However, considering biomass production figures, irrigated fields are almost 15% more productive in terms of biomass in kg/ha (where this number shows the annual value and does not only reflect the growth's seasonality). When comparing the biomass production of rainfed subsistence farming with other rainfed crops, per hectare, it is clear that a typical rainfed field produces approximately 25% more biomass on an annual basis than a subsistence farming field.



Produced by Eleaf

Figure 6.37 WA+ Sheet 3: Agricultural Services in T3 – Mzimvubu

WA+ Sheet 4: Withdrawals – T3 Mzimvubu

The WA+ Sheet 4 for T3 is shown in Figure 6.38. Sheet 4 shows the potential of this catchment to provide sufficient water to several land use types. The results show that irrigated agriculture has an average ET deficit of approximately 8%, despite the Mzimvubu having sufficient water annually (also see Sheet 1). Precipitation exceeds 10 billion m^3 of water, and outflow at the catchment outlet into the ocean exceeds 1 billion m^3 of water. The ET deficits might relate to other causes, e.g. faulty irrigation scheduling or irrigation system design. Water stress (deficits) also occur in most of the natural land use classes, although they are relatively low.

Residential return flow estimates were obtained from Blackhurst et al. (2002a). The estimated return flow from urban areas was 2.3 million m^3/yr, based on information from 1995. The total return flow within the catchment was estimated at close to 4.5 million m^3 of water per year. The additional 2.2 million m^3 comes from irrigated agriculture.

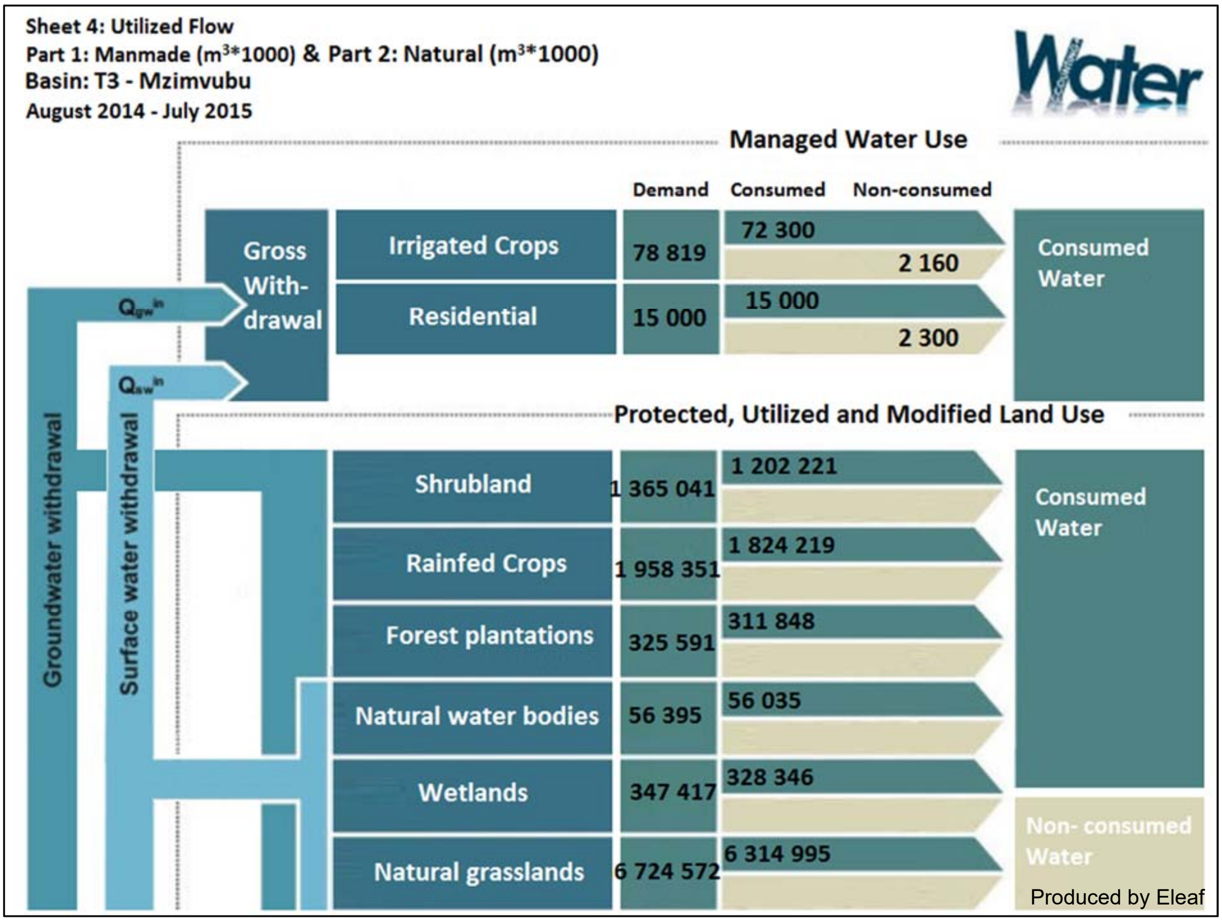


Figure 6.38 WA+ Sheet 4: Water withdrawals in T3 – Mzimvubu

Concluding remarks: T3 – Mzimvubu

To conclude, Sheet 1 shows there are significant amounts of surface water resources available in this catchment, which could be used productively for growing crops. The utilisable outflow far exceeds the ecological reserve by over a billion m^3 of water. This therefore indicates the potential for expansion of irrigated agriculture in this area is large. Within the residential area(s), significant vegetated areas exist, making the residential areas one of the biggest consumers of water throughout the catchment. In terms of the natural areas, extensive areas under natural grassland are responsible for half of the water consumed through ET in this catchment.

6.4.5 Kowie (P4)

Kowie (P4), a relatively small catchment (approximately 1 154 km^2) located in the Eastern Cape, is part of the Albany Coast. Port Alfred is the biggest town in this area, bordering the ocean on the river mouth. There is one major river in the area, namely the Kowie River. Its tributaries originate in the mountainous areas surrounding the catchment, close to Grahamstown. The Kowie River and some additional smaller streams discharge into the Indian Ocean.

The vegetation in the area is very bushy, especially on the slopes surrounding the stream channels (Figure 6.39). The flatter areas in the catchment are mainly used for fruit farming, particularly pineapples. Figure 6.40 shows that these areas have been irrigated during the monitoring period of this project. There is, however, also a significant portion of rainfed agriculture.

P4 was selected for two reasons: 1) it has a significant proportion of irrigated agriculture; and 2) the main river channel directly discharges into the ocean. If water with no productive value (either agriculturally or environmentally) is left in the system, this water will be lost to the ocean and recapturing it would be impossible.

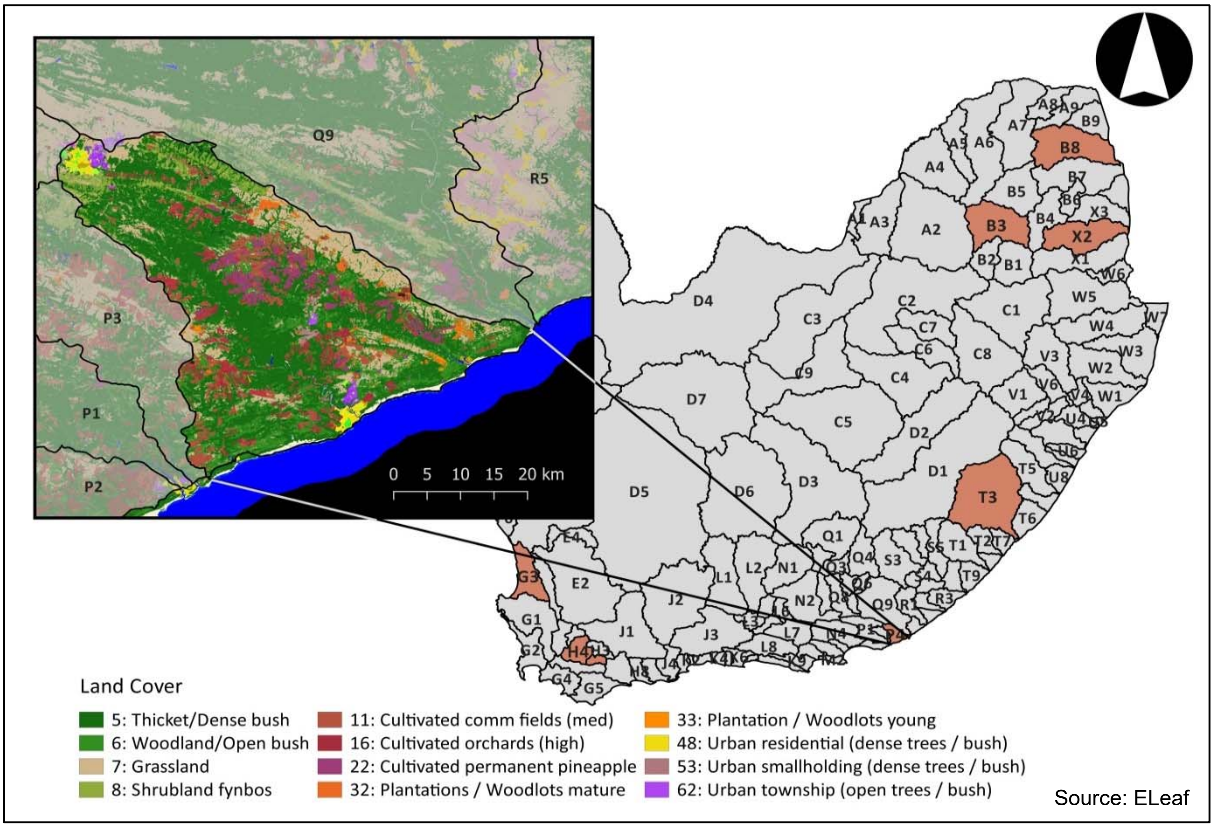


Figure 6.39 Location of secondary catchment P4 – Kowie and its land use based on SALC1314

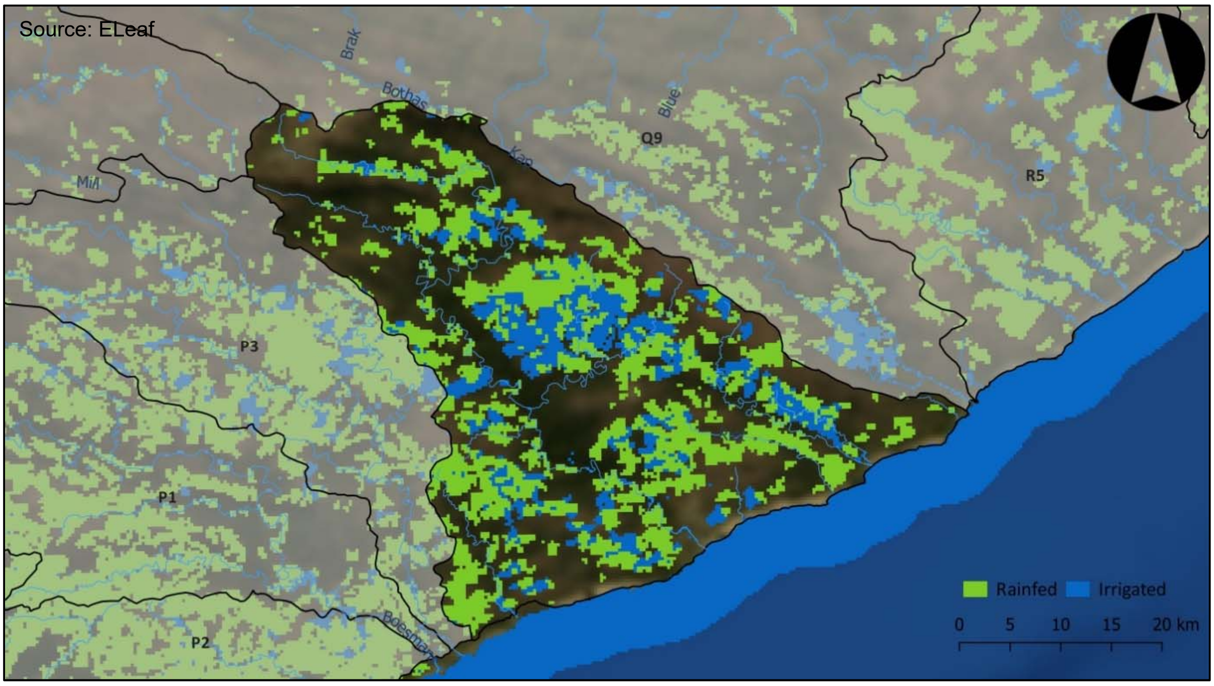


Figure 6.40 Secondary catchment P4, showing non-agricultural areas (brown), rainfed (green) and irrigated agricultural areas (blue)

WA+ Sheet 1: Resources P4 – Kowie

The PLU-class represents 70 km^2 of the catchment, while the ULU, MLU and MWU classes cover 834 km^2, 150 km^2 and 100 km^2 respectively. The resulting Sheet 1 for catchment P4 is displayed in Figure 6.41.

The water resources within the Kowie basin originate mostly from precipitation and there are no large storage dams in the area. The estimated available water from precipitation varies between 785 million m^3 (meteorological station data) and 1 499 million m^3 (GSMaP satellite data), depending on the source used. It appears that the station measurements are more accurate, since it reflects the conditions described in Fish to Sundays Internal Perspective (DWAF 2005). It is possible that the satellite-based precipitation information has been offset due to the proximity of the ocean, but as found in other catchments, the presence of mountains may have contributed to the poor GSMaP rainfall data.

Groundwater extraction occurs in this catchment, as stated in DWAF (2005). Groundwater is mainly utilised by small industrial users. Groundwater abstraction accounts for between 1.6 and 4.8 million m^3/yr for the whole Albany coastal region. For the purpose of this report, groundwater extraction was estimated at 2 million m^3/yr for the Kowie region. The absence of large-scale groundwater extractions in the Kowie region is confirmed by DWA (2010). There are three waste-water treatment works in the area that dispose water to irrigation or directly into the river, with volumes ranging between 1 000 m^3 and 4 000 m^3 a day; or up to 2.19 million m^3/yr.

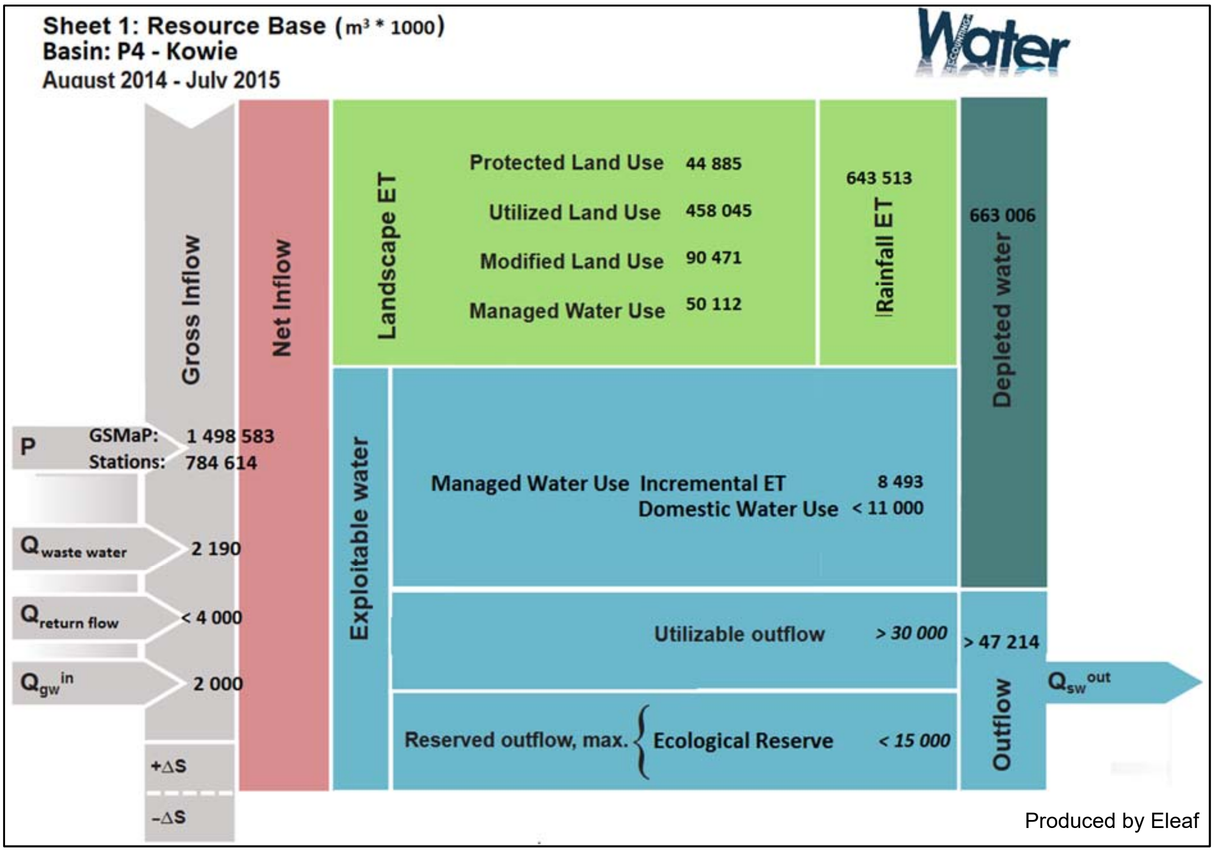


Figure 6.41 WA+ Sheet 1: Resources in P4 – Kowie

According to DWAF (2005), the scheduled water demand for irrigated agriculture in the Bushmans and Kowie/Kariega area is approximately 11 million m^3 of water per year. This is in line with the estimated incremental ET for irrigated agriculture gained from RS information. Incremental ET is the estimated additional water consumption by crops due to the additional use of irrigation water. The domestic water use is at most 11 million m^3, which is listed as the total urban and rural use in the Natural Water Resources Strategy 2004 for the entire Bushman's catchment. The same document does not list any notable demand for water by the industry in the area.

The P4H001 streamflow station is located in the centre of the sub-catchment (Figure 6.42). There is no other station in the area. As a result, only a part of the area's streamflow information is known. The discharge measured at this station between August 2014 and July 2015 is shown in Table 6.13. Large irrigated areas are situated upstream of this measurement station, hence it is safe to assume that the discharge during the monitoring period for the full catchment was at least 47.21 million m^3 of water. However, this does not account for any other water contributed by streams or rivers apart from the Kowie River. The ecological reserve for the Bushmans catchment, which includes Kowie, is 15 million m^3/yr, based on a natural mean annual runoff of 174 million m^3/yr in the entire Bushmans region. If this 15 million m^3 is considered the maximum ecological reserve for Kowie, it appears that there is approximately 30 million m^3 of water left for additional use in the catchment (listed as utilisable outflow in Sheet 1) based on the analysis of this single year.

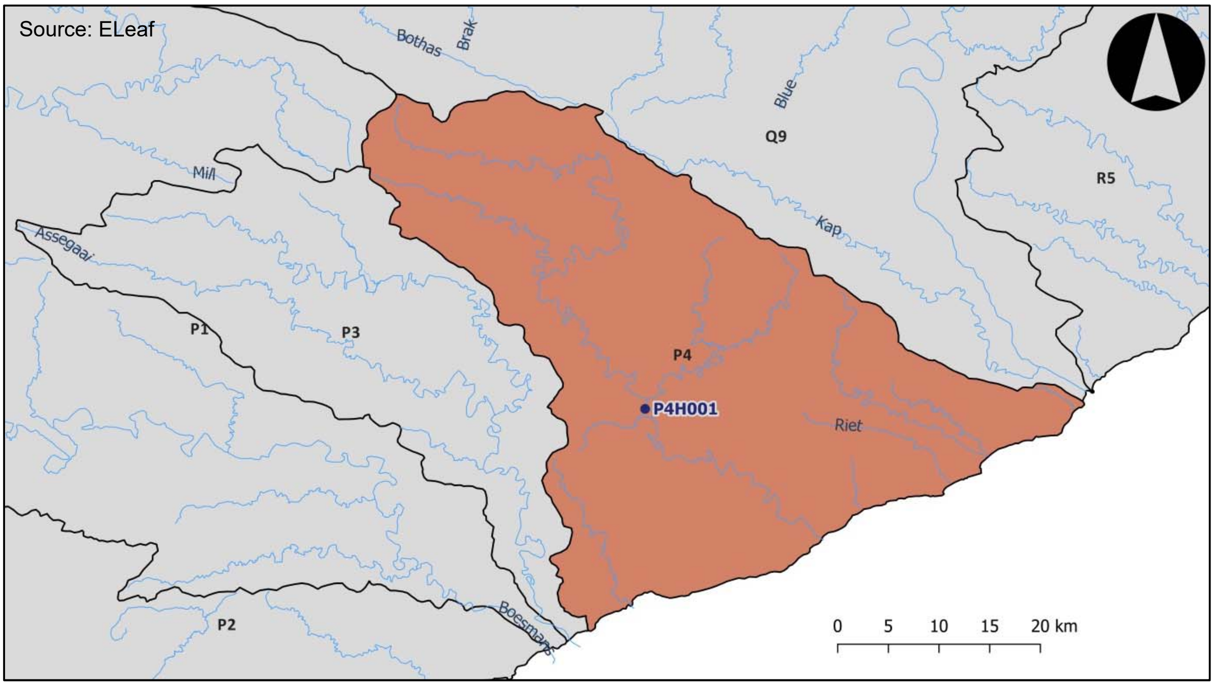


Figure 6.42 Locations of operating DWA water station P4H001 within secondary catchment P4

Table 6.13 Monthly river flow (in million m^3) data of stations P4H004 and H7H006, acquired from DWA

	2014					2015							
station	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Annual
P4H001	0.38	0.335	0.664	1.56	1.21	0.314	1.4	0.351	14.7	1.37	4.13	20.8	47.214

WA+ Sheet 2: Consumption P4 – Kowie

The completed Sheet 2 for P4 is shown in Figure 6.43 and the map depicting annual ET is shown in Figure 6.44. Kowie is a relatively small secondary catchment, which is reflected in the low volumes of water consumption through ET, accounting to 653 million m^3 in total. Half of the ET in this catchment is from shrubland. The second largest consumer is natural grassland, followed by rainfed and then irrigated croplands. Evaporation losses in rainfed crops are approximately 19% on an annual basis, compared to 17% from irrigated agriculture. Total evaporation losses, divided between all land use classes, average at 21% annually.

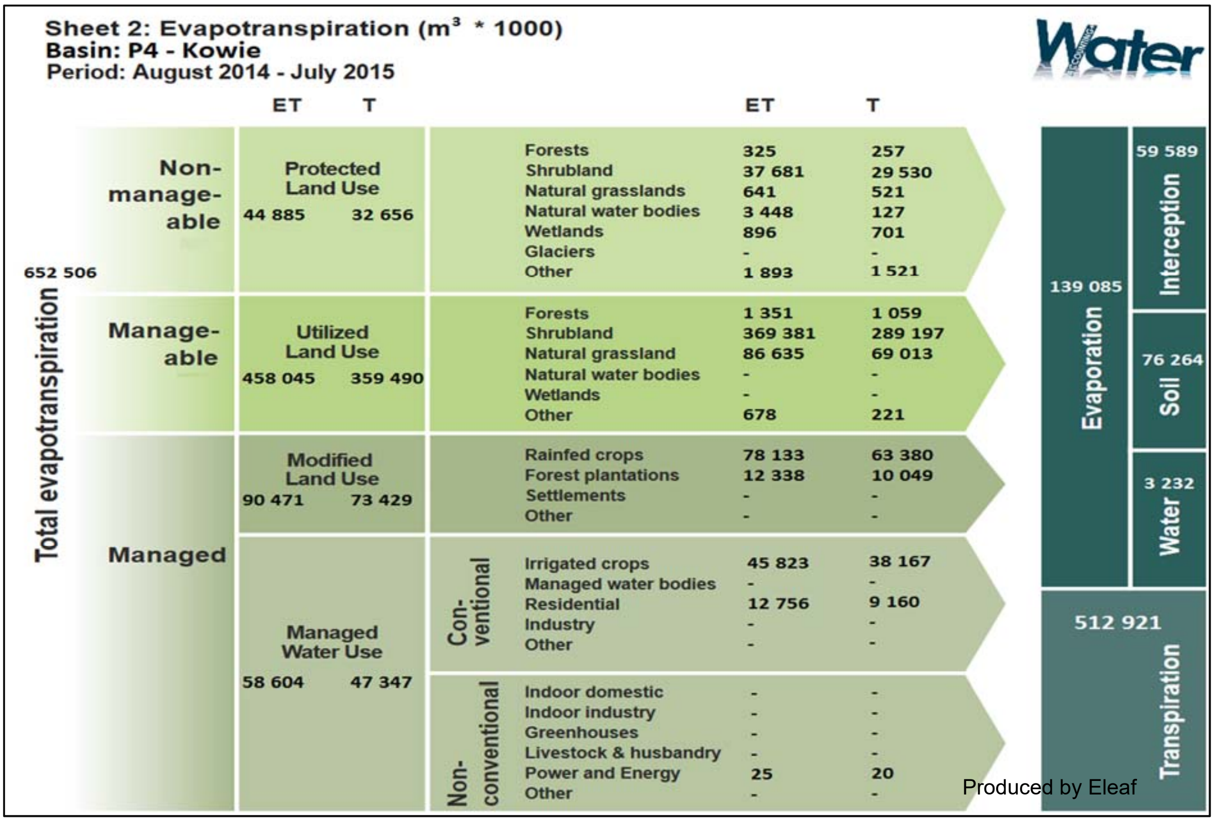


Figure 6.43 WA+ Sheet 2: Evapotranspiration in P4 – Kowie

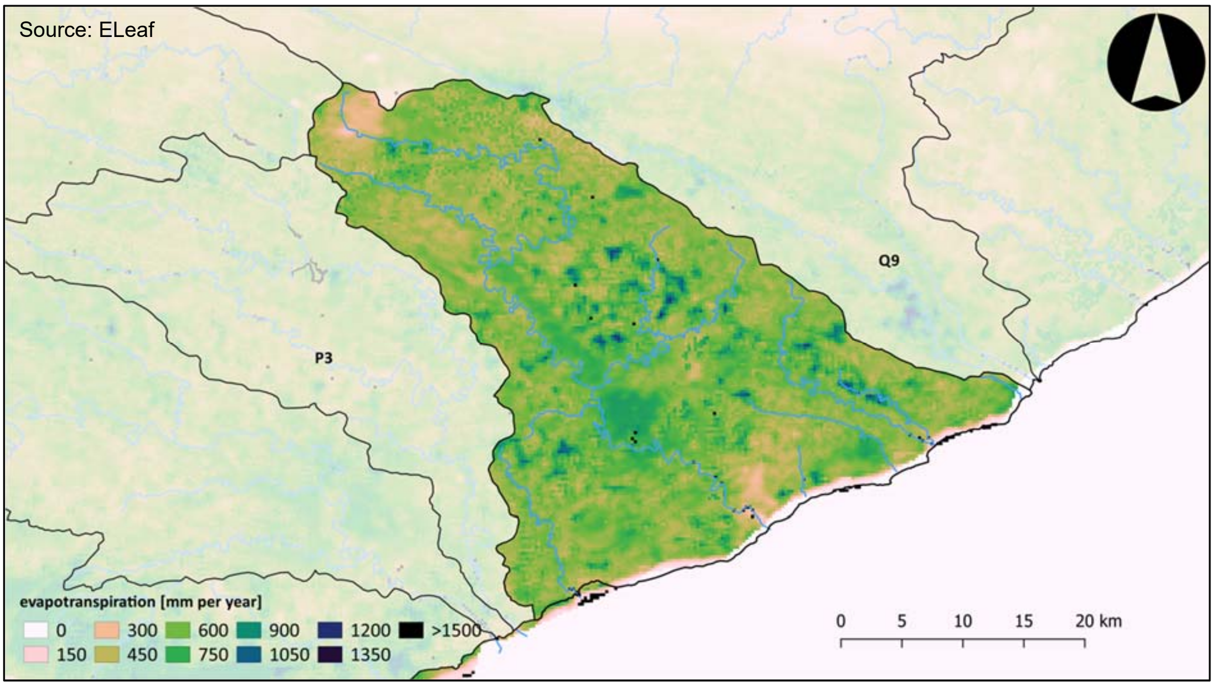


Figure 6.44 Annual ET in P4 – Kowie secondary catchment in mm/yr

<u>*WA+ Sheet 3: Productivity P4 – Kowie*</u>

Table 6.14 shows that the productive land uses consist mainly of (irrigated) vineyards and orchards and regular field crops. This catchment includes some forestry, but almost no pivots or subsistence farming

can be found in the area. All land use information is based on the land use/cover map utilised in this project.

Table 6.14 Area of Rainfed and Irrigated Agriculture per service class based on the 250 m resolution maps used in this analysis

	Area Rainfed (ha)	Area Irrigated (ha)
Field Crops	9 213	1 119
Pivots	69	6
Vineyards & Orchards	3 500	5 588
Subsistence	300	0
Plantations	2 156	50

Figure 6.45 presents the outcome of Sheet 3. The water productivity of rainfed field crops and plantations were the highest in this catchment. There are also significant areas classified as vineyards and/or orchards (mostly pineapples), which had low water productivities. The results suggest that the additional irrigation annually, on average, leads to 5% more biomass production per hectare for vineyards and orchards, which is insignificant. It might have significant impact of the crop yield, but this was not considered in this study. In this region, rainfed field crops typically have higher water productivities than rainfed subsistence farming – 5.6 kg/m^3 compared to 4.49 kg per m^3 of water.

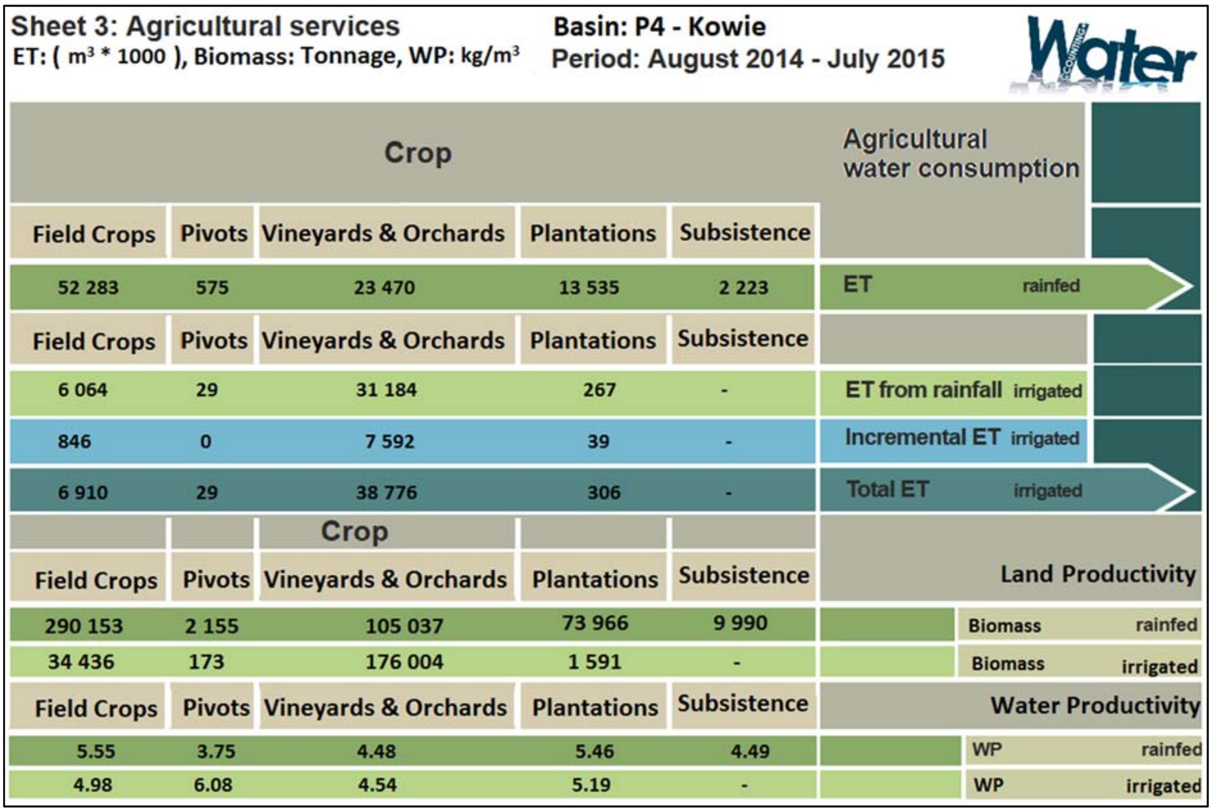


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Figure 6.45 WA+ Sheet 3: Agricultural Services in P4 – Kowie

WA+ Sheet 4: Withdrawals P4 – Kowie

The WA+ Sheet 4 for P4 is shown in Figure 6.46. There is a water deficit of about 5% for irrigated agriculture. Water stress (deficits) also occurs in most of the natural land use classes. This ET deficit does not necessarily directly reflect a shortage of water in the catchment. It can have many other causes, like incidental detrimental weather conditions, drying of cover crops/weeds, an inability to capture sufficient irrigation water in dams, etc.

Residential use and return flows for the full Bushmans river catchment were obtained from (DWAF 2004) and can hence be seen as a maximum. No return flows from irrigated areas is known or was subsequently considered.

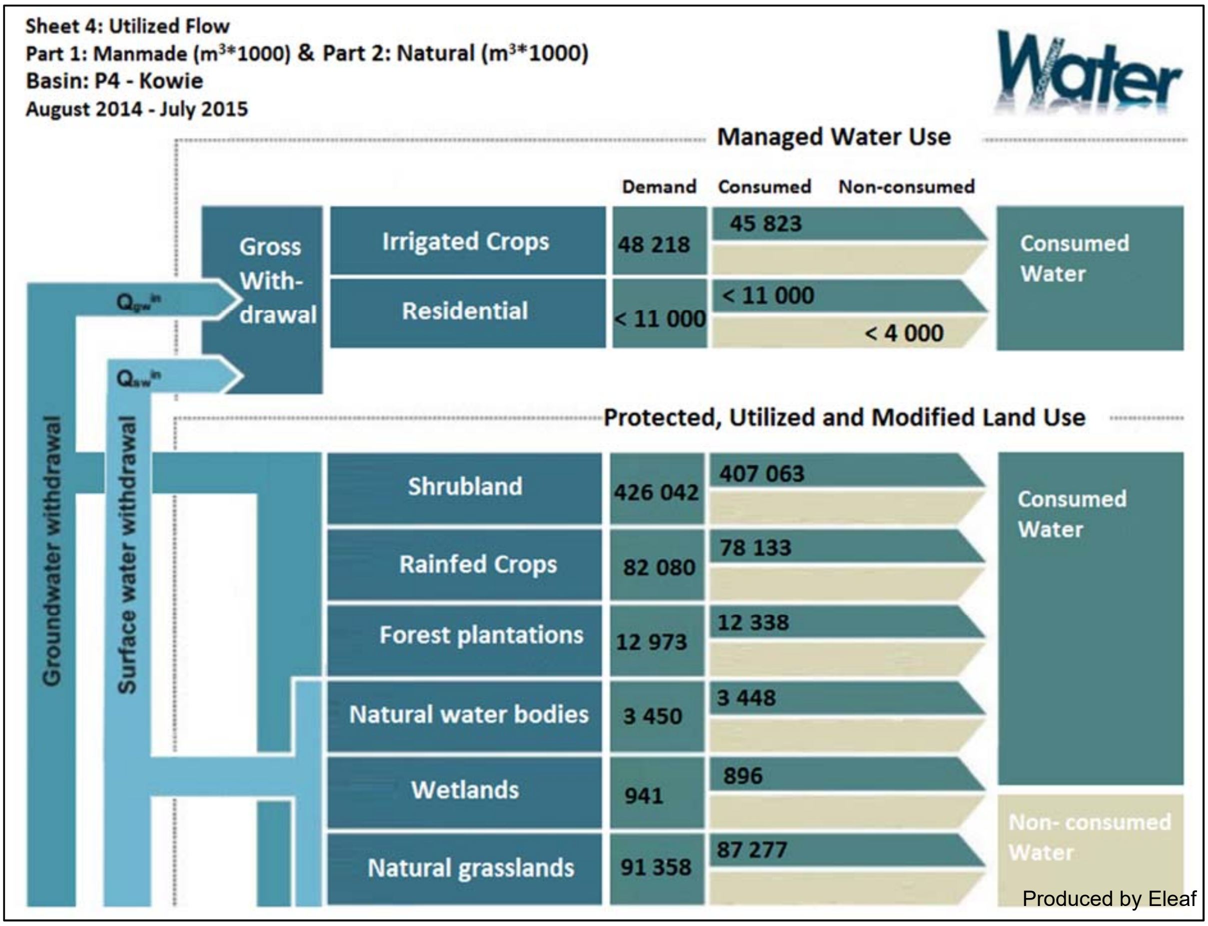

Figure 6.46 WA+ Sheet 4: Water withdrawals in P4 – Kowie

Concluding remarks: P4 - Kowie

The main finding for the P4 – Kowie assessment is that additional water (utilisable outflow) might be available for productive usage in this catchment. Based on the monitoring period, 30 million m^3 of water was likely available for additional productive use as can be seen in Sheet 1. This means irrigated agriculture could potentially be expanded in this area, if these water resources can be captured before they are discharged into the ocean.

6.4.6 Crocodile (X2)

The Crocodile River (X2) catchment is located in Mpumalanga. Nelspruit, with roughly 60 000 inhabitants, the biggest town in the region, is located directly on the river border. The outlet of the catchment is on the South African border with Mozambique. The Crocodile River originates in the

Steenkampsberg Mountains due to high precipitation in this area. The size of the catchment is approximately 10 411 km^2.

The natural vegetation in the area is mostly bushy, with some grassland and patches of forest (Figure 6.47). The elevated regions are dominated by forest plantations. There are significant portions of farmland being used for fruit farming and sugarcane cultivation along the main river channel. Most of these areas are irrigated (Figure 6.48). There are portions of rainfed agriculture, which mostly consists of subsistence farming.

X2 was selected for being both a populated region and having a significant area of irrigated agricultural land. This means water management is of high importance to human prosperity in this region. Being situated on the country's border makes effective management of water even more relevant. The Crocodile River was included in the reconciliation studies undertaken by DWA.

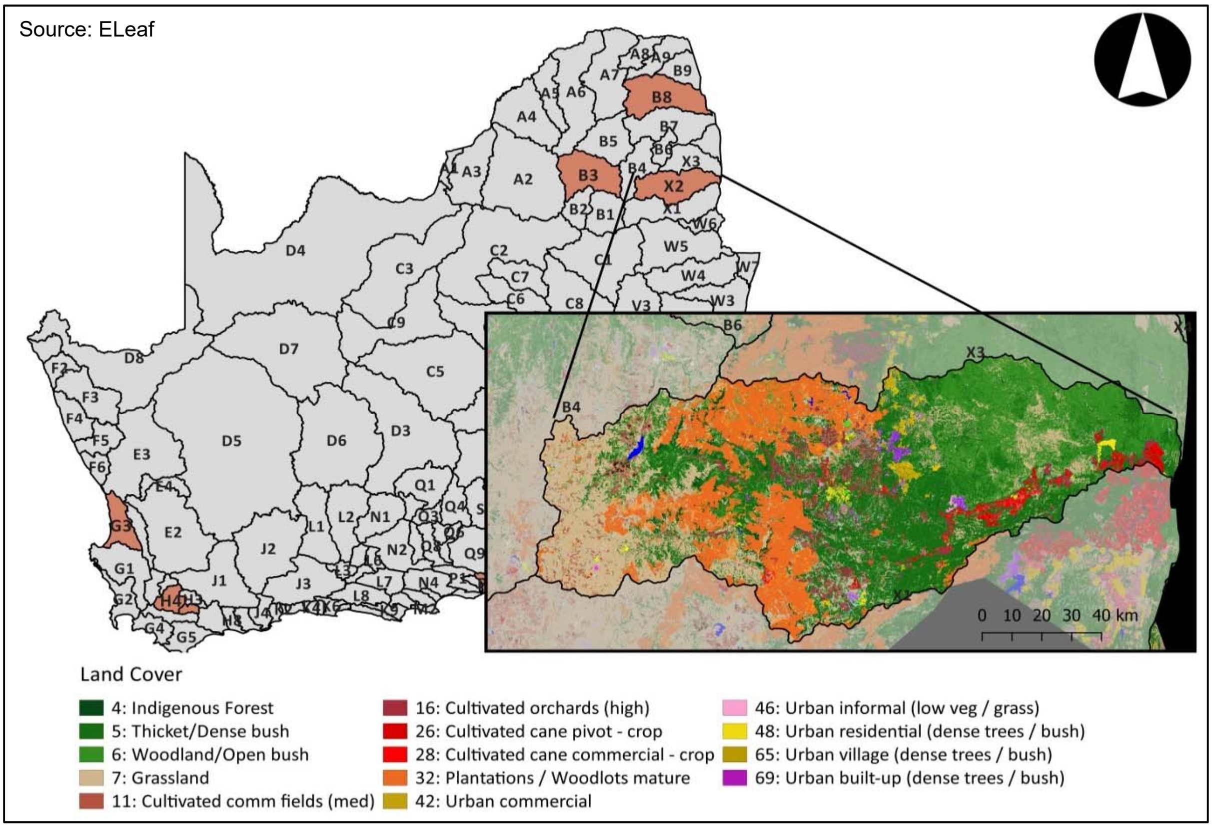

Figure 6.47 Location of secondary catchment X2 – Crocodile and land use based on SALC1314

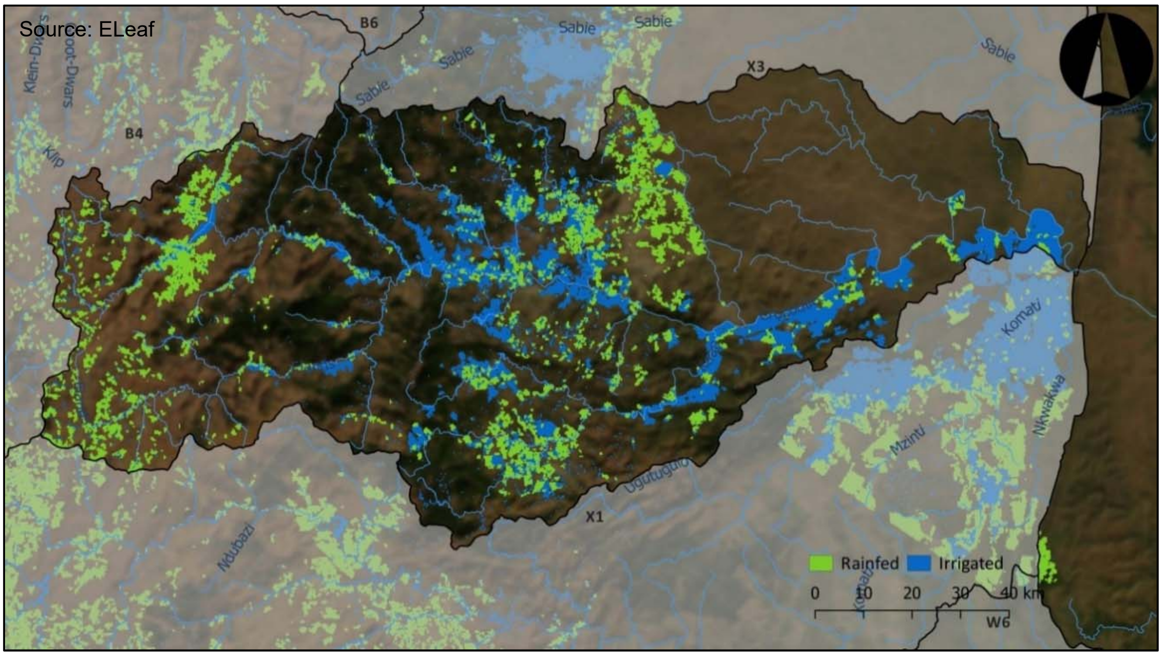

Figure 6.48 Secondary catchment X2, showing non-agricultural areas (brown), rainfed (green) and irrigated agricultural areas (blue)

WA+ Sheet 1: Resources X2 – Crocodile

The PLU-class represents 3 000 km^2 of the catchment, while the ULU, MLU and MWU classes cover 4 469 km^2, 2 193 km^2 and 748 km^2 respectively. The resulting Sheet 1 is displayed in Figure 6.49.

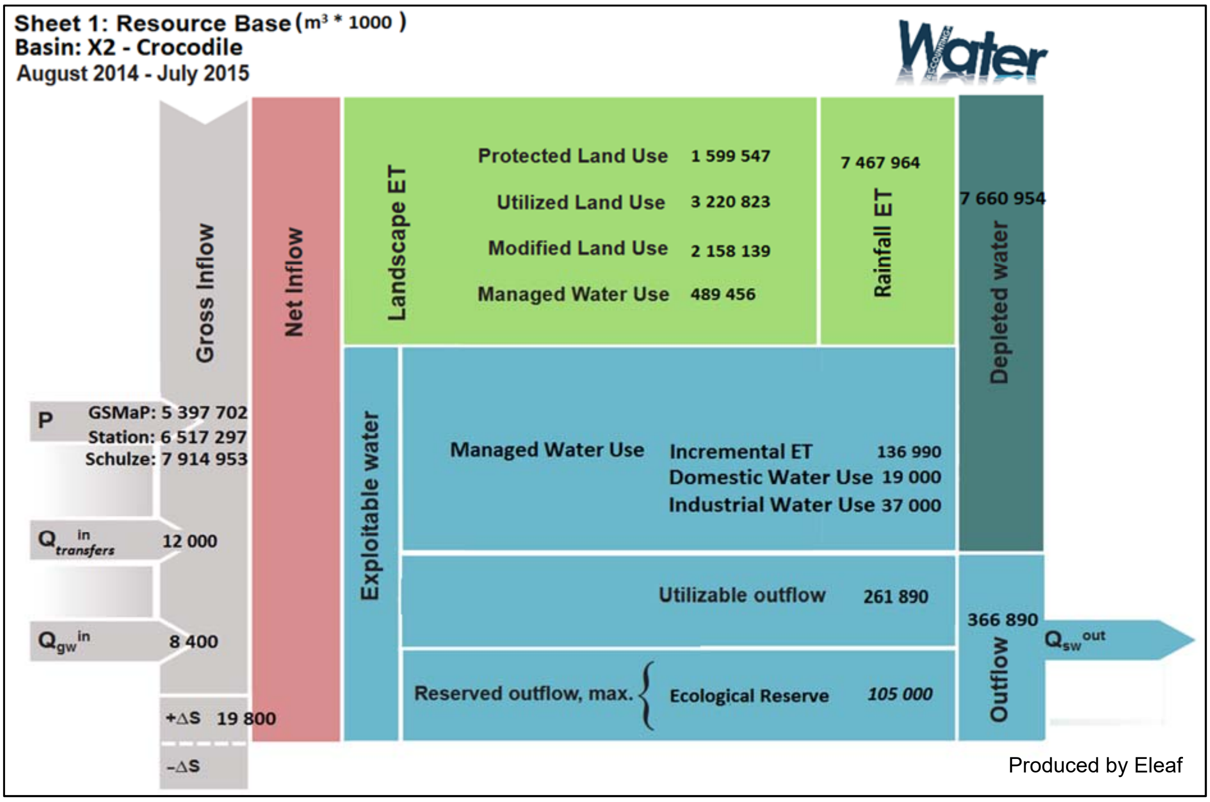

Figure 6.49 WA+ Sheet 1: Resources in X2 – Crocodile

From Figure 6.49 it is clear that most water is consumed by ULU and MLU. Natural forests and forest plantations are significant water users and will affect stream flow as they are mostly based upstream in the catchment. There is a significant portion of protected land use in the Crocodile River catchments, reflected in the associated water use by natural vegetation. There are various water sources in the catchment. Mean annual precipitation ranges from 400 to 1 000 mm/yr, with maximum rainfall estimates of 1 500 mm/yr in the mountainous areas (Mbwana et al. 2008) (Figure 6.50). Crafford et al. (2004) estimated the average water availability from precipitation to be 8 614 million m^3/yr. This is more than the estimated amount from GSMaP and/or the meteorological station data from ARC and NOAA accessible for this project. It appears that both of these sources underestimate the precipitation amount within the mountainous areas of the catchment (significantly), which leads to a negative water balance in Sheet 1. Based on the precipitation map created by Schulze & Lynch (2006), an additional estimate was made on the long-term availability of water from rainfall. This map more accurately reflects the mountainous areas in this region. The estimated availability of water from rainfall, based on Schulze & Lynch (2006), was 7 915 million m^3. This would mean the catchment is nearly a closed system in terms of water availability and water requirements.

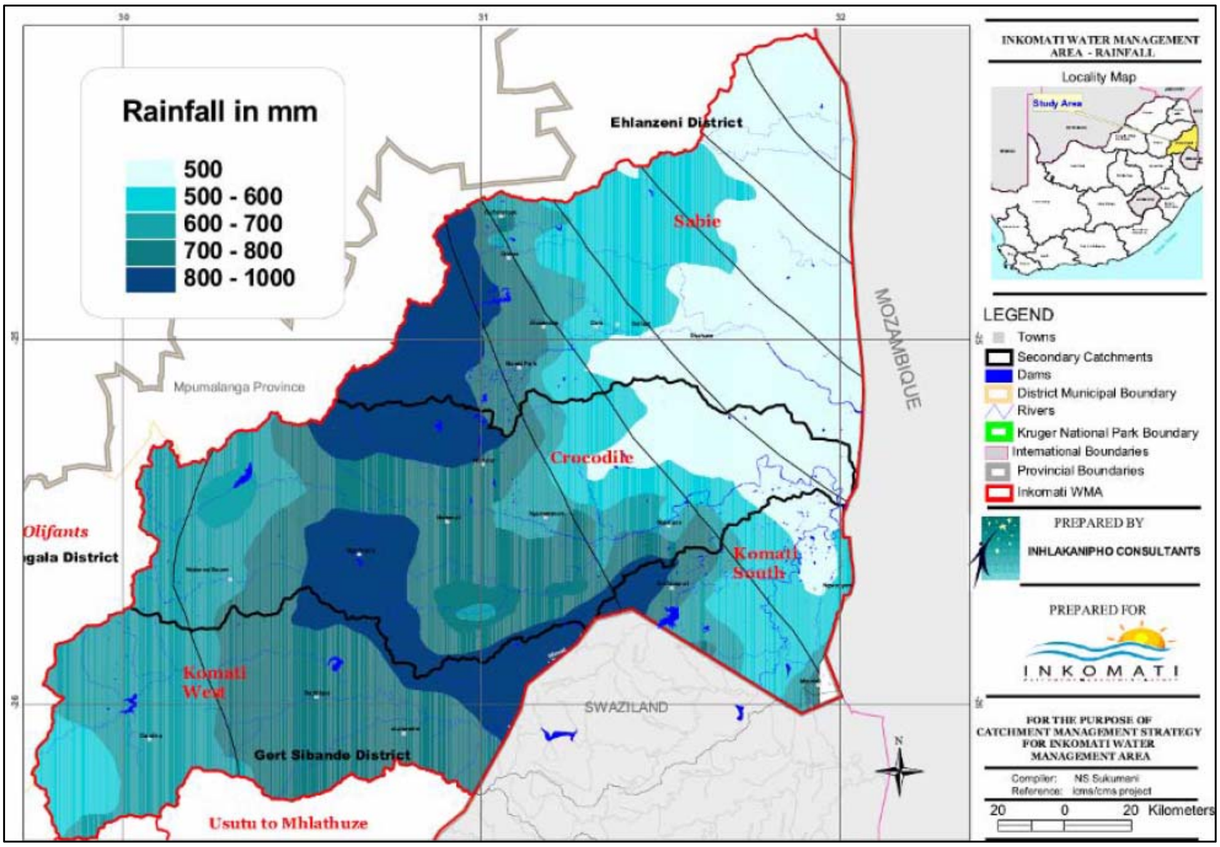

Figure 6.50 Mean annual rainfall in Inkomati basin provided by Mbwana et al. 2008. The Crocodile catchment, as displayed in the image, is part of the Inkomati basin.

There is significant dam storage capacity within the catchment. The NIWIS web portal from DWA (http://niwis.dwa.gov.za/niwis2/SurfaceWaterStorage) was used to access storage information through time. Accordingly, the amount of water sourced from dams within the catchment was estimated at approximately 19.8 million m^3 of water for the study period. Additionally, groundwater abstractions also account for a further 8.4 million m^3 of water. This was sourced from the WARMS database, as listed in Mbwana et al. (2008). Transfers into the catchment add up to 12 million m^3 of water on an annual basis (Mbwana et al. 2008). According to Nieuwoudt et al. (2008), return flows in the Crocodile River catchment are negligible. Domestic and industrial water use were sourced from Mbwana et al. (2008).

Table 6.15 Dams and storage levels in million m^3 between August 2014 and July 2015 within the Crocodile River basin

Dam name	River	FSC (Million m^3)	Storage August 2014 (%)	Storage July 2015 (%)	Storage Change (Million m^3)
Klipkopjes Dam	Wit River	11.8	99.62	91.15	1.00
Kwena Dam	Krokodil River	158.9	100.24	91.92	13.22
Longmere Dam	Wit River	4.3	96.26	70.07	1.13
Primkop Dam	Wit River	1.9	100.27	56.86	0.82
Witklip Dam	Sand River	12.6	100.09	71.24	3.64
Total		189.5			19.80

Source: http://niwis.dwa.gov.za/niwis2/

Various streamflow measurement stations are located in the catchment, one directly at the outlet (X2H016), as shown in Figure 6.51. The discharge measured at this station, which was close to

367 million m^3 during the monitoring period, is shown in Table 6.8. The ecological reserve for the Crocodile River was estimated to be 105 million m^3 (Mbwana et al. 2008).

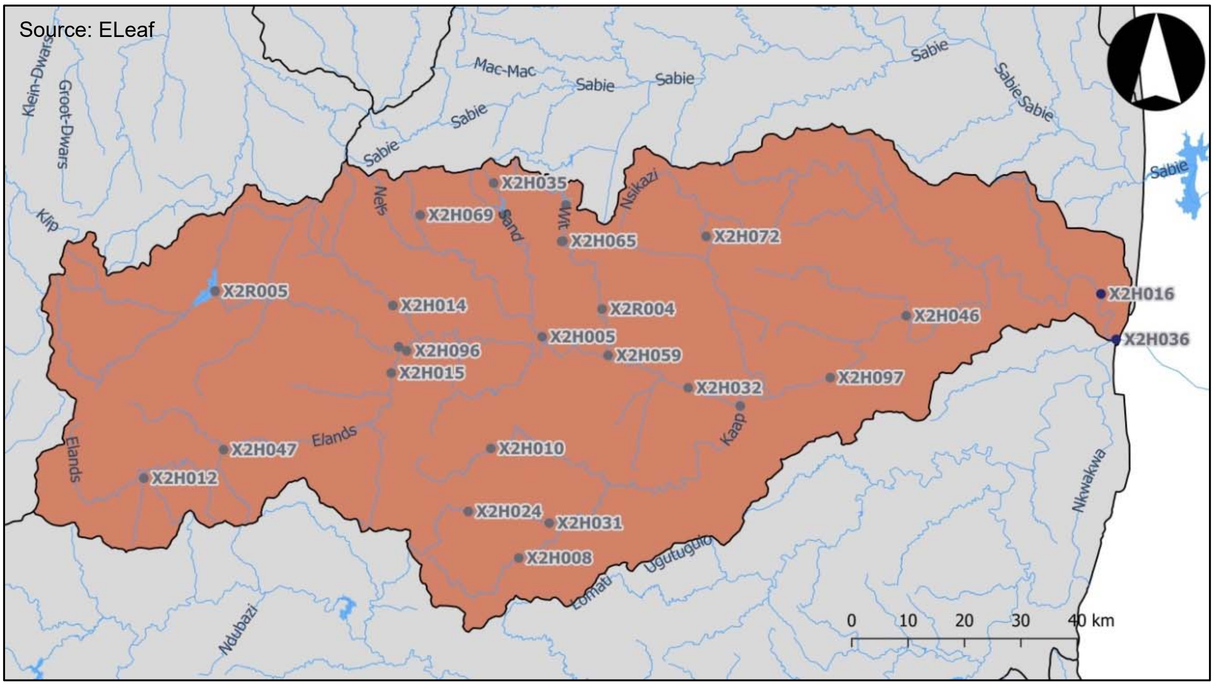

Figure 6.51 Locations of operating DWA monitoring stations, of which X2H004 and H7H006 were used

Table 6.16 Monthly river flow (in million m^3) data of station X2H016 acquired from DWA

	2014					2015							
station	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Yearly
X2H016	20.5	11.3	18.7	27.8	71.4	58.4	68	34	28.7	13.4	8	6.69	366.89

WA+ Sheet 2: Consumption X2 – Crocodile

The completed Sheet 2 is shown in Figure 6.52. The largest consumption of water via ET occurred from the ULU land use class. The Kruger National Park is partly located within the Crocodile River catchment, therefore there is a significant area of protected land use. This is reflected in the water consumption related to this class, which is close to half of the total water consumption for ULU. Shrub- and grasslands are the biggest natural consumers of water.

In terms of modified and managed land use practices, forest plantations (1 897 million m^3 of water) are especially large consumers of water. These plantations are most located upstream in the headwaters of the catchment, as shown in Figure 6.53. Within this catchment there is a strong presence of irrigated agriculture, consisting mainly of citrus, subtropical fruits and nuts. The total ET related to irrigated agriculture was estimated to be 435 million m^3 of water, utilised by both precipitation and irrigated water applied. The total evaporation in this catchment (close to 19%) is relatively high compared to the estimated average of 11% in H4 – Breede. This is in part explained by the difference in rainfall season, (Crocodile River being a summer rainfall and Breede a winter rainfall area), but also because many fruit crops cultivated in the Crocodile catchment are subtropical and evergreens, whereas the Breede catchment is dominated by deciduous fruits.

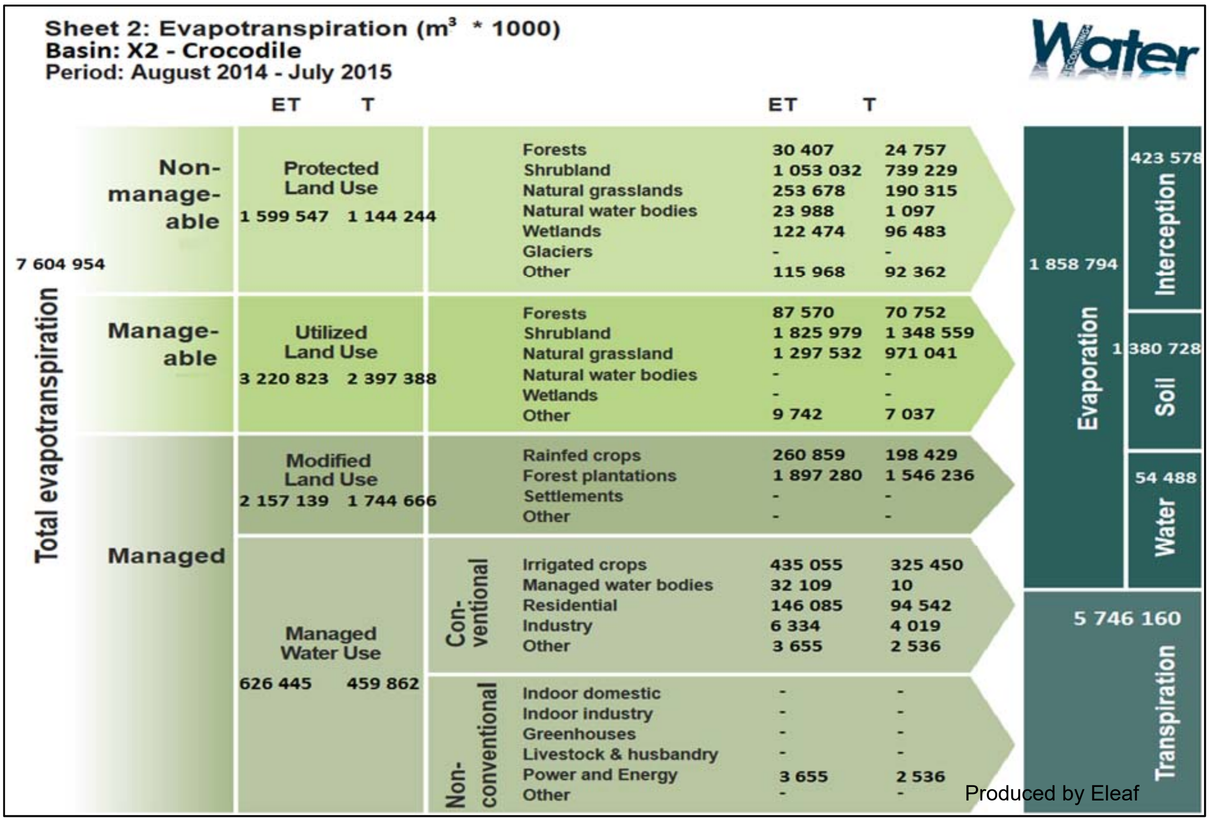

Figure 6.52 WA+ Sheet 2: Evapotranspiration in X2 – Crocodile

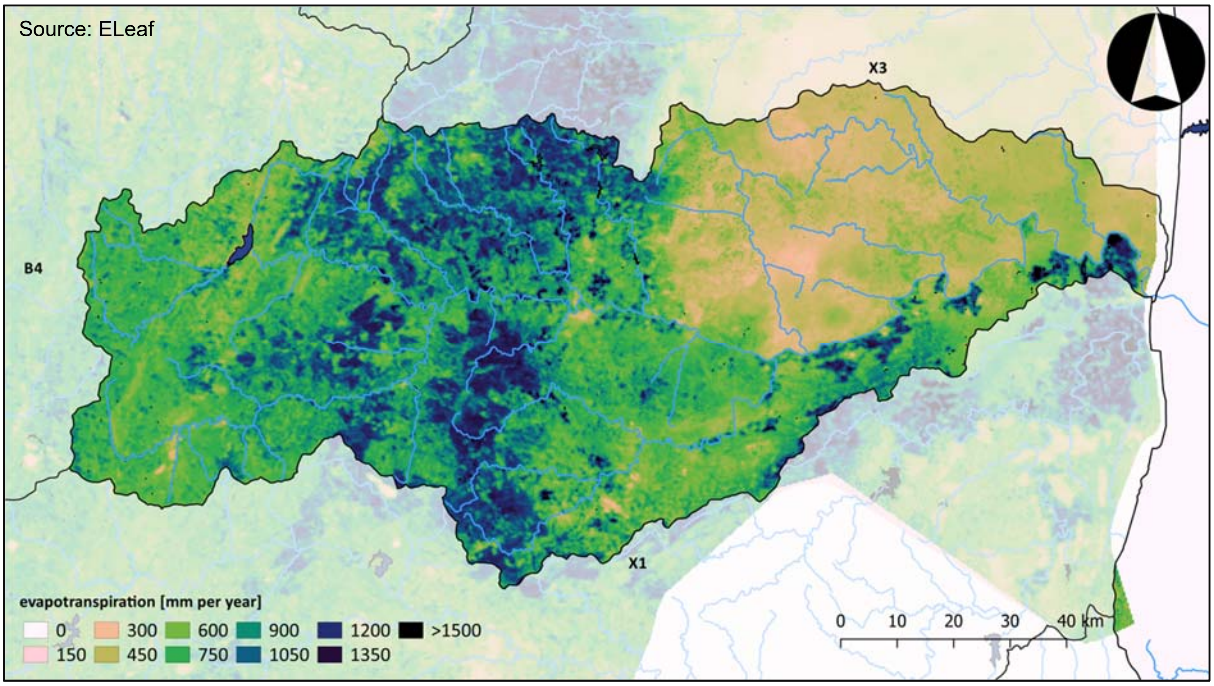

Figure 6.53 Yearly evapotranspiration in X2 – Crocodile

WA+ Sheet 3: Productivity X2 – Crocodile

Table 6.17 shows extensive coverage of rainfed forest plantations. The area covered by these plantations exceeds all other productive land covers combined. There are significant areas of irrigated sugarcane, vineyards and orchards.

Table 6.17 Area of Rainfed and Irrigated Agriculture per service class based on the 250 m resolution maps used in this analysis

	Area Rainfed (ha)	Area Irrigated (ha)
Field Crops	23 219	4 869
Pivots	1 006	363
Vineyards & Orchards	3 006	21 181
Subsistence	2 850	431
Sugarcane	4 750	13 456
Plantations	195 100	3 394

Figure 6.54 presents the outcome of Sheet 3. Water productivity was the highest in forestry regions and areas where sugarcane is cultivated. It is notable that water use efficiencies are lower compared to the water use efficiencies of similar agriculture practices in other catchments in this study. For example, rainfed and irrigated orchards in this catchment produce approximately 3.2 kg of biomass per m^3 of water consumed. In the Breede River catchments, this is approximately 3.5 kg of biomass per m^3 water consumed. This might be due to higher evaporation losses in the Crocodile River catchment, as discussed previously in Sheet 2.

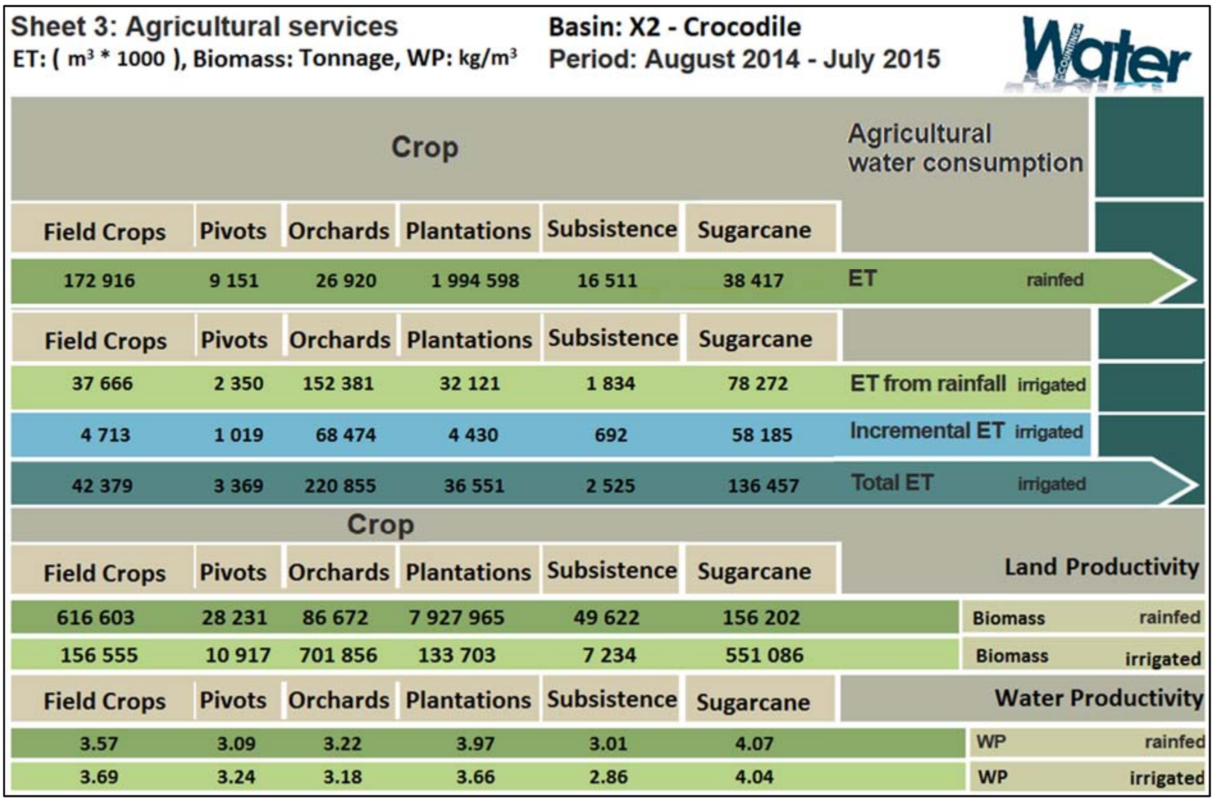

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Figure 6.54 WA+ Sheet 3: Agricultural Services in X2 – Crocodile

WA+ Sheet 4: Withdrawals X2 – Crocodile

WA+ Sheet 4 for X2 is shown in Figure 6.55. Sheet 4 shows the potential of the catchment to provide sufficient water to several land use types. The results indicate that there is a water deficit of about 7% for irrigated agriculture. Water stress (deficits) also occurs in most of the natural land use classes. According to Nieuwoudt et al. (2008) return flows in the Crocodile River catchment are negligible. Domestic and industrial water use estimates are sourced from Mbwana et al. (2008).

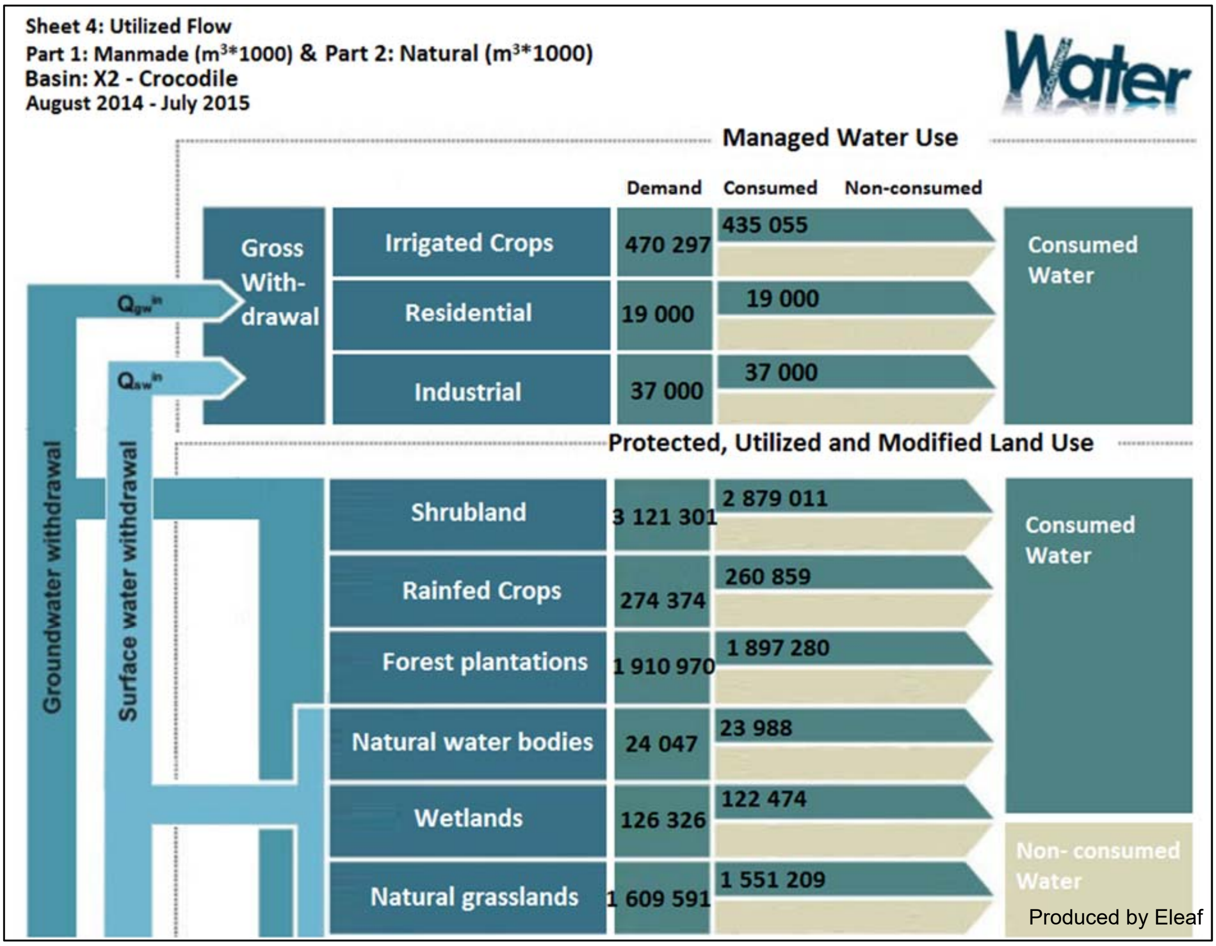

Figure 6.55 WA+ Sheet 4: Water withdrawals in X2 – Crocodile

Concluding remarks: X2 - Crocodile

Based on the discharge measurements used to populate Sheet 1, it seems that there might be room for additional storage of water in this catchment. Discharge at the outlet of the catchment was close to 367 million m^3, while that of the ecological reserve was 105 million m^3. This would mean there was still potentially 262 million m^3 of water left for productive use. However, if precipitation resources, both long- and short-term, and consumption of water through ET are taken into account, the catchment seems to be fully allocated. Hence, no conclusive answer can be given on additional availability of water.

Forest plantations are the largest consumer of water and are mostly located upstream of other (irrigated) agricultural lands and natural areas in the water source areas of the mountainous catchments. Hence, the water consumed or utilised by this land use prevents use by the remainder of the system and therefore needs to be managed carefully. Natural grasslands and shrubland also used a significant amount of water. However, as they are mostly located downstream, it is unlikely that they had a large influence on the catchment water budget. A large part of the natural area is situated in and protected by the Kruger National Park.

6.4.7 Letaba (B8)

The Letaba (B8) is located in the Limpopo Province and is one of the most important tributaries to the Olifants River. The Letaba River also runs through Kruger Park towards SA’s border with Mozambique. The size of the catchment is approximately 13 613 km^2 (Figure 6.56). Precipitation is influenced by the geography. In the low-lying areas less than 300 mm/yr can be expected, while more than 1200 mm/yr falls within the mountainous areas (Querner et al. 2016).

The natural vegetation in the upstream area is mostly bushy. This transcends into grasslands downstream (Figure 6.21). The higher-lying regions are dominated by forest plantations. Along the main river channel, there are significant portions of farmland use for irrigated (fruit) farming. Crops include citrus, subtropical fruit, nuts and vegetables (Querner et al. 2016). Most of these areas are irrigated (Figure 6.57). There are portions of rainfed agriculture, which mostly consist of subsistence farming.

B8 was selected since it is a populated catchment with challenging hydrological conditions. According to local authorities, the system is over-allocated, with extensive demands from various sectors. Proper management and accounting of water is therefore essential. The Letaba River system was also included in the reconciliation studies undertaken by DWA.

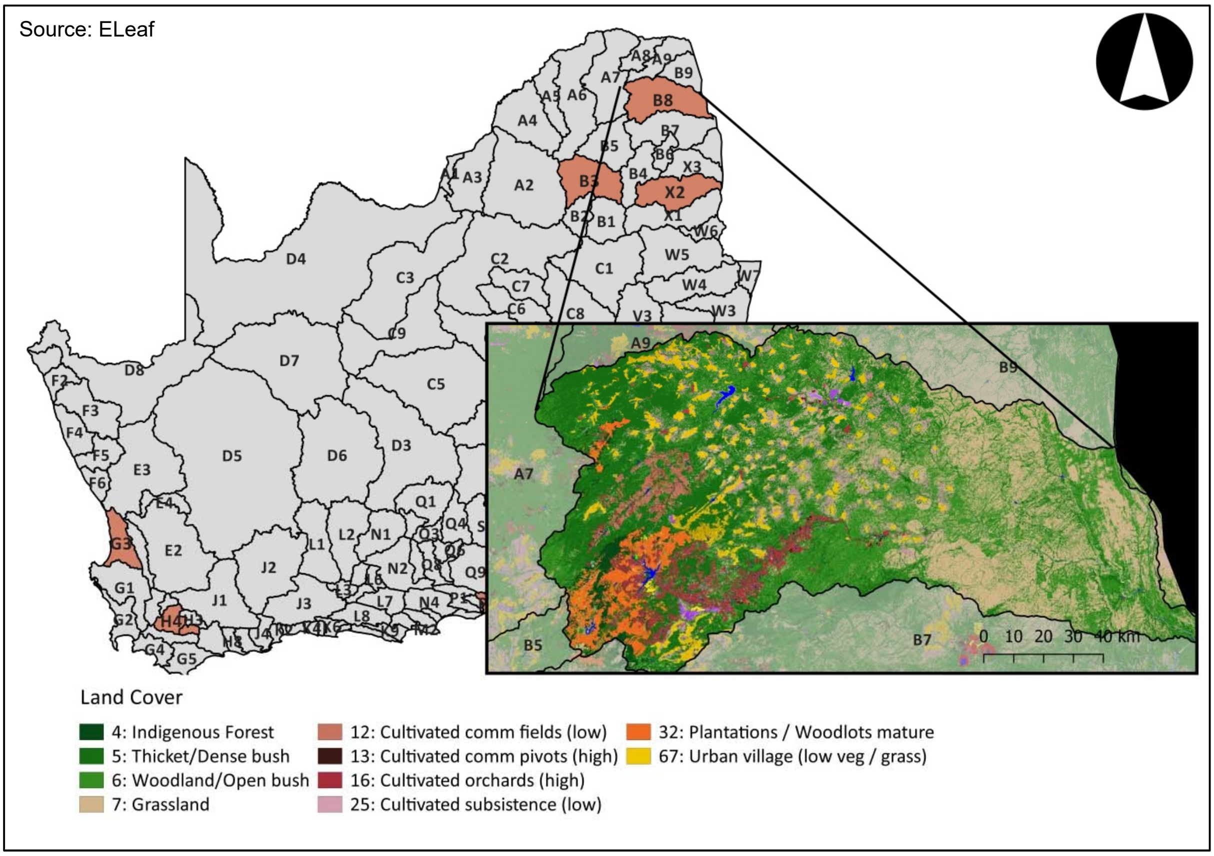

Figure 6.56 Location of secondary catchment B8 – Letaba and land use based on SALC1314

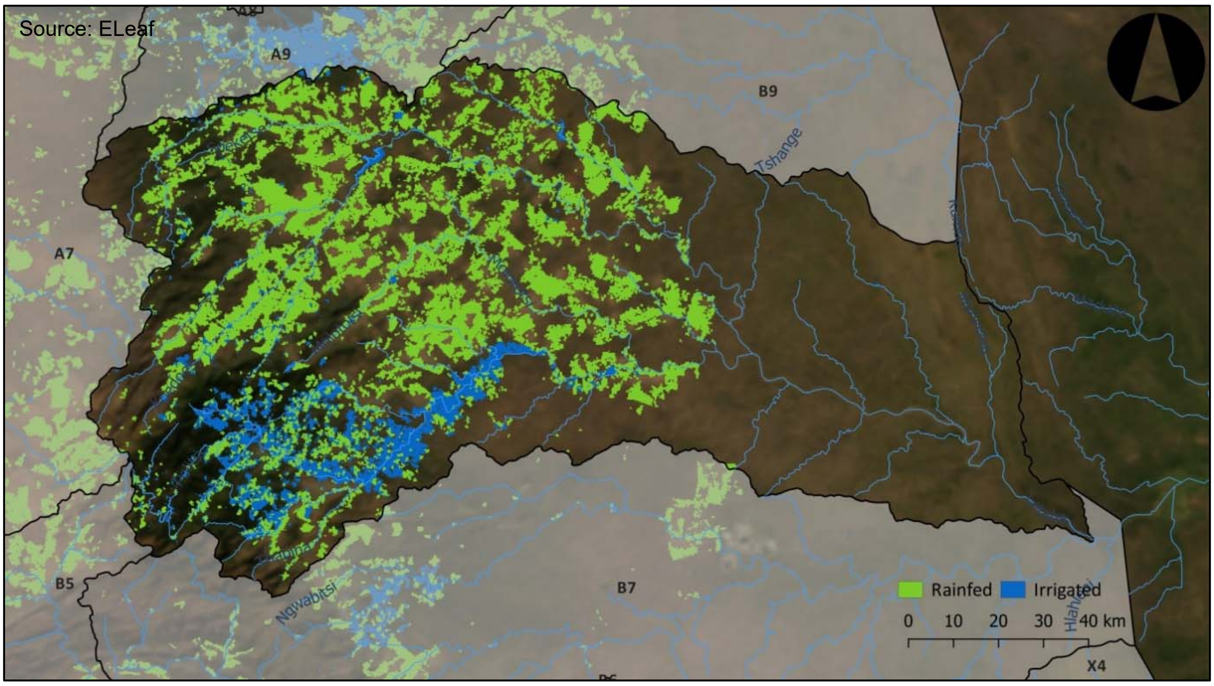

Figure 6.57 Secondary catchment B8, showing non-agricultural areas (brown), rainfed (green) and irrigated agricultural areas (blue)

WA+ Sheet 1: Resources B8 – Letaba

The PLU-class represents 4 248 km^2 of the catchment, while the ULU, MLU and MWU classes cover 6 893 km^2, 1 389 km^2 and 1 083 km^2 respectively. The resulting Sheet 1 for catchment B8 is shown in Figure 6.58.

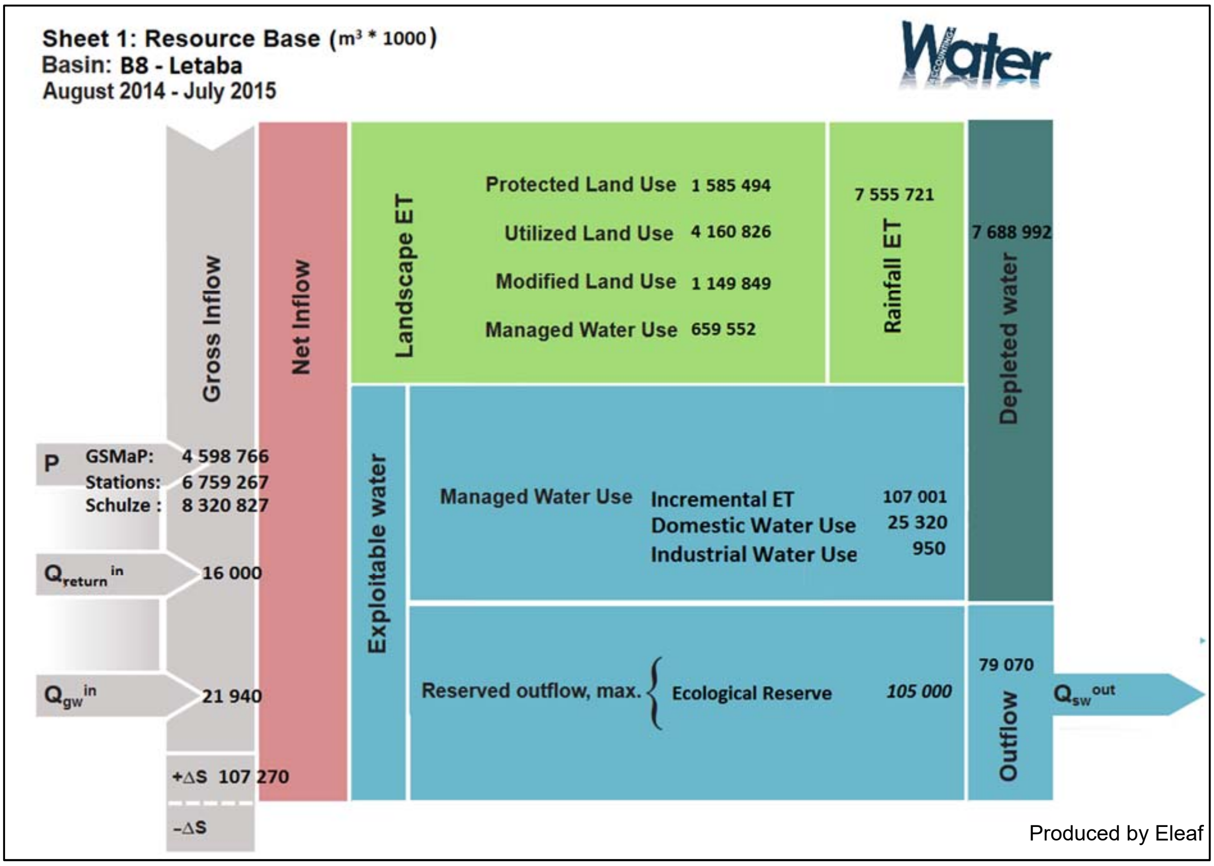

Figure 6.58 WA+ Sheet 1: Resources in B8 – Letaba

Water resources in the Letaba River catchment consist of precipitation and groundwater and significant storage facilities are located in the catchment. The water gained from storage facilities within the monitoring period is approximately 107 million m^3 (from http://niwis.dwa.gov.za/niwis2/, see Table 6.18). Precipitation estimates based on information from local weather stations and GSMaP satellite data range between 4 600 to 6 800 million m^3/yr of water during the monitoring period. Both of these sources seem to underestimate the true precipitation falling within the mountainous parts of the catchment. Schulze & Lynch (2006) was used to make an additional estimation, based on the long-term availability of water from rainfall. The map by Schulze & Lynch (2006) appears to reflect rainfall in the mountainous regions more accurately. The estimated availability of water from rainfall based on Schulze & Lynch (2006) was 8 321 million m^3/yr.

Groundwater use in the catchment is approximately 22 million m^3/yr (Haupt & Sami 2006; Williams et al. 2008). According to Williams et al. (2008), 16 million m^3/yr is recaptured by return flows.

Table 6.18 Dams and storage levels (in million m^3) between August 2014 and July 2015 within the Letaba River catchment

Dam name	River	FSC (Million m^3)	Storage August 2014 (%)	Storage July 2015 (%)	Storage Change (Million m^3)
Dap Naude Dam	Broederstroom River	2	97.32	90.82	0.13
Ebenezer Dam	Groot-Letaba River	69.2	99.90	89.51	7.19
Hans Merensky Dam	Ramadiepa River	1.3	101.84	98.59	0.04
Magoebaskloof Dam	Politsi River	4.9	100.14	100.11	0.00
Middel-Letaba Dam	Middel-Letaba River	172	52.49	35.79	28.74
Modjadji Dam	Molototsi River	7.2	93.37	44.76	3.50
Nsami Dam	Nsama River	21.9	65.90	8.52	12.57
Tzaneen Dam	Groot-Letaba River	156.6	98.23	63.04	55.10
TOTAL		435.10			107.27

Source: http://niwis.dwa.gov.za/niwis2/

There is no surface water inflow as the Letaba is a closed catchment. Outflow estimates can be obtained from DWA station B8H018, located close to the outlet of the catchment (Figure 6.59). According to this station, the outflow of the Letaba River was 79 million m^3 of water between August 2014 and July 2015. This is less than the ecological reserve, which is 105 million m^3 of water per year (Williams et al. 2008). This indicates that the catchment is over-allocated, confirmed by local authorities (Riddell 2017). Most of the manageable water goes to irrigated agriculture and to a lesser extent is applied to domestic use. There is little industrial water use in the catchment (DWAF 2006b).

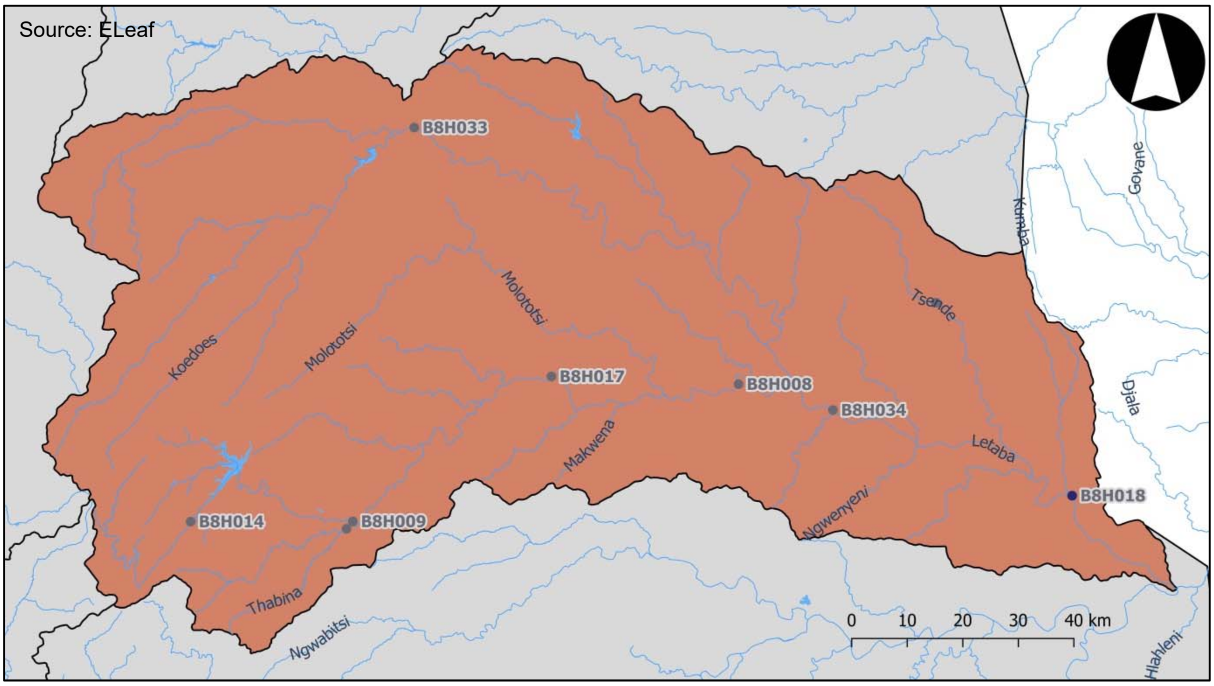

Figure 6.59 Locations of operating DWA water stations in the Letaba

Table 6.19 Monthly river flow (in million m^3) data of stations B8H018 gained from DWA

	2014					2015							
station	aug	sep	oct	nov	dec	jan	feb	mar	apr	may	jun	jul	yearly
B8H018	3.79	2.03	2.32	2.15	19.7	16	13.1	2.24	8.53	5.29	1.84	2.08	79.07

WA+ Sheet 2: Consumption B8 – Letaba

The completed Sheet 2 is shown in Figure 6.60 and the corresponding ET map in Figure 6.61. The Kruger National Park occupies the eastern part of the catchment, leading to significant water consumption within the PLU land use class. This land cover class consists mostly of shrub- and natural grasslands. The same holds for the ULU class, in which shrubland dominates. There are large areas of rainfed crops with substantial subsistence farming. The water consumed via ET through rainfed crop cultivation is approximately 648 million m^3. Irrigated fields are located directly along the river streams and consume 353 million m^3 of water. The residential land use class is also responsible for significant consumption of water through ET at 334 million m^3, which is almost as much as the water consumed through ET in irrigated croplands. When zooming in on this area, it is clear that residential areas are surrounded by vegetated areas, indicating the likelihood of subsistence farming.

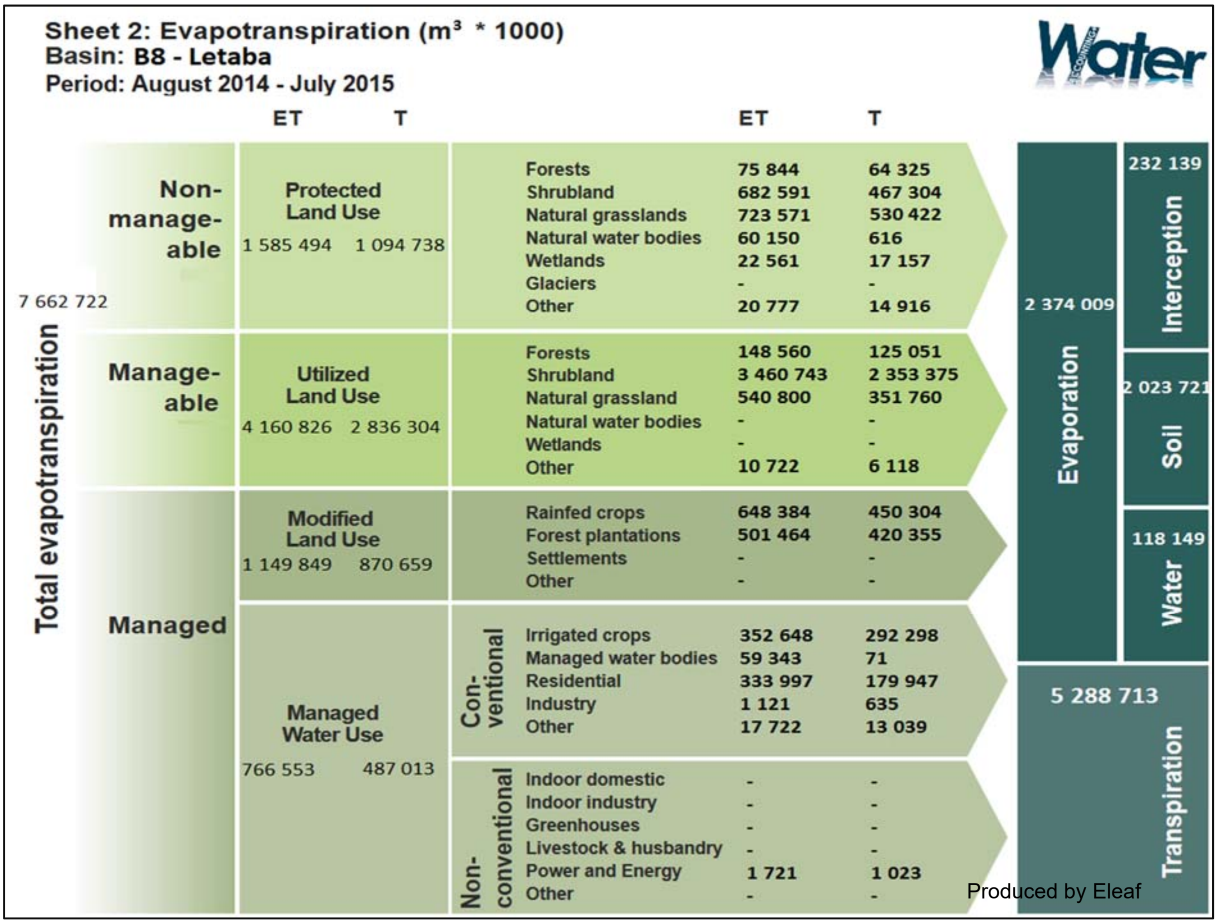

Figure 6.60 WA+ Sheet 2: Evapotranspiration in B8 – Letaba

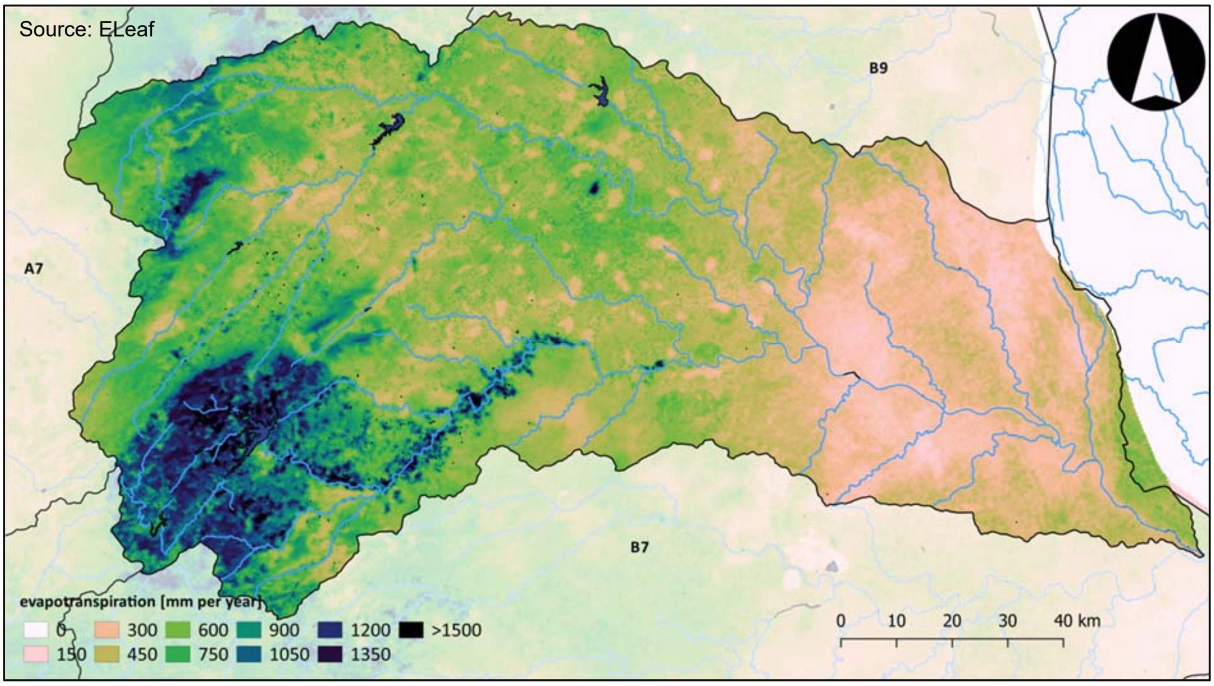

Figure 6.61 Yearly evapotranspiration in B8 – Letaba shown in mm/yr

WA+ Sheet 3: Productivity B8 – Letaba

Table 6.20 shows that the most dominant type of rainfed agriculture in this area is subsistence farming. There are large forest plantations, as well as rainfed and irrigated vineyards and orchards.

Table 6.20 Area of Rainfed and Irrigated Agriculture per service class based on the 250 m resolution maps used in this analysis

	Area Rainfed (ha)	Area Irrigated (ha)
Field Crops	26 800	1 556
Pivots	1 238	375
Vineyards & Orchards	13 525	27 169
Subsistence	55 069	381
Plantations	45 263	2 356

Figure 6.62 presents the outcome of Sheet 3. Forest plantations are the most biomass productive land use class in terms of WUE. Subsistence farming is less productive compared to regular rainfed fields. Similar to Crocodile River (X2), the water use efficiencies of a number of land cover classes for this area are lower than in other catchments located elsewhere in the country.

Sheet 3: Agricultural services | **Basin: B8 - Letaba**

ET: (m³ * 1000), Biomass: Tonnage, WP: kg/m³ | **Period: August 2014 - July 2015**

Crop	Field Crops	Pivots	Vineyards & Orchards	Plantations	Subsistence
Agricultural water consumption					
ET rainfed	176 354	8 836	135 028	516 489	338 288
ET from rainfall irrigated	10 067	2 187	199 308	25 062	2 247
Incremental ET irrigated	2 774	1 174	97 530	3 850	718
Total ET irrigated	12 840	3 361	296 838	28 912	2 965
Land Productivity					
Biomass rainfed	553 027	25 100	420 197	1 941 012	838 662
Biomass irrigated	43 337	9 671	904 774	98 049	7 846
Water Productivity					
WP rainfed	3.14	2.84	3.11	3.76	2.48
WP irrigated	3.38	2.88	3.05	3.39	2.65

Produced by Eleaf

Figure 6.62 WA+ Sheet 3: Agricultural Services in B8 – Letaba

WA+ Sheet 4: Withdrawals B8 – Letaba

WA+ Sheet 4 for B8 is shown in Figure 6.63. Sheet 4 delineates the potential of the catchment to provide sufficient water to several land use types. The results show that there was ~2% water deficit in irrigated agriculture. In comparison, this is close to 8% in rainfed croplands. Water stress occurred in most of the natural land use classes. In the total Letaba catchment area, 14 million m^3 water is gained as return flow from irrigated agriculture and 2 million m^3 water from urban areas (DWAF 2004).

Concluding remarks: B8 - Letaba

The ecological reserve in the Letaba catchment exceeds the river discharge measured at the outlet, indicating that this catchment is likely over-allocated. This interpretation is supported by inputs from local authorities and the literature. As in the Crocodile River secondary catchment (X2), forest plantations are a large consumer of water. Their upstream location in the water source areas of the catchment means that they have a direct influence on the water availability in the catchment, which needs to be managed carefully. Rainfed agriculture and natural vegetation are other big water consumers (based on the substantial area covered by them in this catchment), but the location of these areas compared to the stream channels suggest they will likely have less of an impact on the water availability in the river itself.

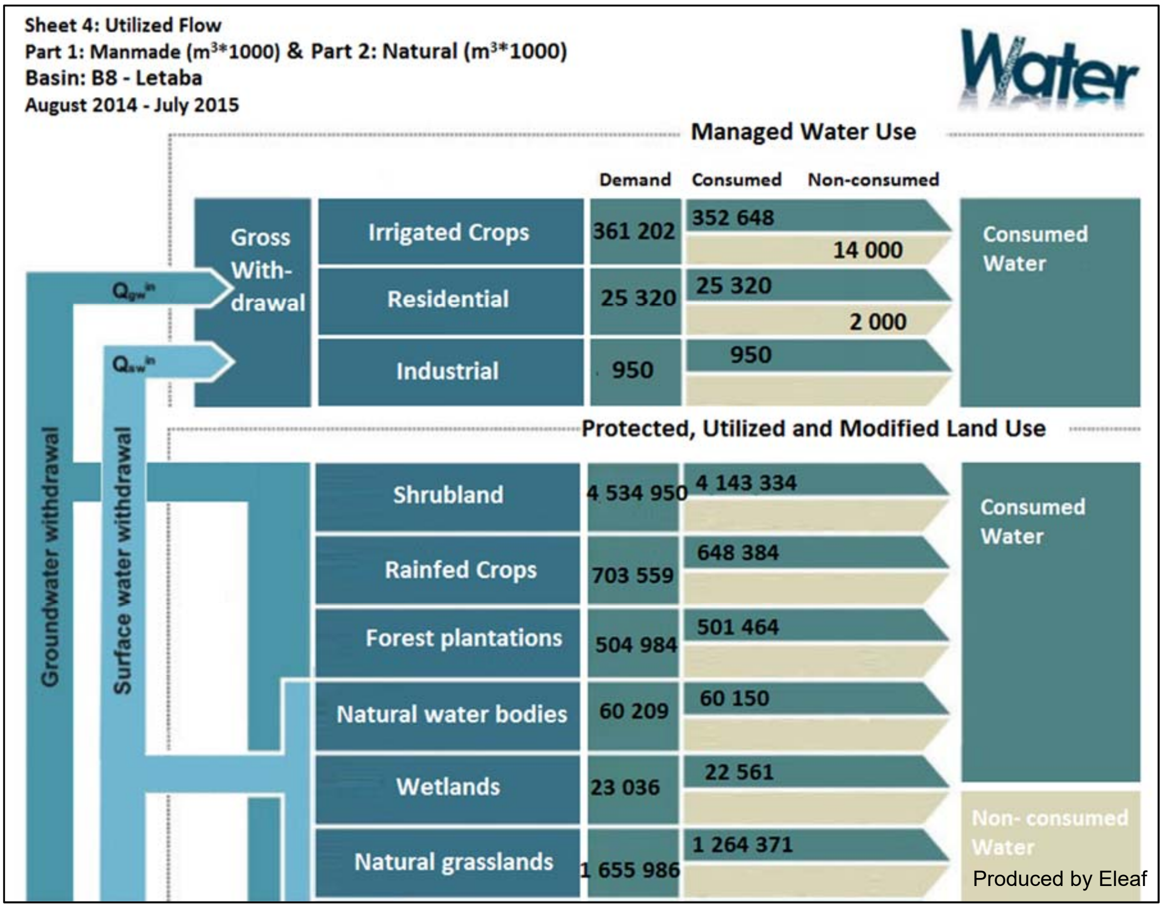

Figure 6.63 WA+ Sheet 4: Water withdrawals in B8 – Letaba

6.5 Summary and conclusion of water accounting in selected sub-catchments

Coping with water scarcity and the growing competition for water among different sectors require sound water management strategies and decision-making. Successful water management strategies are based on a clear understanding of a catchment's hydrological processes. This includes determining manageable and unmanageable water flows, and clarification of the amount of water available for human use. By understanding the interaction between water and land use, the effects of land use change on the catchment water balance can be estimated. To increase the societal benefits of water use, water managers need to understand these interactions before they make decisions. The WA+ framework captures these interactions and provides water managers with a concise overview of the catchment water resources, usage and demand. It is therefore an invaluable tool for informed decision-making.

In applying the WA+ framework to the selected catchments, it was found that the water resources in the Mzimvubu, Kowie and Breede River catchments were sufficient to allow for additional storage and productive use of (surface) water. This additional water can be used by existing irrigators to meet their crop demand in summer or store additional water in wetter years as insurance for drier years. Additionally, this water can be used to support expansion of irrigation in the region. In Mzimvubu in particular, a substantial amount of additional surface water seems to be accessible for productive usage. However, these findings should be interpreted with caution as they do not necessarily represent the long-term situation but are based on the 2014/15 conditions.

An additional challenge for water resource analysis is the unavailability of high-quality rainfall data, especially in mountainous areas where reliable information is limited. Additionally, accurate land use and crop type maps will aid greatly in interpreting the water situation. The availability of water depends on various dynamic factors and more work is needed to monitor changes over multiple seasons, specifically during periods of drought. WA+ should consequently be applied retrospectively (at least from 2015 onwards) and on an ongoing basis, preferably at national scale, to gain a better understanding of the fluctuations in water availability.

7 CONCLUSIONS AND RECOMMENDATIONS

7.1 Main findings

The aim of this research was to update the existing estimates of the amount of water used by irrigated agriculture in SA. To reach this aim, monthly datasets of ET for a 12-month period was generated for the entire SA. This ET dataset describes the water consumption and land productivity (vegetation growth) between 1 August 2014 and 31 July 2015. The monthly data products capture the phenology of natural vegetation, crop production cycles, water availability and climatic conditions, and associated water consumption in SA. It formed the basis for the production of the IAM and the calculated total water use by irrigated crops. The ETLook model used to produce ET data proved to be robust enough for application over an area as extensive and varied as South Africa, despite the challenge of available and accurate (spatial) rainfall data for SA. Although the rainfall data have limited influence on the ET calculation itself (the ETLook is based on an energy balance approach), the absence of high-quality rainfall data hindered the calibration of the ETLook model setup, as the produced ET values are difficult to compare and validate against the rainfall information.

Irrigated area (ha)

A major task of this research was to produce an accurate IAM of SA. Given the large area under consideration, the first step in this process was to eliminate all non-agricultural areas from further consideration. High accuracy was critical, since the map was used to quantify the amount of water used by irrigated agriculture, extracted from the ET dataset. The mapping of irrigated areas included all actively irrigated agriculture, and thus excluded areas usually irrigated but left fallow over the period considered (1 August 2014 to 31 July 2015). A geodatabase of agricultural fields was generated by collating a series of land cover, land use and field boundary data. Each field in the geodatabase was then visually (manually) compared to VHR (1.5 m) satellite imagery and updated/corrected where necessary.

One recognised method for differentiating between irrigated and rainfed fields involves comparing the accumulated (annual) rainfall and evapotranspiration (i.e. $ET_{yr} – P_{yr}$). Theoretically, where ET_{yr} exceeds P_{yr} for a given agricultural area, crops are typically irrigated. This assumption was investigated by comparing the $ET_{yr} – P_{yr}$ of both known irrigated and rainfed fields for 2014/15, with the results suggesting a difference threshold value of 300 mm/yr. Applying this threshold was found to be effective in the drier areas of SA, but performed poorly in regions with higher rainfall (e.g. Limpopo, Mpumalanga and KZN). This was attributed to the large variation in rainfall throughout SA (necessitating the use of multiple or region specific $ET_{yr} – P_{yr}$ thresholds) and the poor spatial accuracy of rainfall data. The difference between $ET_{yr} – P_{yr}$ was generally lower and more variable in wetter regions. The ET and P data used in the classification were consequently supplemented with high spatial resolution (30 m), multi-temporal Landsat 8 imagery to better differentiate between irrigated and rainfed fields. A range of spectral indices were generated from the Landsat 8 images and incorporated into the geodatabase, where each field contained multi-temporal ET, P and spectral index values. To account for the climatic variability of SA, the country was subdivided into nine rainfall regions. Examples (samples) of fields that were known to be irrigated or rainfed were identified within each region and used to train a machine learning classification algorithm (CART). The output of this exercise was a highly accurate (>95%) irrigated area classification for each rainfall region. These regional classifications were merged into a single IAM for SA, which was then assessed through manual inspection by the project team and industry stakeholders.

The IAM was judged highly accurate by participating stakeholders (see Section 4.3.2). Minor errors were identified during a visual assessment and correction process carried out by the project team (Section 4.3.3. Most of the identified errors were related to inaccuracies in the field boundary delineations or where only parts of fields were utilised. All known misclassifications were manually corrected to produce the final, validated version of the map (Version 3). The map showed that 1 334 562 ha (1.1%) of SA's land surface was actively irrigated during 2014/15. This constituted 10% of the total area under cultivation (including fallow areas) of the area used for agriculture in 2014/15. It was found that the Western Cape contributes the most (269 476 ha), with Limpopo having the second largest area under irrigation (218 302 ha) (refer to Table 5.1 for details). Given that it is the first of its kind, it was not possible to compare the IAM spatially with earlier datasets. There is a 3.4% difference between this project's estimated total area under irrigation (1 334 562 ha) for 2014/15 and the last authoritative estimate by the Committee for the development of a food and nutrition strategy for Southern Africa (1990) (1 290 132 ha). To put this figure into perspective, in 2016 the total area under wine grapes was 95 775 ha[19]. The 44 430 ha difference between the 1996 estimate and the area under irrigation in 2014/15 thus represents about half of the area under wine grapes.

The IAM in itself is invaluable for establishing a record of irrigation activities at national level and forms a benchmark against which future assessments can be done. The map was essential for quantifying the water used by irrigated crops at national, provincial and regional (catchment) scales. This was done by aggregating the cumulative ET estimates (as modelled by ETLook and recorded in the geodatabase) of all actively irrigated fields. Although this was a relatively simple procedure, a sensitivity analysis was carried out to better understand the influence of using the relatively low (250 m) resolution ET datasets for quantifications at field level. A number of cases of ET under- and overestimation was noted, mainly due to pixel mixing caused by non-agricultural land cover directly adjacent to fields. For instance, land cover types with high ET (e.g. water and plantations) neighbouring agricultural fields caused an overestimation of crop water use, while land cover types with low ET (e.g. bare soil) caused underestimations. However, the sensitivity analysis (Section 5.3) revealed that the effect of these over- and underestimations are insignificant at regional scales, as they tend to offset (cancel out) one another.

Water use (ET)

The outcome of the sensitivity analysis was supported by an assessment of the ET frequency distributions per selected crop types. Although some outliers and variation within particular crop types

[19] http://www.sawis.co.za/info/download/Vineyards_2016_1.pdf

were noted, all of the ET distributions (histograms) of crop types (for which a sufficient number of fields were available) were unimodal and had acceptable standard deviations (less than 40% of median values). This suggested that the adjacent land covers had a marginal effect on ET and that the median ET values are reliable representations of the water used per crop type. Apart from the validating role that the crop-specific ET analyses played, it also provided a better understanding of how ET varied among crop types and between climatic regions. For instance, citrus recorded the highest median ET values (of the crops assessed), with 911 mm/yr and 678 mm/yr in the summer and winter rainfall region respectively. Wine grapes generally used less water, with rainfed vineyards in the winter rainfall region producing the lowest median ET values (500 mm/yr). The crop-specific analyses of ET also revealed that the ET of irrigated crops are not disproportionate to those of rainfed crops. For instance, the ET of irrigated wheat in the summer rainfall region was 737 mm/yr, while the ET of rainfed wheat in the same region was 611 mm/yr, a difference of only 20%. The frequency of irrigation applications would have had a substantial impact on this figure. The increase in the consumptive water use of irrigated maize, compared to rainfed maize, should be considered within the large increase in yields when maize fields are irrigated.

The national aggregation of ET for all irrigated areas in 2014/15 showed that the total consumptive water use from irrigated agriculture in SA was 10 221 million m^3/yr. This compares well with previous estimates such as the 1996 Overview of Water Resource Availability and Utilisation in South Africa, which estimated the water use by irrigated agriculture to be 10 740 million m^3/yr and 7 836 million m^3/yr in 2000 (as part of the NWRS), with the latter based on a 98% assurance of supply (Backeberg 2003; DWAF 2004). The water use estimate for irrigated agriculture in 2014/15 was marginally lower than this estimate, despite the 44 430 ha increase under irrigation, implying either improved water use efficiencies or production of crops with lower water use requirements. However, differences in accuracies and methods between the 1996 estimations and the current study may also account for these dissimilarities.

It should be noted that crop cultivation is highly dynamic and heavily influenced by climatic and market conditions in a particular season. The estimation of 10 221 million m^3/yr is merely a snapshot of water use in 2014/15 and will likely fluctuate from year to year. This total consumptive water use should also not to be confused with the volume of irrigation applied, which would likely be higher than the 10 221 million m^3/yr water use estimate. Ideally, the water applied should not exceed consumptive use (i.e. 100% efficiency), but in practice irrigation application efficiencies can be as high as 90% for drip irrigation (Brouwer et al. 1989). More work is necessary to investigate the relationship between water applied and water consumed and to improve water use efficiencies and reduce non-beneficial, non-consumptive losses.

Water accounting (WA)

Although the mapping of irrigated areas and the quantification of consumptive water use provides a sound foundation for understanding the *status quo* of irrigation in SA, it does not answer the question of whether water resources are available for extending irrigated agriculture. WA frameworks (comprising quantitative information on water use and water availability) have been developed to simplify and communicate information to policy makers. The process is analogous to financial accounting and provides inter alia information on the water resource base, consumption, productivity and withdrawal within a particular catchment. For this study, the WA+ framework, developed by eLEAF with inputs from IWMI, FAO and the Technical University of Delft, was used to determine whether water resources are available for the extension of irrigated agriculture. This framework, currently being further developed by Wateraccounting.org, was applied to seven secondary catchments throughout SA, selected on the basis of characteristics such as population size, agricultural activities and proportion of irrigation. The results showed that in Mzimvubu, Kowie and the Breede River catchments the water resources were likely sufficient to allow for additional storage and productive use of (surface) water. This additional water could potentially be used by existing water users to meet their crop demand in summer or store additional water in wetter years as insurance for drier years. Additionally, or alternatively, this water could possibly be used to support the expansion of the area under irrigation in the respective regions. In Mzimvubu in particular, a substantial amount of surface water available for productive use. However, since these findings represent conditions in 2014/15 only, it should be interpreted with caution as it does do not necessarily represent the long-term conditions. The availability of water is highly dependent on various dynamic factors and more work is needed to monitor changes over multiple seasons, specifically during periods of drought. An ongoing challenge for applying the WA+ framework is the unavailability of high-quality spatial rainfall data; accurate information on rainfall in mountainous areas is particularly absent. WA+ should consequently be applied retrospectively (at least from 2015 onwards) and on an ongoing basis, preferably at national scale, to gain a better understanding of the fluctuations in water availability.

Application of Earth observation (EO)

An important and significant outcome of this research was the development of capacity in EO and other geospatial techniques. In particular, technical capacity in the use of remotely sensed imagery, OBIA and machine learning techniques within the context of water use and ET estimation, land cover (e.g. crop type) mapping, and WA was created. These skills were not only developed in the three MSc students participating in the project, but were also transferred onto a group of young researchers at the CGA, Stellenbosch University, who were actively involved in the project. This process has strengthened the CGA's research and development capacity and has led to several new projects related to water use quantification[20], water footprint assessment[21], salt accumulation and waterlogging monitoring[22], crop type mapping (e.g. Cofco Agri), terroir studies (Winetech), and yield and soil water content modelling (e.g. SASRI, Winetech, WCPDA). In addition, this new capacity for the application of EO and geospatial technologies to water-related research – coupled with the CGA's competence in image processing automation and experience of working with big data – provides a sound foundation for extending the

[20] *Integrated land use and water use management areas, with a view on future climate and land use changes*, WRC project K5/2520//1 (WRC 2017)
[21] *Water footprint as a sustainability indicator for table and wine grape production*, WRC project K5/2710/4
[22] *Salt accumulation and waterlogging monitoring system (SAWMS) development*, WRC project K5/2558//4, (WRC 2017)

irrigated area mapping and water use quantification beyond SA's boundaries.

Industry involvement was not only critical during the validation of the IAM, but was invaluable throughout the project. As reported in Section 4.3.2, the project team took part in various stakeholder engagement activities during which the datasets uses, technologies employed and initial results were communicated. The preliminary findings were always well received and valuable inputs from participants were obtained. It is clear that irrigated agriculture is universally perceived as a significant component in SA's food security and economy and that the livelihoods of many are dependent on it. Many stakeholders expressed concern about the impact of an unabated expansion of irrigated agriculture and increased WUE was frequently a topic of discussion. Many agreed that WA holds much potential for improved understanding of water availability and that its implementation should be expanded to all catchments where a large proportion of the crops are irrigated.

7.2 Proposals for future research

Land cover mapping

Land cover data played an important role in this project as it was used as input to the ET modelling (to define roughness maps and land use related canopy resistances), irrigated area mapping (to remove non-agricultural areas) and WA (to differentiate between protected, utilised and modified land uses). No recent land cover date were available at the initial stages of the project and much effort and expense went into collating and fusing datasets from various sources, resulting in the WRC South African land cover dataset (WRCLCD). The DEA commissioned a national land cover mapping exercise, which became available during the later phases of the project. This dataset, called SALC1314, was more recent (2013/14) than the WRCLCD and also much more consistent given that it was generated from one source of imagery (Landsat 8). As a result, all the research activities that used land cover data as input were repeated with the updated dataset. This included regenerating the ET dataset and updating the IAM. The additional labour was, however, well worth the effort as the results were of a much higher quality. Although the timely release of SALC1314 benefitted the project, the 2013/14 map is now several years outdated and it seems there is little prospect that it will be updated soon. The absence of frequently (annual) updated land cover/use data have implications for operational implementations of ET monitoring. It is thus essential that research be carried out on cost-effective (fully automated) techniques for mapping land cover on a continuous (annual) basis. Initial research into the application of machine learning techniques for land cover mapping has been very encouraging (Myburgh & Van Niekerk 2013; Verhulp & Van Niekerk 2016), but such techniques are reliant on suitable training data. Unfortunately, the collection and maintenance of this data can be labour-intensive. Based on work currently being carried out at Stellenbosch University, a combination of machine learning and knowledge-based methods appears to be most effective, but more work is needed to investigate how such techniques can be employed cost-effectively across large areas.

Field boundary delineation

As discussed in the previous section, the quality of the field boundary dataset had a significant impact on the accuracy of the irrigated area mapping and water use quantifications. The dataset, which was provided by DAFF, is updated every five years and the latest version (released in April 2017) was produced from imagery dated 2013–2015. This was consequently not an ideal representation of the field boundaries of the study period (1 August 2014 to 31 July 2015). In addition, the dataset attempts to capture contiguous areas where any evidence of previous cultivation is apparent and not where crops are actively grown. As such, the demarcated fields often include fallow areas or even areas that have not been cultivated for many years. Some areas are clearly abandoned (see Appendix V for examples) and have been overgrown with shrubs and even small trees, which can have a negative impact on the irrigated area mapping and water use quantifications. However, given that the field boundary dataset is produced using visual interpretation and on-screen digitising of VHR satellite images (e.g. 2.5 m SPOT 5 and 1.5 m SPOT 6/7), acquired over several seasons/years, it is not possible (and cost-effective) to update the field boundaries on a regular (annual or seasonal) basis. Clearly, a different approach is needed. The advent of high resolution, high temporal, freely available satellite imagery has opened up a multitude of new possibilities and research into the use of such imagery for automated generation of frequently updated (seasonal, even monthly), actively growing crop extent maps (i.e. field boundaries) is urgently needed. Initial research conducted at Stellenbosch University – funded through WRC project K5/2558//4 – appears very promising, but in light of the diversity of crops grown in SA and given that field boundary delineation is a global challenge, much more attention should be given to this matter.

Dynamic crop type mapping

Crop type mapping is another field of research that requires more attention. Crop type maps are used in a wide range of applications (e.g. environmental modelling, yield forecasting, subsidy payments, insurance assessments, land conservation policy actions) and were instrumental in this study to gain a better understanding of the consumptive water used by different crops. In SA, crop type maps are mostly generated at provincial level. Some maps focus only on grain crops, while others involve complete crop censuses. Ideally, complete censuses such as those carried out in the Western Cape in 2013 and 2017, should be commissioned nationally on an annual basis – but that would be prohibitively expensive. Given that *in situ* data collection is invariably the biggest expense in crop type mapping campaigns, more research is needed to investigate how EO techniques can eliminate (or at least reduce) the cost of crop type mapping over large areas. Research carried out as part of this project (Gilbertson & Van Niekerk 2017) suggests that high accuracies (>95%) can be obtained by making use of multi-temporal satellite imagery and a small set of *in situ* observations to train machine learning algorithms such as SVM. However, this research was carried out in a small area (Swartland) and should be extended to other areas in SA where the climatic conditions and crop types are different. The Sentinel-2 for Agriculture system (ESA 2018) that is being developed in Europe and tested in many countries (including South Africa) also shows promise in this regard.

Cost-effective ET modelling and the generation of high resolution biophysical data sets

The ETLook model, developed by eLEAF in the Netherlands, was used to generate the ET dataset used in this study. Apart from the need for minor recalibrations in the Limpopo area, the model produced robust results throughout. The relatively low resolution of the ET product (250 m) was not a major limitation (see discussion in previous section), but higher resolution data (e.g. 50-100 m) would have benefitted the irrigated area mapping, particularly to identify small-scale irrigation activities. Research into the cost-effective generation of ET datasets at high (pixel size of less than 100 m) resolution is thus needed. The validation of ET datasets generated from remotely sensed data should also receive ongoing attention.

Incorporation of remotely sensed data into climate surface interpolation

The ET – P approach used to identify irrigated areas (Section 4.2.3) was not effective in regions where the rainfall data (P) were inaccurate. Inaccuracies in the satellite-based rainfall data were especially apparent in mountainous regions, where rainfall quantity seems consistently underestimated. The sparsity and uneven distribution of rainfall stations from which rainfall surfaces (raster-based datasets) can be interpolated means that this is also an incomplete source of rainfall information. The interpolation of stationary rainfall measurements is particularly challenging, as its geographical variation is much more erratic compared to that of other climatic variables such as temperature (which is well correlated with elevation and distance to large waterbodies). Although some research has been done to improve the interpolation of rainfall data (Van Niekerk & Joubert 2011), more work is needed to improve interpolation methods and investigate how remotely sensed data can be incorporated into the interpolation processes. For instance, the Global Precipitation Monitoring (GPM) satellite provides daily precipitation estimates at a one minute (~10km) spatial resolution by combining data recorded by passive and active microwave sensors. The accuracy of GPM data have not yet been validated within a South African context and needs investigation. Effective methods for incorporating this data into climatic interpolations should also be developed.

Earth observation based water accounting

The application of the WA+ framework to seven selected catchments in SA demonstrated how the IAM, land cover/use data, ET data sets and ancillary datasets can be used in combination to support decisions relating to water management. However, the acquisition, collation, and preparation of all of the required datasets, especially those that required local knowledge, was very time-consuming and costly. More work is needed to investigate the impact of using alternative data sources and inferred information. IHE Delft has made much progress in this regard and has demonstrated how most of the WA+ sheets can be automatically populated using freely available data sources. It is important that South African researchers collaborate with IHE Delft to refine these processes and establish workflows through which WA can be carried out more efficiently.

7.3 Operational recommendations

SA has a limited availability of suitable land and adequate water resources for irrigated crop production. With the added pressures of climate change, population growth and decline in water quality due to salinisation, the need for improved assessments of the current water resources and land uses is critical. Actions related to improved WUE and irrigation expansion, or water reallocation, can only follow once this information is available. With irrigated agriculture being labelled the largest user of surface and ground water, it is important to obtain recent and accurate data on water used by different irrigated crops over time (i.e. throughout the growing season) and space (i.e. in different geographical areas). Combining these datasets into a WA framework will improve our understanding of the true pressures on SA's water resources and will better inform the expansion of irrigated agriculture.

Based on the discussions of the previous two sections, it is clear that this project provides a good indication of the *status quo* of irrigated agriculture water use for the period of 1 August 2014 to 31 July 2015. The study established a methodology that can be replicated for other periods. Given that it is unlikely that the IAM and water use quantifications produced in this project are representative of the long-term situation, the application of the methodology to other periods is essential in aiding sound water management practices and supporting decisions about additional allocations. The FAO recently released an Africa-wide, freely available, monthly open access of remotely sensed derived data (WaPOR) ET dataset at 250 m resolution (also generated using ETLook and thus very similar to the ET dataset used in this project) for the period 2009–2019 (see Section 2.3.6), which will considerably reduce the cost of future implementations in SA. Coupled with the recently released and freely available Sentinel 2 imagery, the FAO ET datasets will allow for the production of seasonal (even monthly) IAMs and water use quantifications up to 2019. If the irrigated area mapping process is automated, the latency (period required for production) can be reduced to a few weeks, which will substantially increase the reliability of the water use estimations, as it will allow for *in situ* validation to be carried out.

Consequently, based on the findings of this research, it is recommended that:

1. the IAM is compared to soil suitability maps;
2. water application in relation to ET crop water requirements is investigated;
3. techniques are developed whereby irrigation type (permanent, supplementary or occasional) and methods (surface, sprinkler or micro/drip) can be determined;
4. actual irrigation is compared to lawful water use;
5. the IAM be used to assess the scale of irrigation schemes (small, medium, large) in South Africa;
6. the WaPOR ET dataset is recalibrated using local climatic and land use data;
7. the irrigated area mapping procedure is fully automated;
8. the IAM is continuously (i.e. on a seasonal or monthly basis) updated;
9. *in situ* observations are used to validate (ground truth) the IAM;
10. consumptive water use of irrigated crops is revised on a continuous (seasonal or monthly) basis at national scale; and
11. the WA+ framework is applied on primary catchment level, preferably to all catchments in SA.

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APPENDIX I: LAND USE CLASSES AS CAPTURED IN THE SOUTHERN AFRICAN LAND COVER (SALC1314) MAP PRODUCED FOR SOUTH AFRICA IN 2013-14

Water seasonal
Water permanent
Wetlands
Indigenous Forest
Thicket /Dense bush
Woodland/Open bush
Grassland
Shrubland fynbos
Low shrubland
Cultivated comm fields (high)
Cultivated comm fields (med)
Cultivated comm fields (low)
Cultivated comm pivots (high)
Cultivated comm pivots (med)
Cultivated comm pivots (low)
Cultivated orchards (high)
Cultivated orchards (med)
Cultivated orchards (low)
Cultivated vines (high)
Cultivated vines (med)
Cultivated vines (low)
Cultivated permanent pineapple
Cultivated subsistence (high)
Cultivated subsistence (med)
Cultivated subsistence (low)
Cultivated cane pivot - crop
Cultivated cane pivot - fallow
Cultivated cane commercial - crop
Cultivated cane commercial - fallow
Cultivated cane emerging - crop
Cultivated cane emerging - fallow
Plantations / Woodlots mature
Plantation / Woodlots young
Plantation / Woodlots clearfelled
Mines 1 bare
Mines 2 semi-bare

Mines water seasonal
Mines water permanent
Mine buildings
Erosion (donga)
Bare none vegetated
Urban commercial
Urban industrial
Urban informal (dense trees / bush)
Urban informal (open trees / bush)
Urban informal (low veg / grass)
Urban informal (bare)
Urban residential (dense trees / bush)
Urban residential (open trees / bush)
Urban residential (low veg / grass)
Urban residential (bare)
Urban school and sports ground
Urban smallholding (dense trees / bush)
Urban smallholding (open trees / bush)
Urban smallholding (low veg / grass)
Urban smallholding (bare)
Urban sports and golf (dense tree / bush)
Urban sports and golf (open tree / bush)
Urban sports and golf (low veg / grass)
Urban sports and golf (bare)
Urban township (dense trees / bush)
Urban township (open trees / bush)
Urban township (low veg / grass)
Urban township (bare)
Urban village (dense trees / bush)
Urban village (open trees / bush)
Urban village (low veg / grass)
Urban village (bare)
Urban built-up (dense trees / bush)
Urban built-up (open trees / bush)
Urban built-up (low veg / grass)
Urban built-up (bare)

APPENDIX II: LIST OF METEOROLOGICAL STATION USED, CONSISTING OF NATIONAL OCEANIC AND ATMOSPHERIC ADMINISTRATION (NOAA) AND AGRICULTURAL RESEARCH COUNCIL (ARC) STATIONS.

NOAA Nr.	NAME	LATITUDE	LONGITUDE	ALTITUDE (m)
673150	VILANCULOS	-22.00	35.32	21
673230	INHAMBANE	-23.87	35.38	15
673270	PANDA-INHAMBANE	-24.05	34.05	150
673310	MAPULANGUENE-MAPUTO	-24.48	32.08	151
673350	XAI XAI	-25.05	33.63	5
673410	MAPUTO/MAVALANE	-25.92	32.57	44
673460	CHANGALANE	-26.28	32.18	104
679910	BEITBRIDGE	-22.22	30.00	457
680020	WINDHOEK EROS	-22.62	17.08	1699
680240	GHANZI	-21.70	21.65	1100
680700	SELEBI PHIKWE	-22.05	27.82	892
680980	WALVIS BAY AIRPORT	-22.98	14.65	88
681040	WALVIS BAY	-22.88	14.43	0
681041	MARIENTAL	-24.60	17.93	1113
681090	BITTERWASSER	-23.87	18.00	1274
681100	WINDHOEK	-22.57	17.10	1700
681120	HOSEA KUTAKO INTL A	-22.48	17.47	1700
681160	GOBABIS	-22.50	18.97	1400
681480	MAHALAPYE	-23.08	26.80	1006
681550	ELLISRAS	-23.68	27.70	839
681740	PIETERSBURG	-23.87	29.45	1224
681760	MARA	-23.15	29.57	897
681820	LEVUBU	-23.08	30.28	706
681830	THOHOYANDOU	-23.07	30.38	618
681850	LYDENBURG	-25.10	30.47	1434
681880	TZANEEN-GRENSHOEK	-23.77	30.07	896
681910	PHALABORWA	-23.93	31.15	407
682120	HARDAP	-24.53	17.93	1100
682260	TSHANE	-24.02	21.88	1100
682340	JWANENG	-24.60	24.67	1189
682400	SERETSE KHAMA INTER	-24.55	25.92	1006
682420	MAFIKENG WO	-25.82	25.55	1281
682530	THABAZIMBI	-24.58	27.42	977
682550	RUSTENBURG	-25.65	27.23	1151
682620	PRETORIA-EENDRACHT	-25.73	28.18	1326
682630	PRETORIA (IRENE)	-25.92	28.22	1523
682635	LANSERIA	-25.93	27.92	1377
682640	WATERKLOOF (SAAF)	-25.83	28.22	1506
682645	MAKHADO AFB	-23.17	29.70	935
682670	ERMELO	-26.50	29.98	1766
682671	GRAND CENTRAL	-25.98	28.13	1623
682672	JOHANNESBURG B/G	-26.15	28.00	1626
682674	SPRINGS	-26.25	28.40	1628
682676	SELEBI PHIKWE	-22.05	27.82	892
682677	POLOKWANE INTL AIRP	-23.85	29.45	1242
682680	WARMBAD TOWOOMBA	-24.90	28.33	1132
682710	POTGIETERSRUS	-24.20	29.00	1097
682720	OUDESTAD	-25.18	29.33	949

NOAA Nr.	NAME	LATITUDE	LONGITUDE	ALTITUDE (m)
682730	WITBANK	-25.83	29.18	1550
682870	GRASKOP	-24.93	30.85	1436
682890	NELSPRUIT	-25.50	30.92	883
682904	KRUGER MPUMALANGA I	-25.43	31.10	862
682905	PILANESBERG	-25.33	27.17	1040
682910	HOEDSPRUIT	-24.35	31.05	510
682960	SKUKUZA	-24.98	31.60	271
682970	KOMATIDRAAI	-25.52	31.90	183
683000	LUDERITZ (DIAZ POINT)	-26.63	15.10	0
683005	LUDERITZ	-26.68	15.23	139
683007	VEREENIGING	-26.57	27.95	1477
683120	KEETMANSHOOP	-26.53	18.12	1100
683200	WERDA	-25.27	23.25	1000
683220	TWEE RIVIEREN	-26.47	20.62	879
683250	GOOD HOPE	-25.45	25.42	1000
683280	TSABONG	-26.05	22.45	1000
683290	VAN ZYLSRUS	-26.88	22.05	928
683310	KATHU	-27.67	23.00	1186
683350	TAUNG	-27.55	24.77	1100
683380	VRYBURG	-26.95	24.63	1234
683410	LICHTENBURG	-26.13	26.17	1487
683420	OTTOSDAL	-26.82	26.02	1500
683430	BLOEMHOF	-27.65	25.62	1128
683450	WELKOM	-28.00	26.67	1342
683465	ERMELO	-26.50	29.98	1737
683470	KLERKSDORP	-26.90	26.62	1324
683490	VENTERSDORP	-26.32	26.82	1496
683500	POTCHEFSTROOM	-26.73	27.07	1351
683530	VEREENIGING	-26.57	27.95	1481
683550	KROONSTAD	-27.63	27.23	1432
683620	FRANKFORT	-27.27	28.50	1503
683680	JOHANNESBURG INTNL.	-26.15	28.23	1720
683700	BETHAL	-26.47	29.45	838
683770	NEWCASTLE	-27.77	29.98	1238
683800	CAROLINA	-26.07	30.12	1700
683870	VRYHEID	-27.78	30.80	1163
683960	MANZINI/MATSAPA AIR	-26.53	31.30	641
683990	BIG BEND	-26.85	31.92	94
684000	MAKATINI	-27.38	32.18	63
684030	ALEXANDER BAY	-28.57	16.53	29
684080	PORT NOLLOTH	-29.23	16.87	10
684110	VIOOLSDRIF	-28.70	17.60	168
684160	POFADDER	-29.13	19.38	990
684240	UPINGTON	-28.40	21.27	836
684290	POSTMASBURG	-28.33	23.07	1321
684380	KIMBERLEY	-28.80	24.77	1196
684420	BLOEMFONTEIN AIRPOR	-29.10	26.30	1354
684490	FICKSBURG	-28.82	27.90	1614
684533	MOSHOESHOE I INTL	-29.45	27.55	1630
684540	MASERU-MIA	-29.45	27.55	1628
684610	BETHLEHEM	-28.25	28.33	1678
684710	VAN REENEN	-28.37	29.38	1680
684740	ROYAL NATAL NAT. PA	-28.68	28.95	1392
684780	ESTCOURT	-29.00	29.88	1144
684790	LADYSMITH	-28.57	29.77	1069

NOAA Nr.	NAME	LATITUDE	LONGITUDE	ALTITUDE (m)
684810	PONGOLA	-27.42	31.60	312
684870	GREYTOWN	-29.08	30.60	1029
684880	BABANANGO	-28.37	31.22	768
684910	CHARTERS CREEK	-28.20	32.42	9
684940	MANDINI	-29.15	31.40	112
684970	MTUNZINI	-28.95	31.70	38
685120	SPRINGBOK	-29.67	17.90	1007
685130	KOINGNAAS	-30.20	17.28	99
685230	BRANDVLEI	-30.47	20.48	923
685240	VANWYKSVLEI	-30.35	21.82	962
685270	PRIESKA	-29.67	22.73	947
685380	DE AAR	-30.65	24.00	1287
685460	ALIWAL NORTH	-30.80	26.88	1351
685580	BARKLY EAST	-30.93	27.60	1819
685720	SHALEBURN	-29.80	29.35	1614
685750	IXOPO	-30.15	30.07	937
685800	CEDARA	-29.53	30.28	1071
685810	PIETERMARITZBURG	-29.63	30.40	673
685830	MOUNT EDGECOMBE	-29.70	31.05	94
685870	PORT EDWARD	-31.07	30.23	12
685880	DURBAN INTNL. AIRPO	-29.97	30.95	14
685890	GIANTS CASTLE	-29.27	29.52	1763
685910	MARGATE	-30.85	30.33	154
686130	LAMBERTS BAY	-32.03	18.33	94
686140	VREDENDAL	-31.67	18.50	33
686180	CALVINIA	-31.47	19.77	975
686240	FRASERBURG	-31.92	21.52	1268
686330	NOUPOORT	-31.18	24.95	1496
686470	QUEENSTOWN	-31.92	26.88	1104
686510	ELLIOT	-31.33	27.85	1463
686680	UMTATA	-31.53	28.67	747
687120	CAPE COLUMBINE	-32.83	17.85	67
687140	LANGEBAANWEG	-32.97	18.17	32
687150	MALMESBURY	-33.47	18.72	102
687170	PORTERVILLE	-30.02	18.98	123
687180	ROBERTSON	-33.80	19.90	204
687220	SUTHERLAND	-32.38	20.67	1459
687230	LAINGSBURG	-33.20	20.87	656
687270	BEAUFORT WEST	-32.35	22.55	899
687370	GRAAFF-REINET	-32.20	24.55	790
687440	CRADOCK	-32.17	25.62	102
687470	FORT BEAUFORT	-32.78	26.63	455
687520	BISHO	-32.90	27.28	590
687540	DOHNE	-32.52	27.47	900
688160	CAPE TOWN INTNL. AI	-33.97	18.60	42
688170	CAPE TOWN-PORTNET	-33.90	18.43	0
688210	WORCESTER	-33.62	19.47	270
688280	GEORGE AIRPORT	-34.02	22.38	190
688320	WILLOWMORE	-33.28	23.50	842
688350	PATENSIE	-33.77	24.82	85
688420	PORT ELIZABETH	-33.98	25.62	63
688430	PORT ALFRED AIRPORT	-33.57	26.88	84
688490	GRAHAMSTOWN	-33.28	26.50	642
688580	EAST LONDON	-33.03	27.83	125
689120	SLANGKOP	-34.15	18.32	8

NOAA Nr.	NAME	LATITUDE	LONGITUDE	ALTITUDE (m)
689160	CAPE POINT	-34.35	18.50	238
689180	HERMANUS	-34.43	19.22	14
689200	CAPE AGULHAS	-34.83	20.02	14
689210	STRUISBAAI	-34.80	20.07	4
689260	RIVERSDALE	-34.08	21.25	116
689280	MOSSEL BAY (CAPE ST)	-34.18	22.15	61
689350	KNYSNA	-34.05	23.08	54

ARC Nr.	NAME	LATITUDE	LONGITUDE	ALTITUDE (m)
30012	DE KEUR	-32.99	19.30	947
30099	AMSTERDAM; ATHOLE	-26.57	30.48	1550
30142	JANKEMPDORP; VAALHARTS	-27.96	24.84	1180
30166	SENEKAL; DRIEPAN	-28.39	27.59	1587
30175	RIVIERA	-32.68	18.70	90
30176	TYGERHOEK PP.	-34.16	19.91	183
30181	GROBLERSHOOP	-28.90	22.00	871
30191	PRIESKA; BLAAUKRANS	-29.53	22.97	944
30202	AUGRABIES-WITKLIP	-28.64	20.35	648
30203	GARIEP (GROOTDRINK)	-28.51	21.72	863
30376	HOPETOWN; LILYDALE	-29.58	24.15	1135
30378	FAIRVIEW	-33.78	18.92	153
30398	MORGENZON	-26.88	29.72	1612
30414	JANUARIESKRAAL	-33.42	18.45	110
30429	INALA: KAALRUG	-25.63	31.55	288
30447	NQADU - WILLOWVALE	-32.22	28.39	701
30458	GLADDEDRIFT: KLIPPOORT	-27.00	28.96	1522
30459	PETIT - MONSANTO	-26.08	28.40	1635
30462	CITRUSDAL-NOORD	-32.44	18.97	161
30535	PONGOLA; SASRI EXP FARM	-27.41	31.59	321
30544	EXCELSIOR - BENCHMARK	-28.89	26.94	1407
30554	BOSHOF	-28.59	25.51	1270
30555	BRONKHORSTSPRUIT	-25.70	28.80	1500
30575	ELUKWATINI: AWS	-26.05	30.80	979
30593	KAMIESKROON-LELIEFONTEIN	-30.31	18.08	1362
30594	BARKLEY WES-ULCO	-28.33	24.20	1209
30597	REITZ; SILOS	-27.80	28.44	1623
30601	VOORSTEKOP	-34.12	20.75	246
30621	PIET RETIEF; SULPHUR SPRINGS	-27.18	31.09	946
30631	SEZELA - LEWISHAM	-30.39	30.38	215
30634	THABAZIMBI: MARAKELE TOWERS	-24.46	27.61	2256
30649	POTCHEFSTROOM: OLIESADE	-26.74	27.08	1349
30656	BONNIEVALE: DREW1	-34.02	20.22	122
30658	MURRAYSBURG	-31.98	23.74	1193
30661	WILLISTON	-31.33	21.02	1150
30668	THABAZIMBI: ROOIBOKKRAAL	-23.93	26.99	869
30672	JANSENVILLE: JANSENVILLE PP	-32.94	24.70	450
30679	KOFFIEFONTEIN: AWS	-29.36	25.13	1238
30690	SCHWEIZER RENEKE: BOSKOP	-27.17	25.45	1348
30691	KOKSTAD EXPERIMENTAL FARM	-30.52	29.41	1373
30707	SAND PP	-32.56	18.52	103
30718	MIDDELTUIN	-32.31	18.84	407

ARC Nr.	NAME	LATITUDE	LONGITUDE	ALTITUDE (m)
30722	KOEDOESKOP	-24.88	27.52	939
30737	BLOEMFONTEIN: WEGSLUIT	-29.45	26.04	1355
30745	METZ	-24.23	30.44	600
30748	MASALALE PACKHOUSE	-23.70	30.79	420
30751	MESSINA: NWANEDI	-22.45	30.50	429
30757	SEKHUKHUNE: GROOTFONTEIN	-24.21	29.91	720
30759	MALAMULELE :MHINGA-XIKUNDU	-22.80	30.84	460
30763	PORTEVILLE: DEHOEK	-33.16	19.03	126
30766	BRAKFONTEIN: DIE BOS CALVINIA	-32.34	19.53	295
30771	SEKHUKHUNE: LEEUKRAAL	-24.92	29.84	1446
30776	ELGIN: BEAULIEU	-34.17	19.03	300
30787	KIRKWOOD	-33.40	25.34	119
30793	KLAWER	-31.79	18.63	79
30797	MARYDALE: KAMEELBOOM	-29.32	22.25	928
30802	ZASTRON: CAMELOT	-30.11	27.03	1475
30803	CALITZDORP: DORINGBOS_BOPLAAS	-33.54	21.67	224
30804	PIKETBERG: POOLS-IDEAL_HILL	-32.80	18.89	161
30805	OUDTSHOORN: ROOIRIVIER	-33.53	22.82	581
30831	DOORNKLOOF	-30.38	24.98	1217
30838	BOULUST	-22.71	28.60	812
30855	GROOTZUURFONTEIN	-30.34	25.81	1494
30861	VILJOENSLAAGTE	-27.28	27.42	1373
30873	RUSOORD	-26.82	28.31	1508
30875	PONTDRIFT	-22.20	29.19	508
30884	WATERBERG: STAANKRAAL	-24.49	27.12	890
30888	WATERBERG: WITPOORT	-23.33	28.01	820
30891	DOUGLAS: DUIKERSVLEI	-29.24	23.79	998
30893	KENHARDT: DRIEKOP	-29.28	21.13	815
30900	WOLMARANSTAD: HARTBEESPAN	-27.49	25.98	1279
30901	PIENAARSRIVIER: WATERBERG	-25.24	28.31	1044
30905	BELFAST: DRIEFONTEIN	-25.75	30.16	1775

APPENDIX III: STAKEHOLDER ENGAGEMENT ACTIVITIES

Table AIII.1 Number of fields edited on web application

WMA	Number of fields edited
Berg/Olifants	18
Breede/Gourits	27
Inkomati/Usuthu	107
Limpopo	19
Mzimvubu/Tsitsikamma	48
Olifants	23
Orange	90
Pongola/Mtamvuna	19
Vaal	0

Table AIII.2 Events where presentations on this project were given.

Date	Event name	Sector	Location
18 November 2014	South African National Committee on Irrigation and Drainage (SANCID) symposium	Water and agriculture	Muldersdrift
4 March 2015	Water Task team (Water Use and Irrigation Working Group)	Water and agriculture	Pretoria
16 March 2016	WRC-SAGEO Workshop	Water and agriculture	Pretoria
5 April 2016	Water Footprint Research Alliance Conference	Water and agriculture	Cape Town
4 May 2016	Natural Resource Inventories (NRI) group	National and provincial agriculture	Pretoria
27 Sep 2016	South African Association of Geographers Conference	Academia	Stellenbosch
12 Oct 2016	SANCID symposium	Irrigation and drainage	Worcester
10 February 2017	Crop Estimates Liaison Committee meeting	Agriculture	Pretoria
9 March 2017	SABI branch meeting	Irrigation and water	Klapmuts
19 April 2017	NRIA SWG meeting	Agriculture and Land	Pretoria
4 May 2017	Water Task team (Water Use and Irrigation Working Group)	Water and agriculture	Pretoria
8 June 2017	Workshop held with DAFF staff at Stellenbosch University	National agriculture (DAFF)	Stellenbosch
29 June 2017	WMA CEO Meeting	WMA CEO's	Nelspruit
29 June 2017	IWMI workshop	Water management	Stellenbosch
1 Aug 2017	SABI congress	Irrigation	Somerset West
15 Aug 2017	Agricultural Business Chamber (Agbiz) Mini Symposium	Agriculture (grains)	Pretoria
28 Nov 2017	Breede-Gouritz Catchment Management Agency (BGCMA)	Water	Worcester

Table AIII.3 List of institutions informed about this project

Organisation	Organisation
PULA consultants	Citrus Research international
National Water Resource Planning, DWS	Hortgro science
WARMS, DWS	SATI
SABI and Irrigation boards via SABI	VINPRO/WineTech
BGCMA, various catchment management areas (CMAs) and irrigation boards (IBs)	Potatoes SA
IWM	SASRI/SASA
SAEON	Agricultural Chamber of Commerce – Grain, Crop Estimates Liaison Committee (CELC)
SANPARKS	Provincial and National Departments of Agriculture
IWMI/CGIAR	Produce Marketing Association
Tropical and Subtropical fruits	GWK
RCL foods	SAGIS
Directorate: Water use and Irrigation Development, DAFF	Provincial departments of Agriculture
Agricultural Business Chamber	

APPENDIX IV: CROP TYPE MAPPING

Methodology and Approach

Crop Type maps were required in support of the modelling of water use and water availability for agricultural cultivation and cropping activity. As part of this requirement, the three main provinces which contribute to South Africa's summer grain production, namely Free State and Mpumalanga were mapped and classified. The classification was performed using Landsat 8 imagery at a resolution of 30 metres for the 12 months cycle from July 2014 through to June 2015. All available Landsat 8 imagery for this period was downloaded and processed to ensure a full coverage of satellite imagery that represented the entire crop growth cycle for all grain crops. The Landsat 8 data were then assessed province by province to select the optimal cloud free images for each individual province, while ensuring available imagery at regular intervals throughout the cropping season.

Techniques Used

Once all the imagery were prepared, the crop type information recorded during the PICES (Producer Independent Crop Estimate System) survey was used to calibrate (train) the satellite imagery. This process linked field reference points for known crops to spectral values in the satellite imagery, which are required to perform a supervised classification. Ground verification data were available for all the major grain crops, which included summer crops such as maize, sunflower, soya beans, sorghum and groundnuts. Other classes that were set up during training were Planted Pasture and Fallow fields, as well as wheat, which is cultivated during winter. Once the training process was completed, the classification procedure was performed to assign a crop type to each pixel using the MLC algorithm. The crop type information was then transferred from the classified image by assigning a crop to each individual field. For this process the national DAFF field boundary shape file was used, which comprised all cultivated fields in South Africa, with area (hectares) calculated for each individual field. The dataset also distinguishes between rainfed and irrigated fields, where fields that represent centre pivot structures, are labelled separately.

Deliverables

The crop type maps were delivered as ArcGIS shapefile format, as a separate file for each individual province, projected to the applicable UTM / WGS 84 zone. Each provincial shapefile contained polygons delineating each individual agricultural field, to which a crop type code was assigned. This information allowed individual field data to be aggregated up to broader administrative levels such as districts or catchments.

Accuracy and Limitations.

This dataset is useful to analyse patterns and trends of grain crop cultivation in the northern Highveld region of South Africa on an annual basis. However, fields which are cultivated for grain crop production can potentially have a different crop every year; therefore the crop type maps can only be used as representative statistics for the 12 month cycle during which the imagery was selected.

The accuracy was calculated using the F-test, which is commonly used to determine classification accuracy of EO derived geographical map data. Map classification classes (crop types) were compared against a set of ground truth test sites at locations (farm fields) of the class (crop type) based on a portion of the recorded PICES field survey information not used in the training. The overall F score achieved was 83%, with maize (85%), wheat (88%), soya beans (81%) and sunflower (77%) also scoring highly.

Fanie Ferreira

GeoTerraImage

APPENDIX V: EXAMPLES OF FIELD BOUNDARY DELINEATION ISSUES

The quality of the field boundary dataset used to map the irrigated areas and to quantify water used by irrigated agriculture was one of the main challenges of this study. Below are some examples of issues identified. Most of these problems are related to the use of outdated imagery and manual methods for digitising fields. As discussed in Section 7.2, more research is needed to establish a method whereby actively cultivated fields can be mapped automatically so that boundaries are updated to the latest imagery.

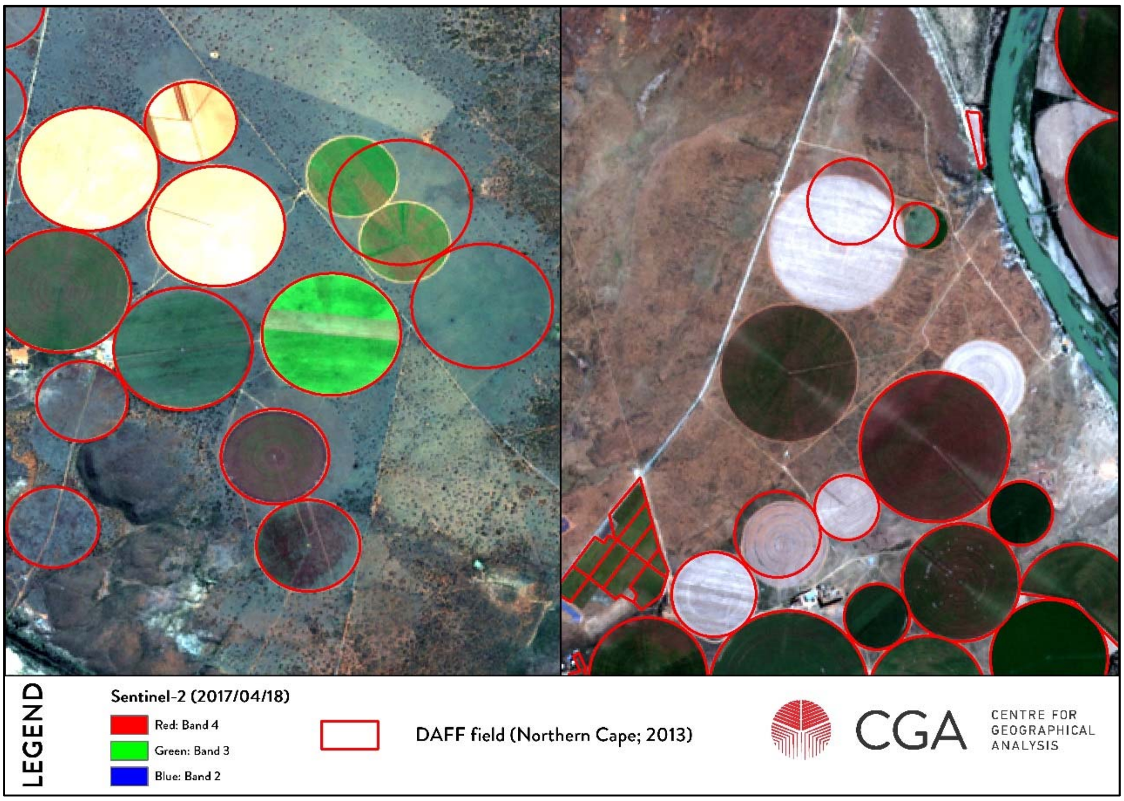


Figure AV.1 Examples of spatial inaccuracies of fields in the DAFF dataset

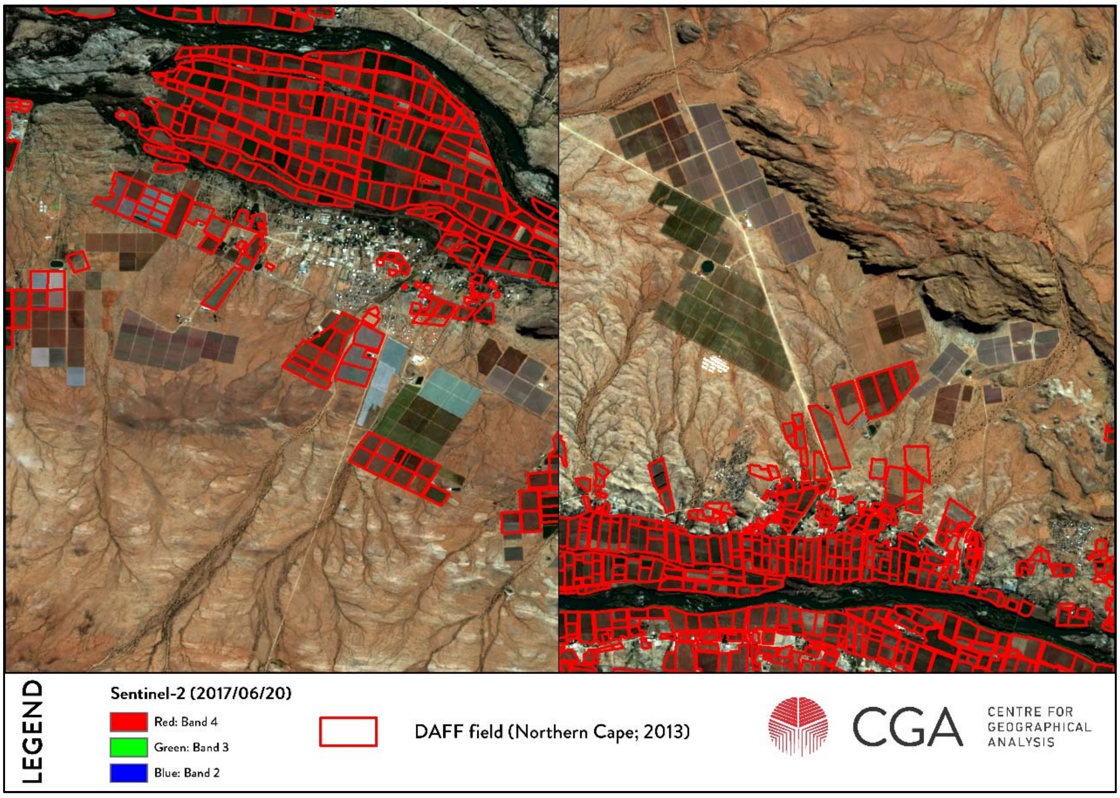


Figure AV.2 Examples of actively irrigated fields excluded from the DAFF dataset

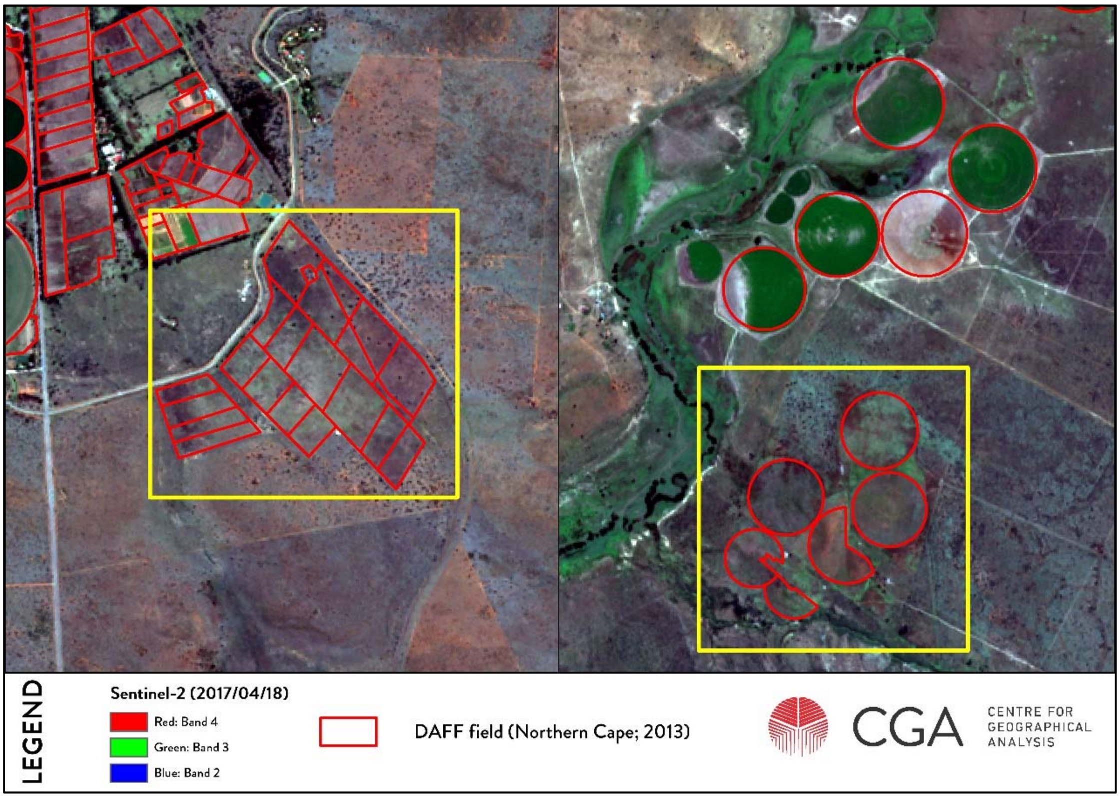
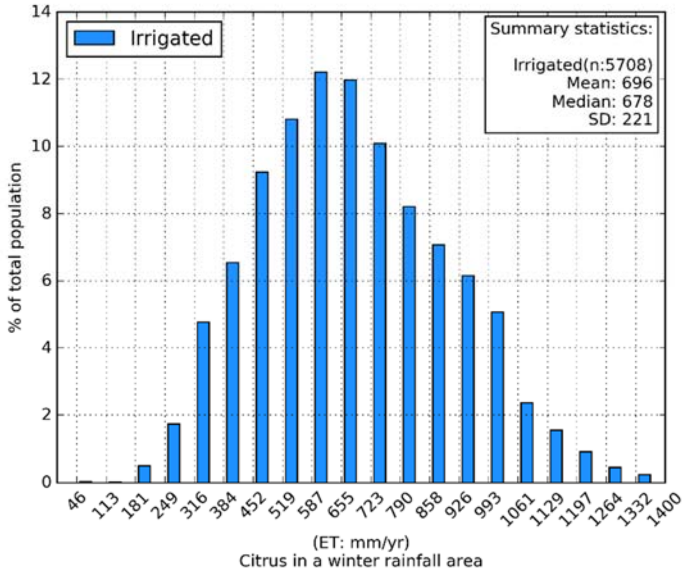
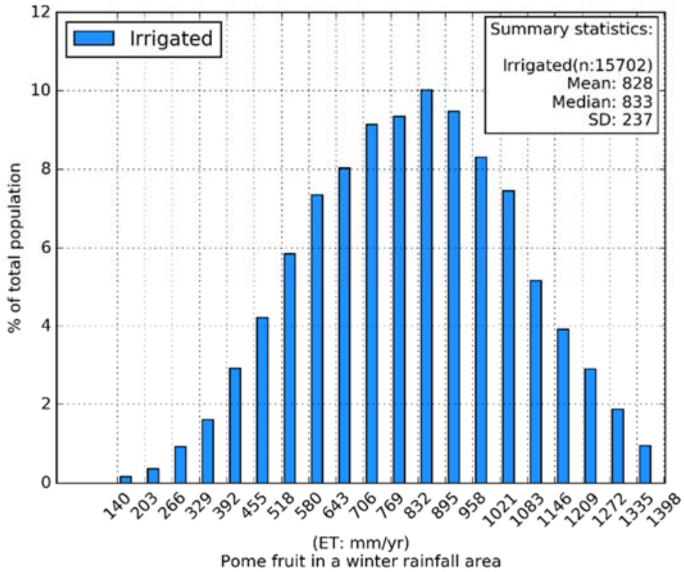
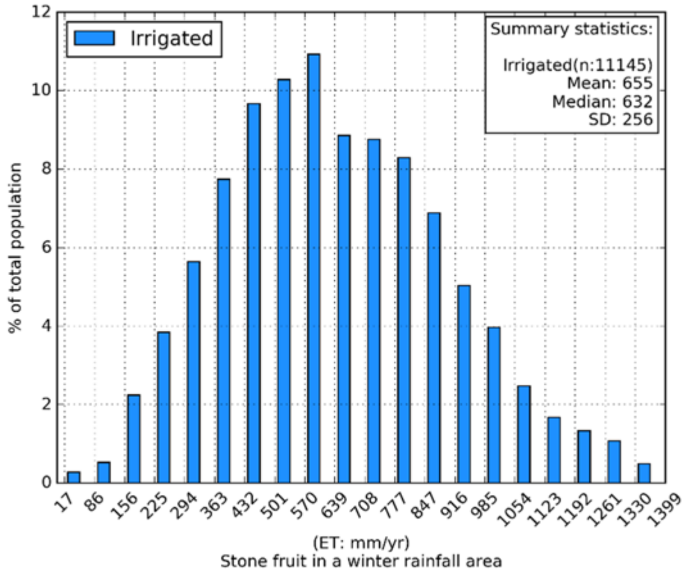


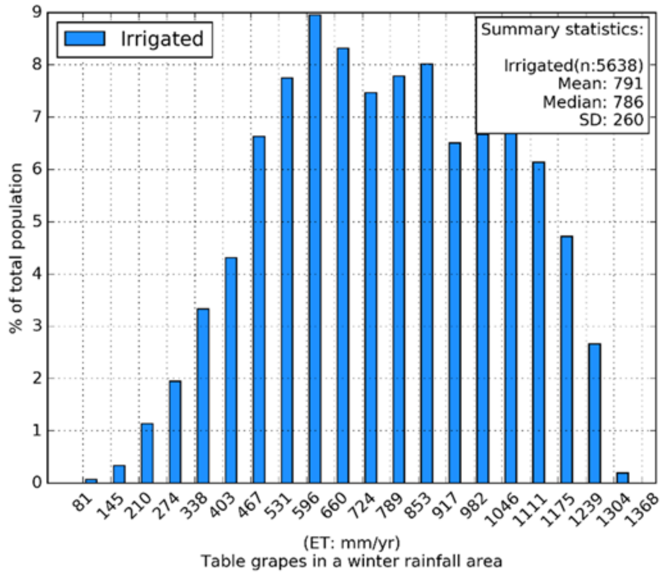
Figure AV.3 Examples of abandoned fields included in the DAFF dataset (Northern Cape)

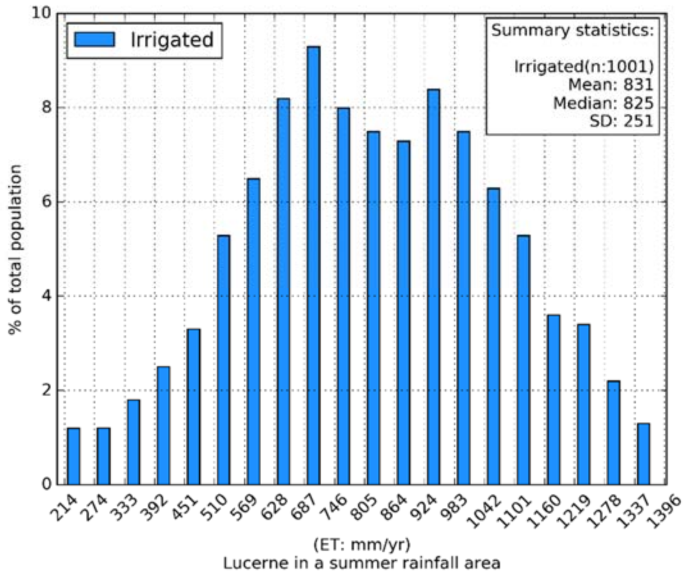
APPENDIX VI: FREQUENCY DISTRIBUTION OF ET AS SHOWN IN HISTOGRAMS FOR SELECTED CROPS

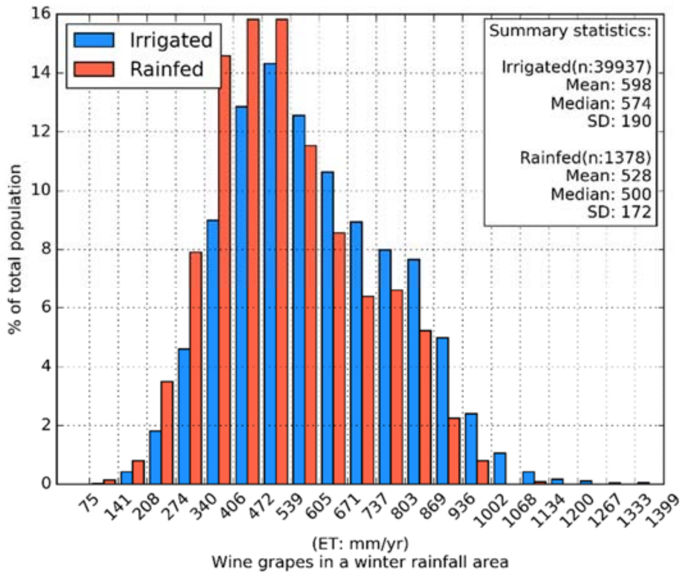


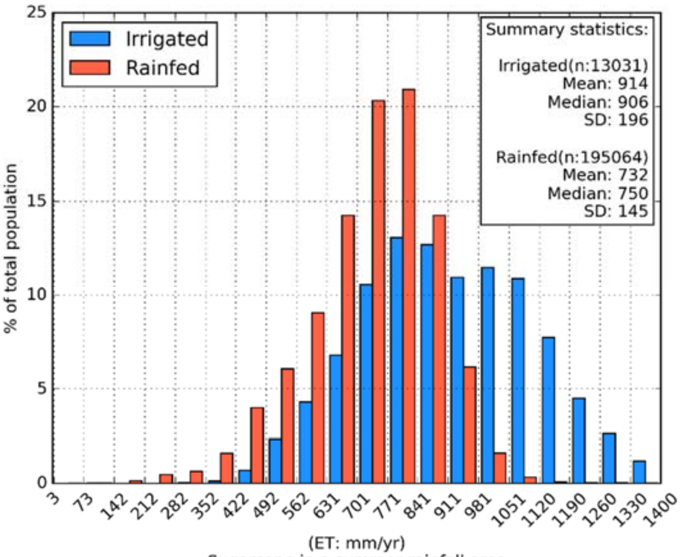




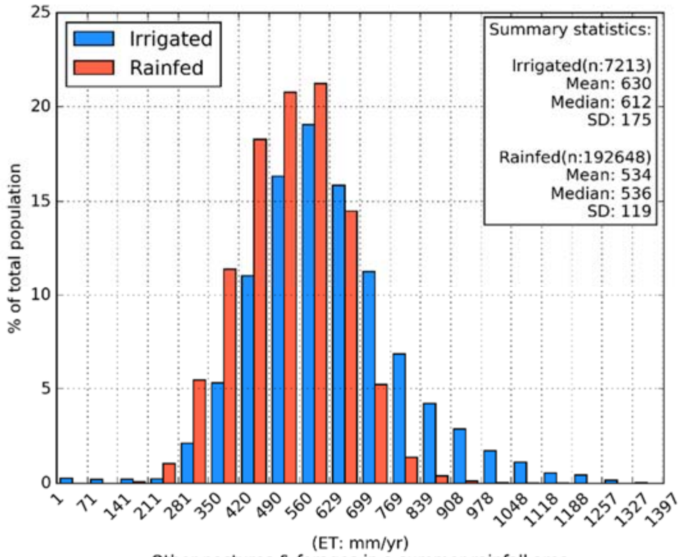




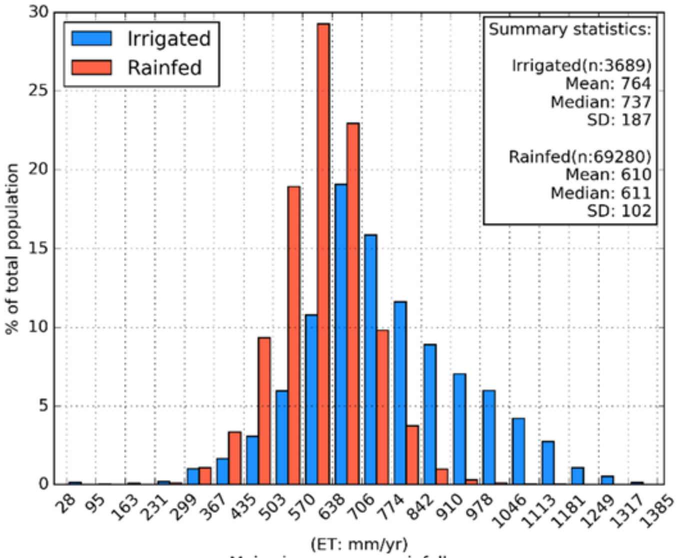




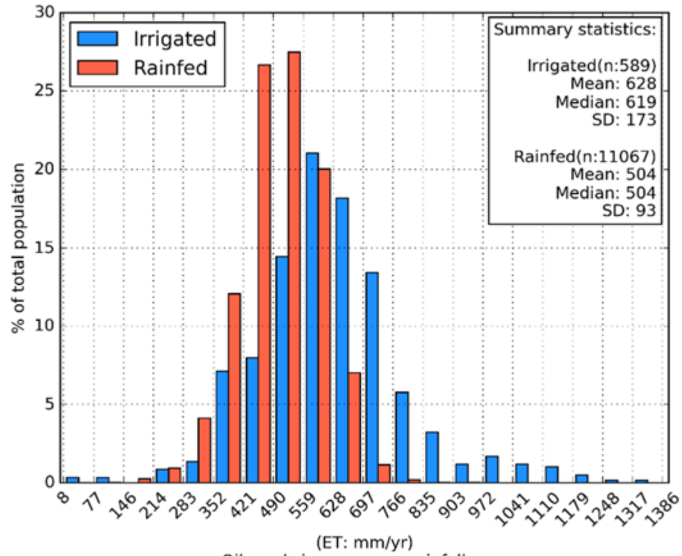
Sugarcane in a summer rainfall area



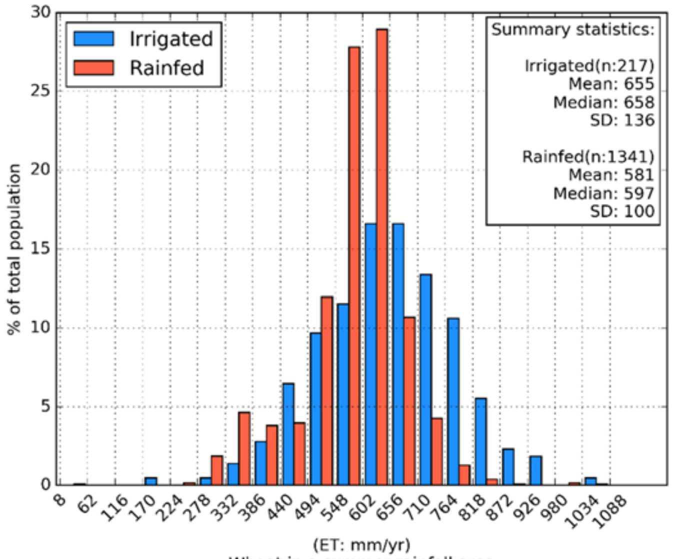
Other pastures & forages in a summer rainfall area



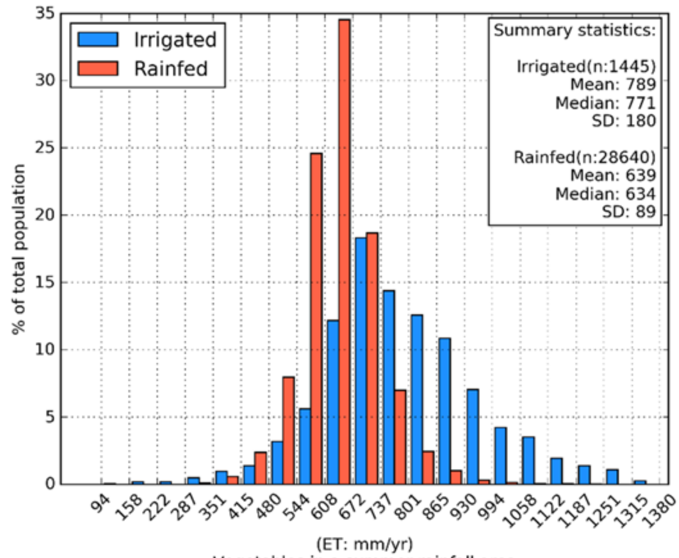
Maize in a summer rainfall area



Oil seeds in a summer rainfall area

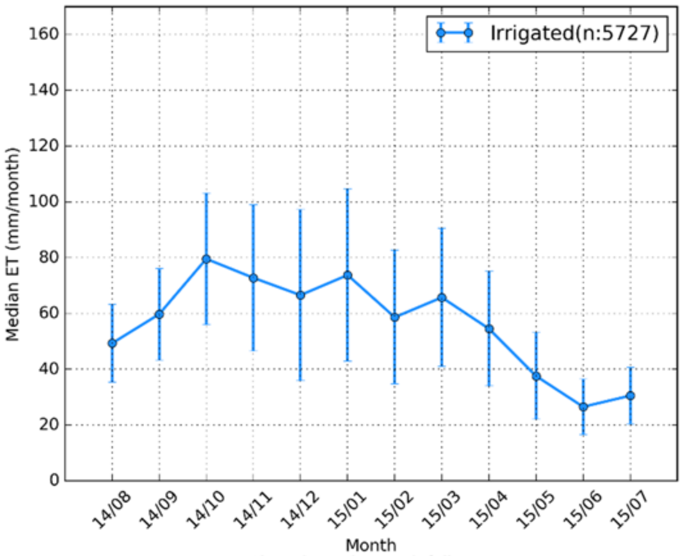


Wheat in a summer rainfall area

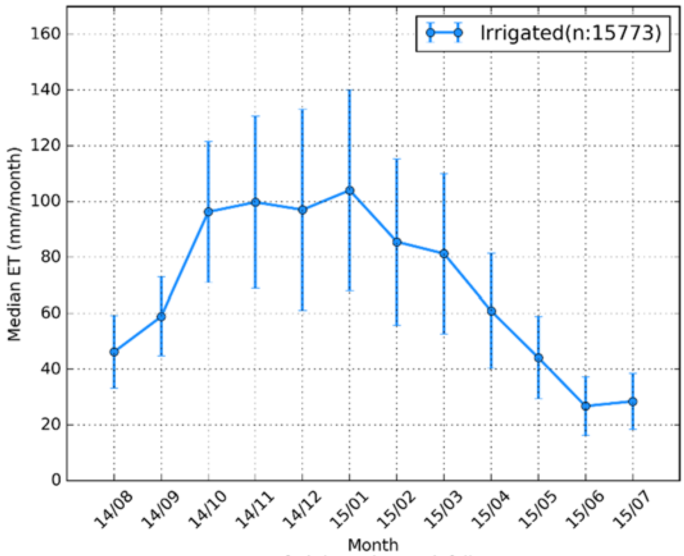


Vegetables in a summer rainfall area

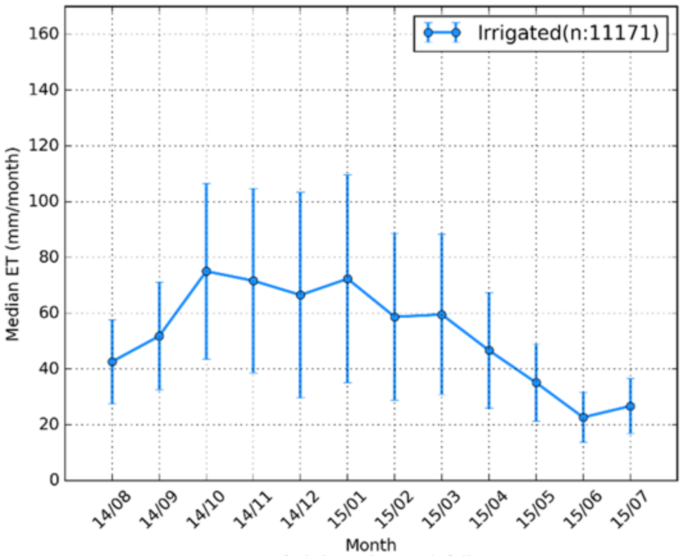
APPENDIX VII: TEMPORAL PROFILES IN ET AS SHOWN AS MONTHLY ET ESTIMATES, FOR SELECTED CROPS



Citrus in a winter rainfall area



Pome fruit in a winter rainfall area



Stone fruit in a winter rainfall area

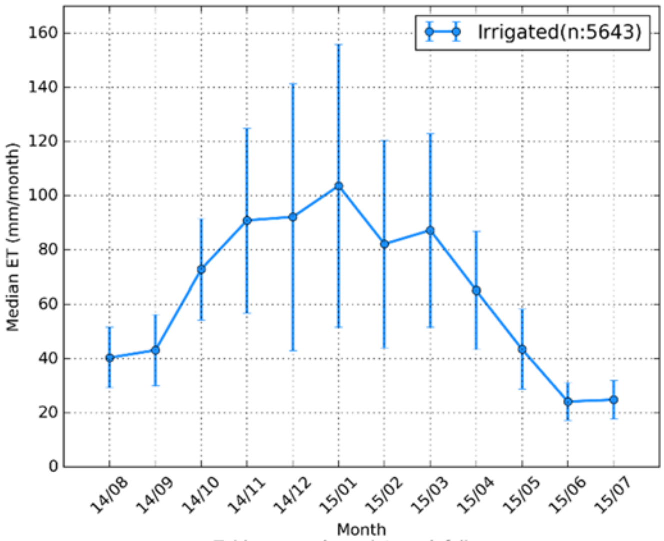
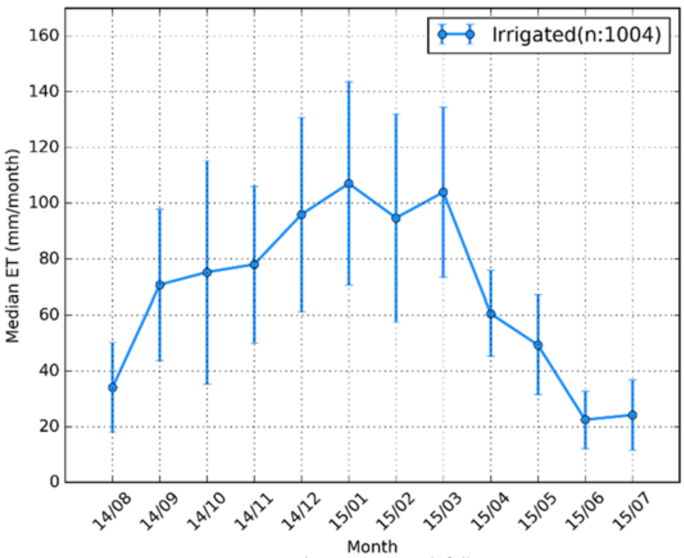
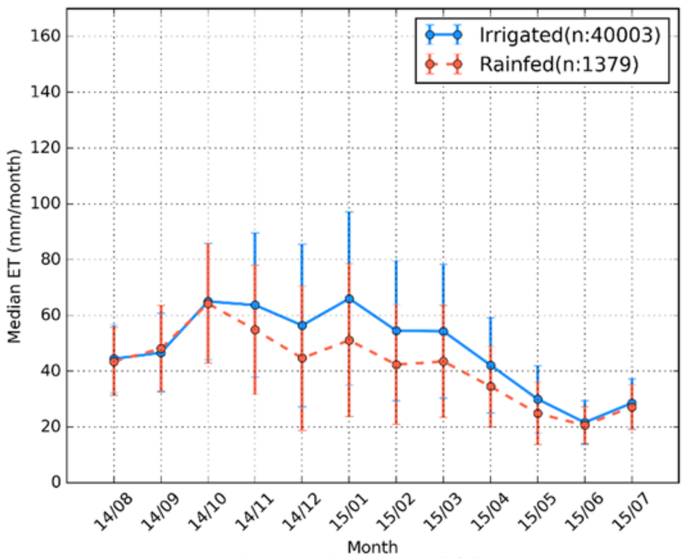


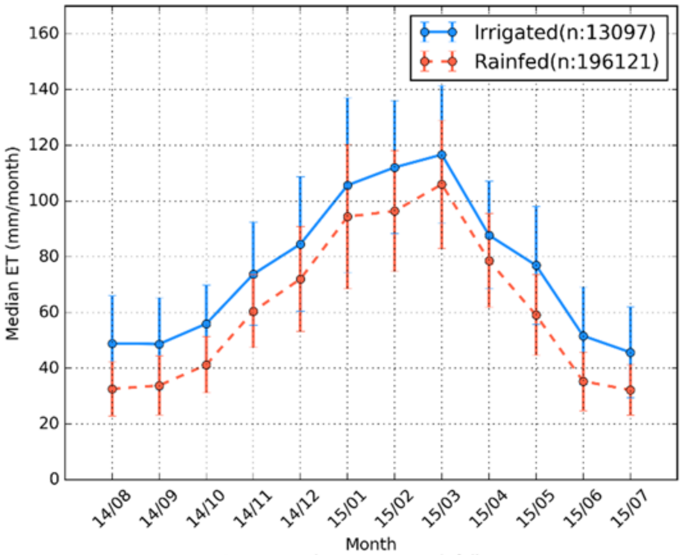
Table grapes in a winter rainfall area



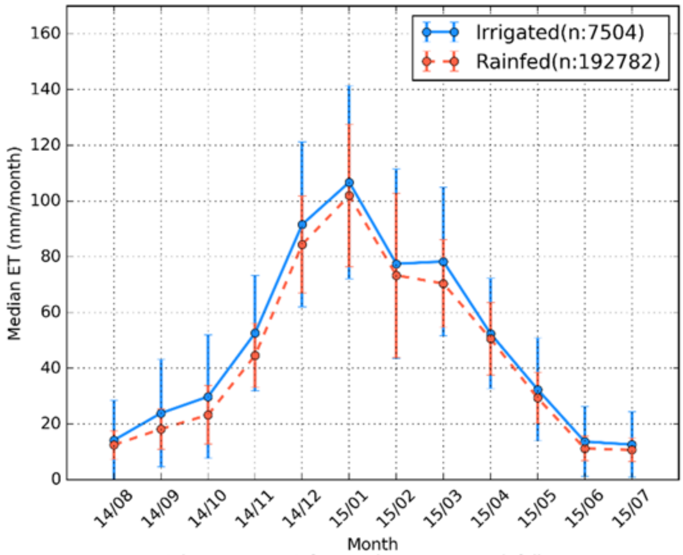
Lucerne in a summer rainfall area



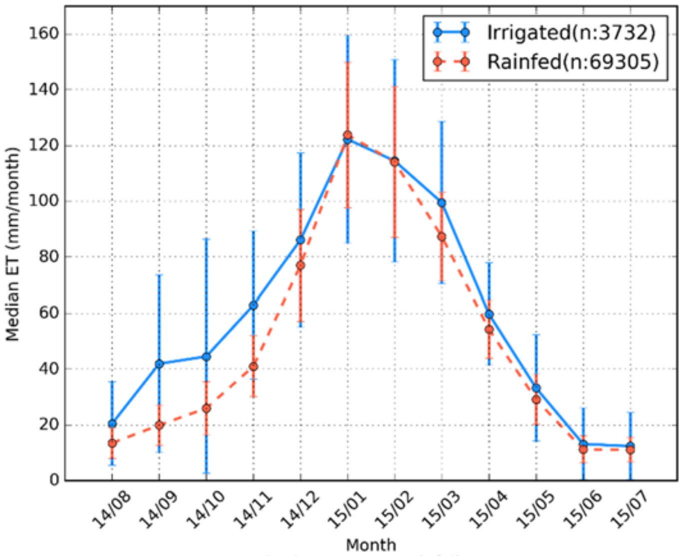
Wine grapes in a winter rainfall area



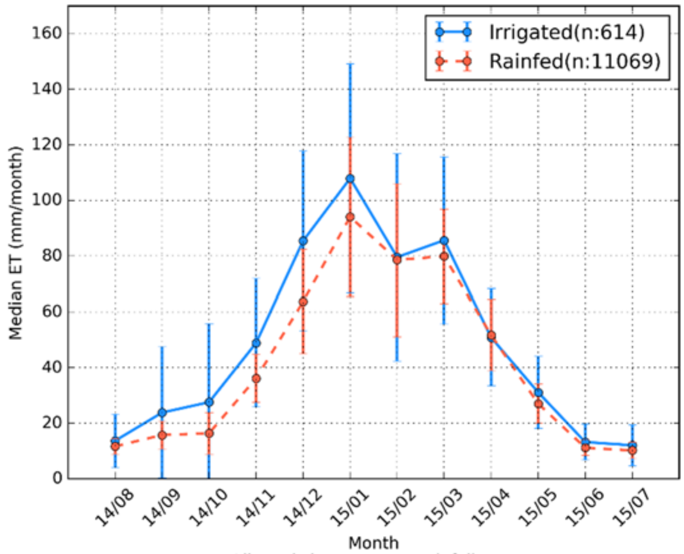
Sugarcane in a summer rainfall area



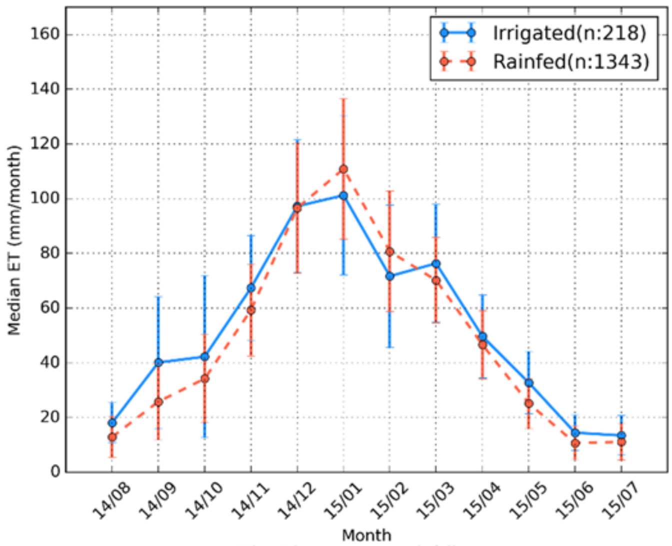
Other pastures & forages in a summer rainfall area



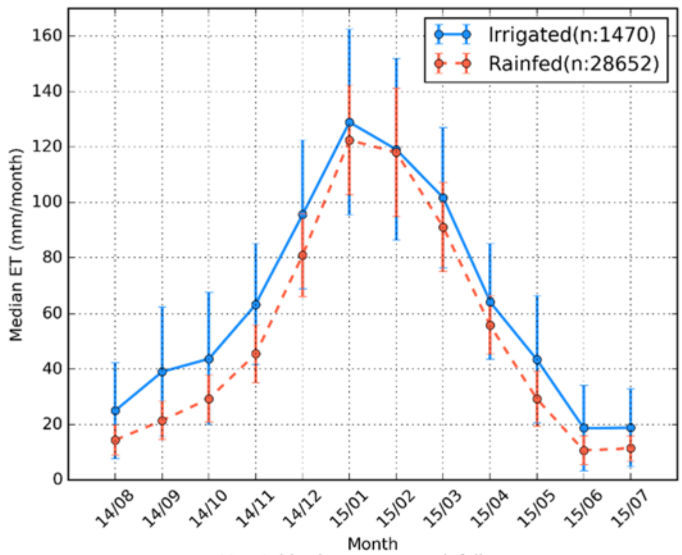
Maize in a summer rainfall area



Oil seeds in a summer rainfall area



Wheat in a summer rainfall area



Vegetables in a summer rainfall area

APPENDIX VIII: CAPACITY BUILDING

Four students (Jason Gilbertson, Helgard Meyer, Michelle Arzul and Grace Maponya) were initially involved in the project, but Miss Michelle Arzul suspended studies early on (2014) due to health reasons and was replaced by Mr Jos Louw. Unfortunately, Mr Louw also dropped out in 2017 (personal reasons). Messrs Gilbertson and Meyer received support from the project for their honours research projects in 2014. Both students graduated in December 2014 and continued with at masters level, starting in 2015.

Mr Gilbertson completed his masters research and graduated (cum laude) in December 2017. The title of his thesis is: *MACHINE LEARNING FOR OBJECT-BASED CROP CLASSIFICATION USING MULTI-TEMPORAL LANDSAT-8 IMAGERY.* Two international journal articles emanated from his thesis (see APPENDIX IX).

Mr Meyer is working full time and was by the time of writing this report still actively continuing with his MSc research on a part-time basis. He has collected and pre-processed all of the satellite imagery required for his research and is investigating various object-based methods for optimizing the segmentation of the images for automated water body delineation. The results of this work was presented at the GEOBIA2016 conference in the Netherlands. Mr Meyer's research on water body mapping is essential for producing products that can be used as input to water accounting. He expects to submit his thesis, titled *IDENTIFICATION AND EXTRACTION OF SURFACE WATER BODIES USING HIGH RESOLUTION SATELLITE IMAGERY* for examination in 2018.

Miss Maponya, a Professional Development Programme (PDP) student at the Agricultural Research Council (ARC), is working under the supervision of Prof Van Niekerk and Dr Mashimbye on a full time basis. As with Mr Gilbertson, her work also focusses on crop type mapping, but with an emphasis on exploiting the high spatial, spectral and temporal resolution of Sentinel-2 imagery. She plans to complete her research in 2018. The running title of her thesis is *CROP TYPE MAPPING USING MULTI-TEMPORAL SENTINEL-2 IMAGERY.*

It should be clear that this project has developed and applied new, innovative techniques and has made significant contributions to capacity building. The use of remote sensing data in South Africa is still not widespread. This project provided new examples of the application of this type of data in support of water resources assessment and management. The usefulness of remote sensing data for large spatial scale assessments was demonstrated and various methodologies and frameworks for subsequent studies were developed. Remote sensing data is currently not actively used in water use monitoring or verification of water use, but this project illustrated the potential of such technology for doing so. Various uses of remote sensing data in assessing, monitoring and improving the efficiency of water use in the irrigation of agriculture were demonstrated.

APPENDIX IX: PUBLICATIONS

A range of research and popular publications have emanated from this study. At the time of writing, two scientific journal papers and six industry (popular) journal articles have been published. Several additional publications are envisioned.

The research articles that have been published to date are:

Gilbertson JK, Kemp J & Van Niekerk A 2017. Effect of pan-sharpening multi-temporal Landsat 8 imagery for crop type differentiation using different classification techniques. *Computers and Electronics in Agriculture* 134: 151-159. https://goo.gl/pzuV3s

Gilbertson JK & Van Niekerk A 2017. Value of dimensionality reduction for crop differentiation with multi-temporal imagery and machine learning, *Computers and Electronics in Agriculture* 142: 50-58. https://goo.gl/n6pSVv

The six industry journal articles published are:

Jarmain C 2016. Satellite imagery for estimating water use by irrigation. *Position IT*, 15 August 2016, https://goo.gl/5cxpwR

Van Niekerk A & Jarmain C 2016. Using satellite Imagery for Estimating water Used by irrigated Agriculture. *AgBiz Congress 2016*. https://goo.gl/WYvtxY

Matthews S 2017. Project modelling irrigation water use through satellite technology progresses. *WaterWheel* July / August 2017. https://goo.gl/KoGKFW

Jarmain C, Van Niekerk A, Muller J & Goudriaan R 2017. Extent of irrigated agriculture in South Africa: the new *status quo*? *SABI Magazine* April / May 2017. http://www.sabi.co.za/0-magazine/MagazinePreview-april-may.pdf

Jarmain C & Van Niekerk A 2017. Omvang van besproeide landbou in Suid-Afrika: Die nuwe *status quo*? *Die Burger (Landbou)*, 12 May 2017.

Jarmain C & Van Niekerk A 2017. Omvang van besproeide landbou in Suid-Afrika: Die nuwe *status quo*? *Wynland Magazine*, Augustus 2017.

APPENDIX X: ACCESS TO THE DATA GENERATED DURING THE PROJECT

All the data that was collected as part of this project is stored (electronic and hardcopy), and is accessible from the Centre for Geographical Analysis at Stellenbosch University. Kindly contact Prof Adriaan van Niekerk at avn@sun.ac.za to gain access to the data. Alternatively, Mr Garth Stephenson at garth@sun.ac.za can be contacted.