

Applications of Remote Sensing in Sugarcane Agriculture at Umfolozi, South Africa

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ABSTRACT

The aim of this study was to evaluate potential applications of remote sensing technology in sugarcane agriculture, using the Umfolozi Mill Supply Area as a case study. Several objectives included the evaluation of remotely sensed satellite information for the following applications: mapping of sugarcane areas, identifying sugarcane characteristics including phenology, cultivar and yield, monitoring the sugarcane inventory throughout the milling season and yield prediction.

Four Landsat 7 ETM+ (Enhanced Thematic Mapper Plus) images were obtained for the 2001-2002 season. Mapping of sugarcane areas was conducted by means of unsupervised hierarchical classifications, on three relatively cloud free, Tasseled Cap transformed images. The Brightness, Greenness and Wetness bands for each Tasseled Cap transformed image were combined into a single image for this classification.

The investigation into relationships between satellite spectral reflectances and phenology, cultivar and yield involved the cosine of the solar zenith angle (COST) method for atmospheric correction of all four Landsat 7 ETM+ images. Detailed agronomic records and field boundary information, for a selection of sugarcane fields, were used to extract the at-satellite reflectances on a pixel basis. These values were stored in a relational database for analysis.

Monitoring of the sugarcane inventory throughout the milling season was conducted by means of unsupervised classifications on the Brightness, Greenness and Wetness bands for each of the four time-step Tasseled Cap transformed images. Accurate field boundary information for all sugarcane fields was used to mask out non-sugarcane areas. The remaining sugarcane areas in each time-step image were then classified by means of unsupervised classification techniques to ascertain the relative proportions of the different land covers, namely: harvested immature and mature sugarcane by visual interpretation of the classification results.

The yield forecasting approach utilized a time-step approach in which Vegetation Indices (VIs) were accumulated over different periods or time frames and compared with annual production. VIs were derived from both the National Oceanic and Atmospheric Administration (NOAA) and Landsat 7 ETM+ sensors. Different periods or times were used for each sensor.

The results for the mapping of sugarcane areas showed that the mapping accuracies for the large-scale grower fields was higher than for the small-scale growers. In both instances, the level of accuracy was below that of the recommended sugar industry mapping standard, namely 1% of the true area. Despite the low mapping accuracies, much benefit could be realized from the map product in terms of identifying new areas of sugarcane expansion. These would require detailed accurate mapping.

The results for monitoring of the sugarcane inventory throughout showed that remote sensing, in conjunction with detailed field information, was able to accurately measure the areas harvested in each time-step image. These results may have highly beneficial applications in sugarcane supply management and monitoring.

The results for time-step approach to yield forecasting yielded poor results in general. The Landsat derived VIs showed limited potential; however, the data were only available for one season, making it difficult to quantify the impact of climatic conditions on these results. All results for the time-step approach using NOAA data yielded negative results.

The results for the investigation into relationships between satellite spectral reflectances and phenology, cultivar and yield showed that that different phenological stages of sugarcane growth were identifiable from Landsat 7 ETM+ at-satellite reflectances. The sugarcane yields and cultivar types were not correlated with the at-satellite reflectances. These results combined with the sugarcane area monitoring may provide valuable information in the management and monitoring of sugarcane supply.

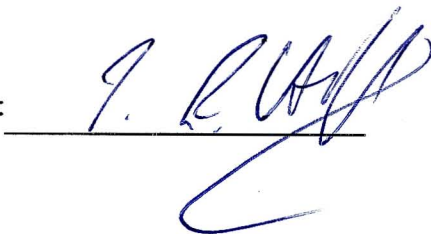
Keywords remote sensing, sugarcane, sugar cane, yield forecasting, yield prediction, cultivar spectral characteristics, phenology, cultivar, variety, thermal age, mapping, Landsat, NOAA, Normalized Differential Vegetation Index, NDVI, Infrared Index, II.

PREFACE

I hereby certify that the research presented in this dissertation is my own original and unaided work except where specific acknowledgement is made.

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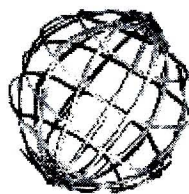
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SASEX GIS



GEOSPACE

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LIST OF ABBREVIATIONS

ANOVA	Analysis of Variance
ASTER	Advanced Spaceborne Thermal Emission and Reflection Radiometer
AVHRR	Advanced Very High Resolution Radiometer
COST	Cosine of zenith angle
DGPS	Differential Global Positioning System
DN	Digital Number
EOS	Earth Observing System
ETM+	Enhanced Thematic Mapper Plus
GCP	Ground Control Point
GIS	Geographic Information System
GPS	Global Positioning System
II	Infrared Index
LADAR	Laser Detection and Ranging
LAI	Leaf Area Index
LSD	Least Significant Difference
Landsat	Satellite
LOMS	Length of Milling Season
LTM	Long-Term Mean
MAP	Mean Annual Precipitation
MGB	Mill Group Board
MODIS	Moderate Resolution Imaging Spectroradiometer
MSA	Mill Supply Area
NDVI	Normalised Difference Vegetative Index
NIR	Near InfraRed
NOAA	National Oceanic Atmospheric Administration
PCA	Principle Component Analysis
r^2	coefficient of determination
SAR	Synthetic Aperture Radar
SASEX	South African Sugar Association Experimental Station
SPOT	Satellite Probatoire d'Observation de la Terre
SWIR	Shortwave InfraRed
VI	Vegetation Index

LIST OF DEFINITIONS

Ratoon

The above ground components of the plant that regenerate from the root system after harvesting.

Thermal time

Heat accumulation over calendar time. Also known as heat units or growing degree days.

Tasseled Cap Transformation

A spectral enhancement method aimed primarily at analyzing vegetation.

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1 INTRODUCTION

1.1 Introduction to the South African Sugar Industry

The South African sugar industry is one of the world's leading cost-competitive producers of high quality sugar and contributes approximately five billion Rand annually to the South African economy (Anon, 2003c). It is a complex and diverse industry combining agricultural activities of sugarcane cultivation with the industrial factory production of raw and refined sugar, syrups and specialised sugars, and a range of by-products. The sugar industry is comprised of two central groups, namely the growers who cultivate the sugarcane and the millers that process the sugarcane. The milling sector employs approximately 11 000 people concentrated around 15 mills.

The 15 Mill Supply Areas (MSAs) extend from Northern Pondoland in the Eastern Cape Province through the coastal belt and midlands of KwaZulu-Natal, to the Mpumalanga Lowveld of South Africa. Of the 412 000 hectares currently under sugarcane, approximately 68% is grown within 30 km of the coast and 17% in the high rainfall area of the KwaZulu-Natal midlands. The remainder is grown in the northern irrigated areas, which comprise Pongola and Mpumalanga lowveld (Figure 1.1). Approximately 2.5 million tons of sugar is produced annually of which about 50% is exported (Anon, 2003c).

There are 47 000 registered sugarcane growers, which includes nearly 2 000 large-scale farmers, farming freehold property, and some 45 000 small-scale growers farming on tribal authority land. The large-scale commercial growers are responsible for more than 66% of total sugarcane production (Anon, 2003c). Sugarcane agriculture provides a vehicle for economic and social development for many small-scale growers (Anon, 2004a).

The small-scale grower sector plays an important role in the sugar industry, given the South African political climate in which Black Economic Empowerment (BEE) and development form fundamental socio-economic policies of the government in addressing the historical inequalities of our past. In this regard, the small-scale sugarcane production plays an important role in empowering and developing previously disadvantaged communities (Anon, 2004a).

The common goal shared in the sugar industry partnership of millers and the growers, is to maximise profitability from sugar and sugar related products. In this regard, the mills would like to ensure maximum utilization of their milling capacity to maximise the amount of sugar extraction. There is, however, a delicate balance between sugarcane supply and milling capacity that must be considered. Sugarcane expansion should not exceed the milling capacity because of sugarcane pests that infest

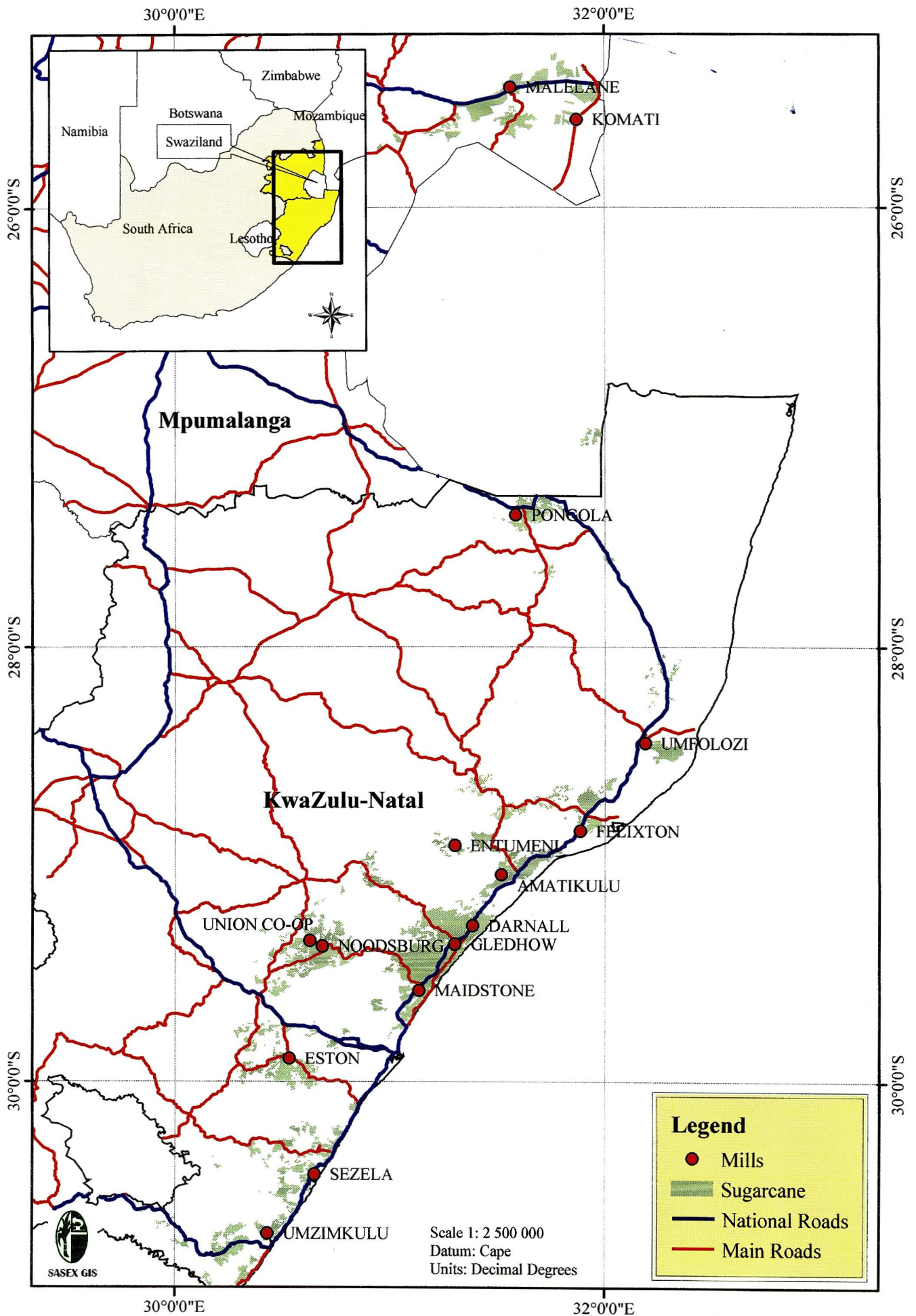


Figure 1.1 Map showing distribution of the South African sugar industry.

sugarcane fields that are carried over from one season to the next. This in turn reduces the sucrose quality and yield of the crop (King, 1989).

Eldana saccharina, a sugarcane stalk borer, is the sugar industry's major pest, and impacts significantly on the yield and sucrose losses. It is estimated that production lost to *Eldana* costs the industry more than R260 million annually (Anon, 2003b). To minimise the spread and damage caused by *Eldana*, growers in the coastal and irrigated regions are forced to cut their sugarcane on an annual, or 12 month, cycle. While the sucrose content of immature (12 month) sugarcane is lower than that of fully matured (older) sugarcane, the overall profitability, considering *Eldana*, is increased. In this regard the milling sector is forced to take a more holistic approach in maximising the amount of recoverable sucrose by ensuring that the sugarcane supply does not extend far beyond the milling capacity.

The yield of sugarcane is highly correlated with the water available for crop transpiration (Thompson, 1976). As a result, adverse weather conditions can have severe impacts on the annual sugarcane production. In addition to reduced yields during drought conditions, the susceptibility of certain sugarcane cultivars to *Eldana* infestation is increased. Given the high dependence of sugarcane production on available water, estimates of the standing crop, still to be harvested, are required at regular intervals throughout the milling season. This enables the mill to schedule and regulate sugarcane supply in relation to a limited milling capacity and time to crush the sugarcane.

Remote sensing is the science of acquiring information about the Earth's or other planetary surface from afar. This is done by sensing and recording reflected or emitted energy of the surface and processing, analyzing, and applying that information (Anon, 2003a). Remote sensing is frequently employed in agriculture to measure, monitor or predict trends over large areas, given the ability of satellite imagery to evaluate information in an unbiased manner. A range of remote sensing applications in agriculture include: mapping, precision farming, crop yield estimation, the identification of smart-sampling points and the identification of homogenous agricultural management zones or units. When one considers the relatively large geographic areas of sugarcane production in South Africa, remote sensing applications may have many practical and beneficial applications in sugarcane production.

Since the re-introduction of the small-scale grower sector into the South African sugar industry in 1986, rapid expansion of their sugarcane areas has taken place in the tribal areas. The monitoring of their increasing production has been of great concern to the South African sugar industry, especially in those MSAs whose milling capacity is limited. For such areas, the balancing and management of sugarcane supply in relation to the limited milling capacity, is crucial to both millers and growers in maximizing sustainable profitability for both stakeholders (Schmidt, 2002).

The Umfolozi MSA was selected for the case study, as the situation and challenges facing the mill were largely representative of other mills in the South African sugar industry. In particular, the

problem of monitoring a growing small-scale sector in marginal dryland areas is compounded by highly variable climatic conditions and a limited milling capacity. These, amongst other factors, complicate the management of rateable sugarcane supply (Groom, 2003; de Lange 2003; Adendorff, 2003).

There are many potential applications for remote sensing that can assist the sugar industry in improving profitability through improved agronomic and sugarcane supply management. It is the purpose of this thesis to explore different applications of remote sensing in sugarcane agriculture, which, if successful, may ultimately lead to wider application in the South African sugar industry.

1.2 Aims and Objectives

The aim of this study was to evaluate potential applications of remote sensing technology in sugarcane agriculture, using the Umfolozi MSA as a case study.

1. The first objective was to evaluate the potential of remote sensing data for mapping sugarcane areas for both the large and small-scale growers.
2. The second objective was to evaluate the potential of remote sensing data for identifying sugarcane characteristics. These included phenology, cultivar and yield.
3. The third objective was to evaluate the potential of remote sensing for identifying the percentage of the total MSA harvested throughout the milling season.
4. The fourth objective was to evaluate the potential of remote sensing for the prediction of sugarcane yields using broad and high-resolution satellite imagery.

The *Environmental Setting* chapter explores in detail the reasons why the Umfolozi MSA was selected for the case study by drawing on the local climatic, political, agronomic and administrative dynamics. This chapter summarises the main problems and concerns at Umfolozi.

The *Literature Review* begins by introducing the subject of remote sensing, followed by a high level review of various applications of remote sensing in agriculture. The next section in this chapter deals with the image preprocessing requirements associated with agricultural applications, followed by feature extraction and yield estimation using vegetation indices. The last section in this chapter reviews applications of remote sensing in sugarcane agriculture, both internationally and in South Africa. For reasons of consistency, all chapters following the *Literature Review* will follow the order of the objectives described above.

The *Materials and Methods* chapter starts with sugarcane area mapping by remote sensing, followed by the analysis of the sugarcane spectral characteristics with respect to phenology, cultivar and yield. The next section deals with the sugarcane inventory assessment throughout the milling season, followed by yield prediction. A summary is provided at the end.

The chapter on *Results and Discussion* explains and describes the results of the sugarcane area mapping by remote sensing, analysis of the sugarcane spectral characteristics with respect to age, cultivar and yield, followed by inventory assessment throughout the milling season and yield forecasting. A summary is provided at the end.

The chapter on *Recommendations* describes the limitations of the results and recommends future research for each of the topics of sugarcane area mapping by remote sensing, analysis of the sugarcane spectral characteristics with respect to age, cultivar and yield, followed by inventory assessment throughout the milling season and yield forecasting. A summary is provided at the end.

The *Conclusion* summarizes the research outcomes with respect to the initial aims and objectives of this study; namely, sugarcane area mapping by remote sensing, analysis of the sugarcane spectral characteristics with respect to phenology, cultivar and yield, followed by inventory assessment throughout the milling season and yield forecasting. The application of these results, as well as the potential benefit to the South African sugar industry, are discussed.

2 ENVIRONMENTAL SETTING

The Umfolozi MSA was selected for the case study as the situation and challenges facing the mill are largely representative of the other MSAs in the South African sugar industry. Firstly, the Umfolozi MSA includes a large number of small-scale growers, that contribute approximately 30% of the total production. Over the past few years, the small-scale growers have expanded their sugarcane production into the low rainfall, marginal production areas (Groom, 2003). Furthermore, the rainfall at Umfolozi is highly variable (de Lange, 2003). During favourable climatic conditions, the small-scale growers produce good yields and high quality sugar and conversely, very low yields in drier years. Given this strong dependence of sugarcane production on favourable climatic conditions, in particular for the small-scale growers, the management of sugarcane supply is critical (de Lange, 2003; Groom, 2003; Adendorff, 2003). Umfolozi also has good inventories of geographic and industrial sugarcane delivery information that can be used to assist in this research and, their proactive interest in the use of remote sensing applications in sugarcane supply management cemented their selection for the case study.

A brief history of the sugarcane production at Umfolozi will be provided, after which a more detailed motivation for the selection of this study area will follow.

2.1 The History of Sugarcane Production at Umfolozi

Umfolozi was historically settled by white veterans that were granted land by the government following the Great War. Large-scale grower sugarcane production began in 1916 with the establishment of the St Lucia Sugar Company Mill that was later destroyed by floods in 1918. The current Umfolozi Mill (28.43° S, 32.18° E, 40 metres above sea level) at Riverview, Mtubatuba, South Africa, started in July 1927. The Umfolozi MSA is unique in that it is the only mill in South Africa that currently makes use of a tramline network to transport sugarcane to the mill (Adendorff, 2003).

The first industrial records of small-scale growers go as far back as 1978/1979 when 809 tons of cane were delivered. In 1985 the Umfolozi Mill established the Small-Scale Cane Development Office to equip the small-scale growers with the necessary agronomic skills and training to successfully cultivate sugarcane (Adendorff, 2003). In addition, the Small-Scale Cane Development Officers are responsible for the monitoring of the sugarcane areas planted by the small-scale growers, through digital ortho-photography, allocation of delivery quotas as well as ensuring high quality sugarcane is produced. A summary is provided at the end. production. The small-scale growers are highly dispersed within the tribal areas at Umfolozi. The average field size is around one hectare.

The large-scale growers are predominately situated in an area referred to as the Umfolozi Flats. Historically, this was a large wetland system situated along the Umfolozi River. In the early 1920s, agricultural expansion and the need for arable land resulted in the drainage of certain parts of these wetlands. By the mid 1940s, accelerated drainage resulted in the flats. The Umfolozi Flats are characterized by intensive agriculture on limited available land (Adendorff, 2003).

2.2 The Umfolozi Mill Supply Area Today

Currently the Umfolozi MSA includes about 100 large-scale growers and some 5500 small-scale growers (Anon, 2002). The number of small-scale growers varies considerably from year to year, depending on whether one considers the registered small-scale growers or alternatively growers who actually delivered sugarcane (see Table 2.1).

The unavailability of new agricultural land within the large-scale grower sector limits the amount of horizontal expansion that can take place. This is not the case, however, for the small-scale-grower sector, which cultivates predominately in the rural tribal areas. Rapid horizontal expansion of geographically dispersed, small-scale sugarcane plots, typically 0.5 to 2 hectares in size, has continued in the marginal production tribal areas over the past few years.

The well-established large-scale growers currently produce about 70% of the total sugar and the small-scale growers about 30% (Table 2.1). The majority, if not all the large-scale growers, are able to apply full or supplementary irrigation, unlike the small-scale sector that, with the exception of a single irrigation scheme at Mzondeni, cultivate under lower rainfall, dryland conditions. The small-scale grower sector in general, do not have access to the same financial and agronomic resources as the large-scale growers, such as purchasing equipment through farm co-operatives. These combining factors make the production of the small-scale sector highly dependent on agronomic management and climatic conditions. As a result, intensive management of delivery allocations and monitoring of the quality of sugarcane delivered to the mill are requirements of the Small-Scale Cane Development Officers to ensure rateable deliveries of high quality sugarcane.

Table 2.1 Production information for large-scale and small-scale growers at Umfolozi for the 2000/2001 season (Source: Anon, 2002).

	Number of Growers		
	Large-scale	Small-scale	Total
No. of registered growers who delivered in 2001	97	4100	4197
Registered growers in 2001	104	5623	5727
Tons cane (t)	918 464	407 541	1 326 005
Tons cane as % of total	69%	31%	100%
Tons Relative Value (RV)	110 900	48 124	159 024
Tons RV as % of total	69.7%	30.3%	100.0%

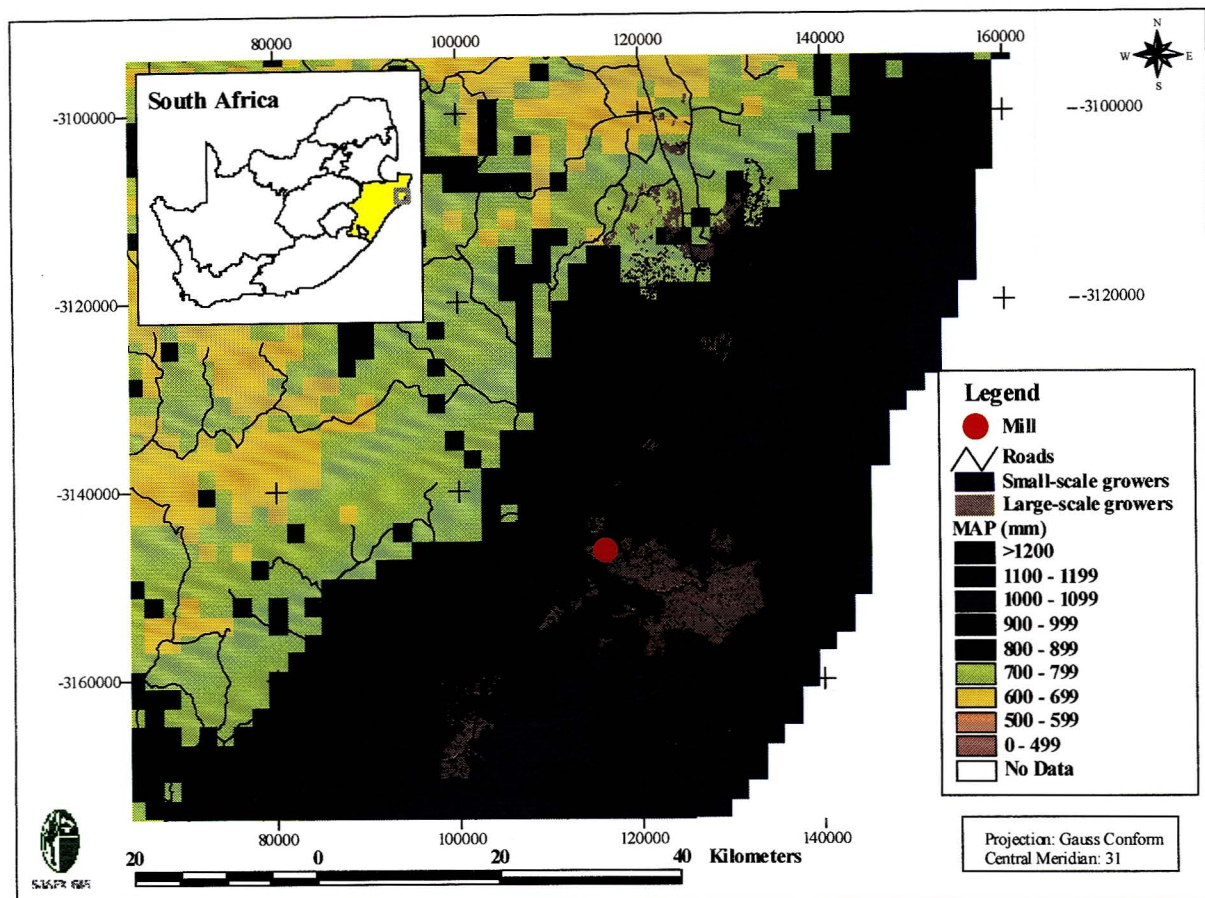
2.3 Climate at Umfolozi

Umfolozi lies at the northern-most extremity of dryland sugarcane cultivation. The rainfall is highly variable and a steep rainfall gradient extends from the coast inland. The long-term mean precipitation drops from above 1400 mm/annum at the coast, to below 800 mm/annum, 35 km inland (see Figure 2.1 and Table 2.2). The large-scale growers on the Umfolozi Flats receive high rainfall, while the small-scale growers inland cultivate sugarcane under lower rainfall conditions. The rainfall in this area is highly variable between years.

Table 2.2 Long Term Mean (LTM) rainfall statistics for Umfolozi sugarcane growers (Source: Schulze, 1997).

LTM rainfall statistic (mm/y)	Large-scale growers	Small-scale growers
Min	729	762
Max	1295	911
Range	566	149
Mean	967	839
Median	952	839
Std Dev	141	36

Figure 2.1 Map showing the long-term Mean Annual Precipitation (MAP) at Umfolozi, South Africa (Source: Schulze, 1997).



2.4 Sugarcane Expansion

Sugarcane production is perceived by many as an agronomic means of socio-economic reform for the previously disadvantaged individuals in the rural areas. This perception has been fuelled by the readily available private sector financial loans for the development of sugarcane production provided by Umthombo Financial Services, formerly known as the South African Sugar Association Financial Aid Fund. Umthombo is the largest private sector funding service for agricultural development in South Africa (Anon, 2003d), and has been one of the key driving forces in the development and expansion of sugarcane in the small-scale grower areas.

The Umfolozi MSA expanded from 15 821 ha in 1989, to 20 565 ha in 2001. Figure 2.2 shows a steady increase in both the proportion of the total MSA cultivated by the small-scale growers, and their increased annual production for the period 1990 to 2001. During this period, the large-scale proportion of the total MSA decreased steadily. Between 1995 and 1996, dramatic small-scale grower horizontal expansions took place in the rural tribal areas. To keep abreast of this increasing production, the milling capacity was extended in 1999. The Length Of Milling Season (LOMS) could not be

extended to address this increased production since the marginal losses due to declining sugarcane quality and quantity, over the hot (low sucrose yielding) summer months, would exceed the benefits gained from the increased milling capacity utilization.

Figure 2.3 shows the production of the small-scale and large-scale growers in relation to the total production. It can be seen that the contributions of the small-scale growers from 1989 to 2001 were less than those of the large-scale growers. This is not surprising, given that they cultivate mostly under dryland conditions. Furthermore, the yields of the large-scale growers tend to be far more stable over time. The decrease in large-scale production in 1998 was due to sugarcane being diverted from the Bushlands Estate, a large sugar producing estate at Mkuzi, to the Felixton mill (Groom, 2003).

Surprisingly, during the wetter years, the production of the large-scale growers tends to decrease, while that of the small-scale growers increases. This is largely due to waterlogging in the Umfolozi Flats. Conversely, during the drier years, the Umfolozi Flats produces better yields, while the small-scale grower yields decrease dramatically, especially during drought years (Adendorff, 2003; de Lange, 2003). The lack of irrigation facilities on the part of the small-scale growers results in their production being more erratic and climate dependent. This has severe implications for the mill, considering that 40% of the total area (2001) is made up of small-scale grower sugarcane, which is likely to increase.

The rapid sugarcane expansion and fixed milling capacity raised concern over the mill's ability to crush the existing crop within the specified LOMS, particularly in good rainfall years. This is currently a fiercely debated topic in the drafting of local area sugarcane supply agreements between the mill and its growers.

2.4.1 Monitoring of the Small-Scale Grower Sugarcane Supply

During the 1990s, the Small-Scale Cane Development Officers mapped the abounding small-scale sector, using a combination of differential global positioning systems and digital orthophotography, in an effort to monitor their ever-increasing expansion. This was recently updated with 1:20 000 photography, captured in 2001, and has been both difficult and expensive to maintain given the large number of small, geographically dispersed fields.

In an effort to control the supply of sugarcane by the small-scale growers to the mill, a ticketing system was introduced. Only growers issued with tickets were allowed to deliver sugarcane. Since the Small-Scale Cane Development Officers knew the area planted to sugarcane by each grower, ratable delivery of sugarcane was controlled by the careful allocation of tickets to the small-scale growers throughout the milling season. (Given the small size of the small-scale grower plots, all fields belonging to a grower are typically harvested in order to meet their delivery obligations.)

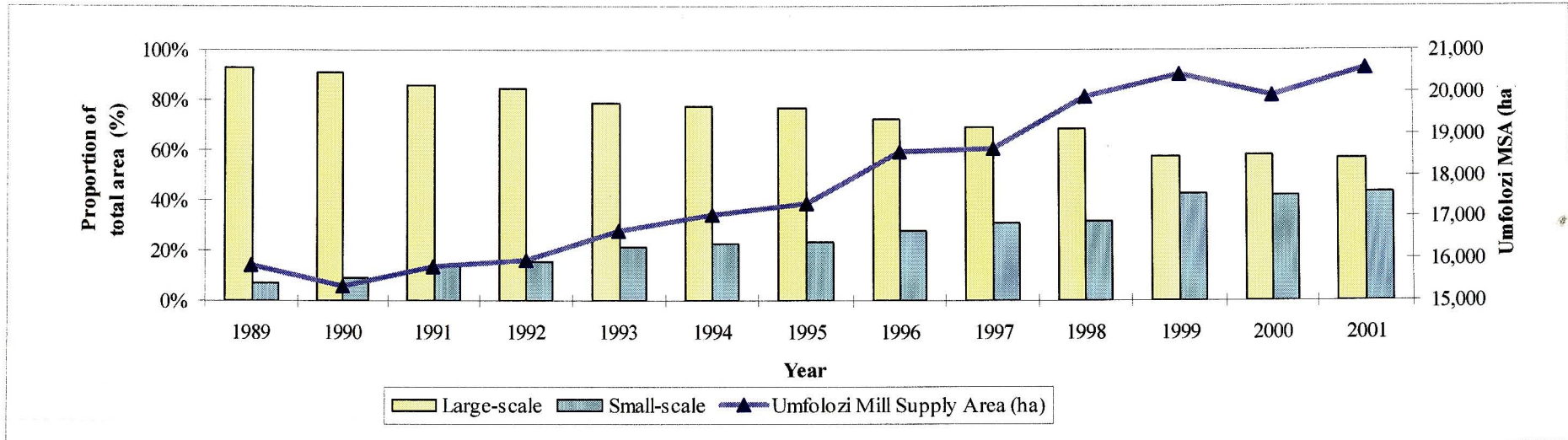


Figure 2.2 Bar chart showing the area proportions of sugarcane of large and small-scale growers (%) and the Umfolozi Mill Supply Area from 1989 to 2001 (Source: Groom, 2003).

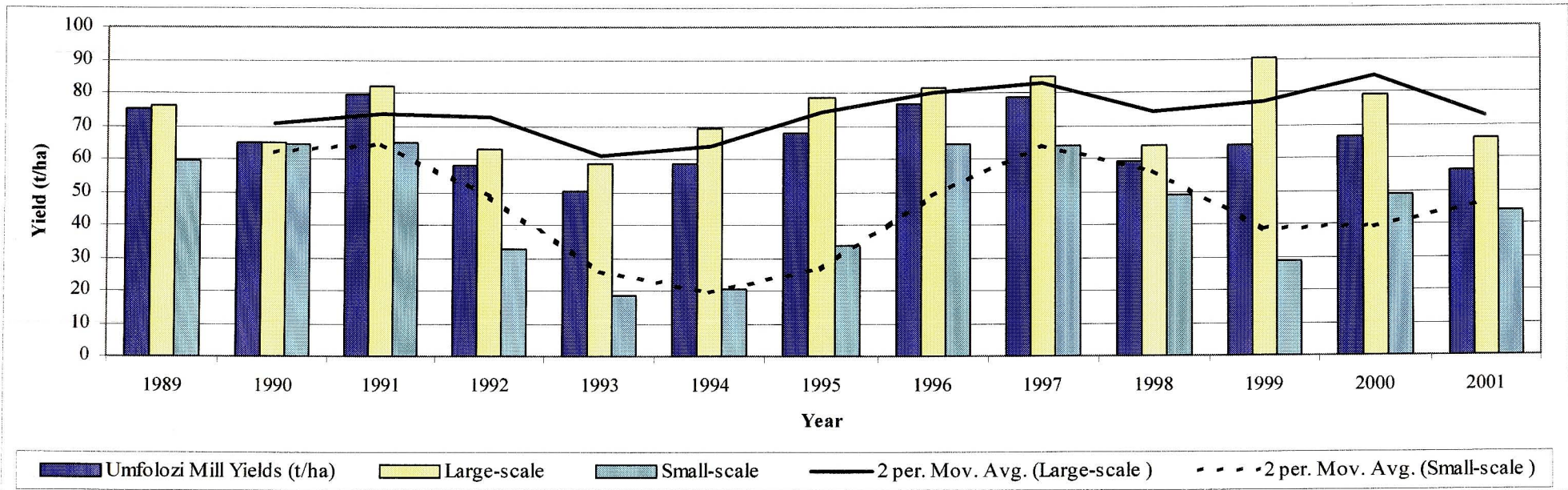


Figure 2.3 Bar chart showing production (t/ha) for the Umfolozi Mill Supply Area and large and small-scale growers from 1989 to 2001 (Source: Groom, 2003).

Shortfalls in the ticketing system, however, include:

- delivery of sugarcane from non-registered sugarcane areas,
- delivery of sugarcane from somebody else's land (sugarcane piracy).

The ticketing system has been reasonably successful. However, like any system, it has been open to abuse. Many of the small-scale growers have agricultural loans that require servicing. Furthermore, the debt repayments are serviced by the sugarcane deliveries from the growers. In an effort to avoid servicing these loans, many growers send their sugarcane to the mill under a kinsman's grower code.

The lack of field information captured at the mill weighbridge, prohibits analysis of field numbers for the monitoring of harvested and non-harvested fields across the MSA for both large-scale and small-scale growers. This is unlikely to change, given that no real incentives exist for growers to submit accurate field information and that many growers are illiterate.

2.5 Summary of Key Issues at Umfolozi

Estimation of the standing crop throughout the milling season is important to the mill in balancing milling capacity and sugarcane supply, given the highly variable rainfall conditions. This is particularly difficult in view of the ever-increasing small-scale sector that has been expanding into the marginal production tribal areas. Whilst the total production of the small-scale sector is fairly well established, estimation of the standing crop inventory throughout the milling season has been difficult to establish. Their production has been highly dependent on rainfall (Groom, 2003).

The following items summarize key issues at Umfolozi:

- Estimation of the annual production before the opening of the season is important in setting an optimum start date to maximize sugar production.
- Estimation of the sugarcane inventory throughout the milling season is important in balancing milling capacity and sugarcane supply.
- The MSA for Umfolozi has increased from 15 851 ha in 1989 to 20 565 ha in 2001, the majority of which has occurred in the small-scale grower sector, into low rainfall, marginal production areas.
- In 2001 the small-scale grower sector made up 40% of the MSA and produced 30% of the total production, predominantly under dryland conditions.
- Despite the increase in MSA between 1985 and 2001, the proportion of total area planted by the large-scale growers has decreased steadily while the small-scale sector has increased.
- There are concerns that the sugarcane supply area has increased beyond the milling capacity, given that the past few years have been characterized by normal to below normal rainfall.

- Expansion into the marginal areas has resulted in an erratic production, as a result of the climatic dependence of small scale-sector sugarcane.
- The relatively static large-scale growers have been accurately mapped.
- The expanding small-scale growers have been mapped. However, their dynamic agricultural practices and increasing horizontal expansion make map information difficult to maintain and update.
- While the total production of the small-scale grower is known, estimates of the areas harvested throughout the season are difficult to determine.

2.6 Summary

Umfolozi is one of the oldest sugarcane producing regions in the South African sugar industry and is characterised by two distinctive grower groups, namely, the large-scale growers and the small-scale growers. In general, the large-scale growers cultivate under higher rainfall conditions than the small-scale growers. Furthermore, the large-scale growers have better access to capital equipment, agronomic, financial and land resources. Their agriculture is intensive by comparison with the small-scale growers that are geographically dispersed throughout the tribal areas.

Since 1989, the number of small-scale growers and their contribution to the total mill production has increased annually to about 30%. This has made management of cane supply critical, given that the majority of the small-scale growers cultivate in the marginal production areas and, as a result, realise good yields in high rainfall years and very low production in drought years. Sugarcane supply management is important in the Umfolozi MSA in order to reduce and control the ‘feast or famine’ extremes created by the highly variable rainfall conditions. The Umfolozi mill established a Small-Scale Cane Development Office to monitor the sugarcane production of the small-scale growers, as well as provide this sector with agronomic advice and incentives to ensure that high quality sugarcane is delivered to the mill.

3 LITERATURE REVIEW

3.1 Introduction to Remote Sensing

Remote sensing refers broadly to measuring reflected electromagnetic energy, using a camera or sensor from afar. Application of this technology to agriculture makes use of a wide range of instruments, from airborne cameras to sensors mounted on orbiting satellites. The data recorded by the sensor can be used to manage crop production through: mapping and area measurement, monitoring of crop condition, estimating production levels and precision farming (Schmidt *et al*, 2001).

Different surfaces absorb and reflect electromagnetic radiation differently. This creates what is referred to as a spectral fingerprint or signature that can be used to identify or map characteristic reflectance patterns.

3.2 Applications of Satellite Remote Sensors in Agriculture

There are many advantages to using satellite remote sensing in sugarcane agriculture, namely in-season crop observation, crop inventory, crop health monitoring, watershed management, damage assessment and land degradation (Sirvastva *et al*, 1999). The advantages of using satellite remote sensed data are that it can be collected frequently for large areas and that the data are unbiased. It therefore lends itself well to agricultural applications (Sirvastva *et al*, 1999; Krishna Rao *et al*, 1999; Narciso and Schmidt, 1999; Noonan, 1999).

There are many different types of remote sensors that can be applied to agriculture and, more specifically, to sugarcane monitoring. These can be categorized into two distinctive groups, namely active and passive sensors. Active sensors transmit a signal onto the target area and measure the reflected signal or backscatter. Passive sensors make use of existing energy sources, such as the sun, to illuminate the target, from which measurements of the reflected radiation are made. There are also passive microwave reflectance sensors that measure the electromagnetic energy radiated from the target surfaces.

3.2.1 Satellite Sensor Characteristics

There are many different satellite sensors, which can be applied to an agricultural context. These vary considerably in spatial, temporal and spectral resolution. The choice of a satellite sensor for any particular agricultural application will therefore depend on the objectives. Furthermore, higher spatial resolution data tends to be more costly. Ultimately, a balance between the cost of the data and the benefits derived from its application must be found (Olsson, 1986).

In many of the older satellites, there has been a trade-off between spatial and temporal resolution, which vary considerably in an inverse relationship. For example, the National Oceanic and Atmospheric Administration's Advanced Very High Resolution Radiometer (NOAA AVHRR) has a nadir spatial resolution of 1.1 km, 2399 km wide swath, and a daily temporal (Anon, 2003e) resolution whereas Landsat 7 ETM+ has a nadir spatial resolution of 30 m, 185 km swath and a temporal resolution of 16 days (Irish, 2000). While 16 days may not be a long period, one must consider that, if cloud cover obscures a scene, the next scene can only be obtained 16 days later (i.e. an interval of 32 days).

The desirable high temporal resolution characteristics, traditionally associated with low resolution satellites, such as NOAA, is changing as a result of recent developments in data compression algorithms, storage capacity, computing power and the designs of the new generation satellites. These new generation satellites have dramatically improved spatial, temporal and spectral resolutions. For example, the Moderate Resolution Imaging Spectroradiometers (MODIS) aboard the Terra (EOS AM) and Aqua (EOS PM) satellites, which view the entire Earth's surface every 1 to 2 days with a swath of 2330 km, and 36 multi-spectral channels with variable spatial resolutions of up to 250 m (Anon, 2003f). Similarly, Spot 5, one of the more recent satellites, has a multi-spectral resolution of 10 m, a swath of 60 km and 1 to 4 day temporal resolution, depending on latitude (Anon, 2003g).

Currently there are many experimental satellites, such as the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER), that are well suited to a range of agricultural applications. Dependence on these satellites for ongoing commercial applications is, however, unsuitable, given the likelihood of data discontinuity. The commercially orientated satellites, such as Spot or Landsat, should take precedence over experimental satellites, as they are more likely to provide continuous data access. Furthermore, in the event of satellite decommissioning or failure, it is likely that replacement sensors will be launched to ensure continuity. This has been the case for both the Spot and Landsat satellites.

3.2.2 Types of Satellite Sensors

Traditionally, passive remote sensing, that is the measurement of reflected sunlight, has dominated agricultural applications. Evidence of this can be seen in the many applications of remote sensing for crops such as maize and wheat.

The most important satellite bands to consider in agricultural based studies are those bands most sensitive to vegetation. High reflectance values are typically associated with the Visible Red, Near Infrared, Middle and/or Shortwave Infrared bands of vegetated surfaces. These bands typically describe most of the variability associated with different vegetation types.

More recently, however, the rapidly evolving science of synthetic aperture radar (SAR), is showing much promise in agricultural applications. Key benefits of these active sensors include the ability to measure the soil and vegetation moisture content, vegetation height and surface roughness, by the transmission and backscatter of radio waves of different frequencies and of different polarizations. The acquisition of SAR data is not dependent on prevailing weather conditions, as is the case for optical remote sensing (Dabrowska-Zielinska *et al*, 2003; O'Neill *et al*, 2003; Jackson, 2003). For this reason, SAR is of particular interest to the European and North American countries, where cloud cover plays a significant role in reducing the number of cloud free satellite images that can be acquired.

Recently, the terms 'hyperspectral', 'ultraspectral' and even 'superspectral' have been used to refer to sensors with a high spectral resolution. Hyperspectral data differs from conventional remote sensing, in that it covers more narrowly defined spectral channels, whereas conventional remote sensing looks at several broadly defined spectral regions (Anon, 2003h). Hyperspectral data have many exciting applications, particularly with respect to feature discrimination and extraction.

Hyperspectral data are generally large in volume, and as such require both advanced computer hardware and storage devices to manage and analyze data for large areas. Furthermore, hyperspectral data are very costly, given the limited availability and high costs in the production of these precise instruments. It is the opinion of the author that the current high costs of hyperspectral data limit many of the potential applications in agriculture, given the relatively low value associated with many agricultural based commodities such as wheat, maize and sugarcane. Mineral exploration and geological surveys have made extensive use of these sensors, given the scale of economies for the mining and petroleum industries.

Finally, laser detection and ranging (LADAR) has been successfully applied in agricultural applications within South Africa, particularly in the timber industry. The ability of the sensor to measure the vegetation surface and ground height simultaneously, allows for the measurement of

crop heights. This, in conjunction with supplementary data such as tree counts, provides accurate estimates of timber volumes (Banks, 2003).

3.3 Satellite Image Pre-Processing for Agricultural Applications

Since the mid 1970s, image preparation methodologies and newly-found agricultural applications based on Earth Observation (EO) multi-spectral data, have increased in both number and complexity. Evidence of this can be seen in remotely sensed agricultural applications that have developed in a variety of diverse disciplines, such as crop classification and thematic mapping (Thompson, 1996), inventory assessment (Noonan, 1999) and growth modeling to model parameterization (Flügel and Müschen, 1999). Many of these applications have been well established and documented for a host of agricultural crops such as timber and cereals.

Most, if not all, of the abovementioned applications of remote sensing require some degree of (image) pre-processing before a result can be achieved (Olsson, 1986; Thompson, 2003). Pre-processing techniques are essentially mathematical models that are applied to satellite imagery in order to correct the raw, distorted and/or degraded imagery of inaccuracies (Kiefer and Lillesand, 1994). A brief summary of the different types of image pre-processing techniques within an agricultural context follows.

The preparation, or pre-processing, of satellite imagery is highly dependent on the characteristics of satellite sensor, type of application and methodologies employed. According to Kiefer and Lillesand (1994), image pre-processing can broadly be divided into three general processes, namely geometric correction, radiometric correction and noise removal. Pre-processing, as its name implies, precedes the manipulation and/or analysis of imagery. Each of these steps will be discussed briefly.

3.3.1 Geometric Correction

Geometric correction processing removes significant geometric distortions inherent in raw satellite imagery such that they can be used as maps. Sources of geometric errors vary widely from sensor to sensor: altitude, attitude, velocity, platform to earth curvature, atmospheric refraction and relief displacement (Kiefer and Lillesand, 1994). Applications requiring accurate area measurements of different land surfaces require a high degree of accuracy and precision in geometric correction and in particular the use of a digital elevation model, to correct for relief displacement.

3.3.2 Radiometric Correction

As with geometric correction, the type of radiometric correction applied to any digital imagery varies greatly between sensors and the intended application. Radiometric corrections are applied to reduce the effects that changing in-scene illumination, atmospheric conditions, viewing geometry and instrument response characteristics have on the radiance measured by the sensor. When working with single date imagery, the radiometric corrections required are much less than in the case of multi-temporal imagery (Olsson, 1986). Additional corrections to multi-temporal imagery become necessary in order to make absolute or quantitative comparisons between different images. Chavez (1996), Olsson (1986), Huang (2001), Kiefer and Lillesand (1994) and Schott *et al* (1988), discuss and provide various radiometric correction techniques for multi-temporal imagery:

1. Differences in sun elevation and earth-sun distances (i.e. seasonal differences in solar illumination angles and time of day at which the image is taken),
2. Different sensor characteristics,
3. Atmospheric effects.

Each of these elements will be discussed.

3.3.3 Solar Elevation, Earth-Sun Distance and Satellite Sensor Corrections

Radiometric correction methods frequently involve the conversion of digital numbers (DNs), measured by the sensor, to at-satellite radiances. Radiances are tangible measurements (Olsson, 1986). Radiance calculations assume a linear response function of the sensor and, as such, require gain (slope) and bias (intercept) values (Figure 3.1) for each channel, or band, as determined by calibration lamps on board the satellite sensor. According to Irish (2000), great efforts have been made by the Landsat 7 Enhanced Thematic Mapper Plus (ETM+) in minimizing the instrument errors of standard image products through pre-launch, post-launch and daily sensor calibration.

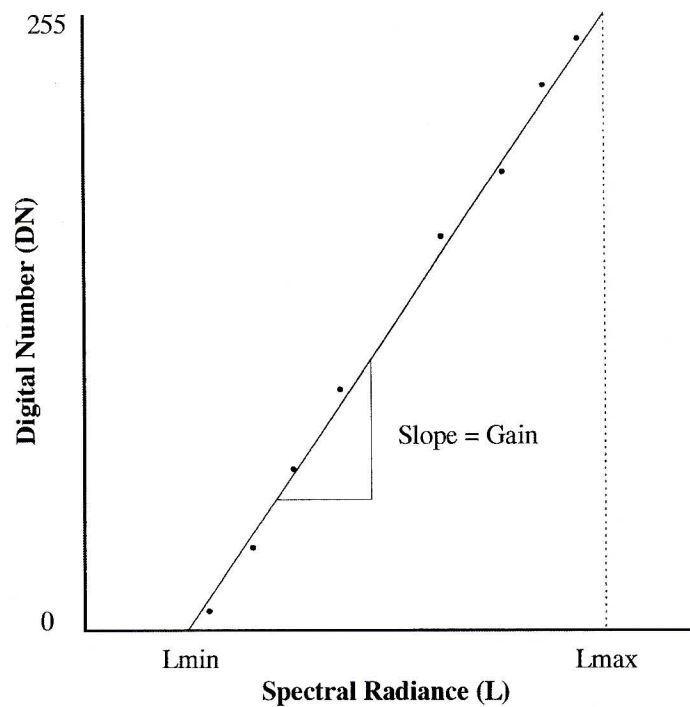


Figure 3.1 Radiometric response function for an individual Thematic Mapper channel (Source: Kiefer and Lillesand, 1994, pp 535).

Corrections for solar elevation angles and earth-sun distance corrections require radiance values for each band to reduce noise arising from the satellites, changing view and illumination geometry associated with multi-temporal data (Equation 3.1).

Equation 3.1 [A] Equation calculating at-satellite radiance values from Digital Numbers (Source: Irish, 2000).

[B] Equation for earth-sun distance solar elevation and sensor radiometric correction - calculation of a unitless at-satellite planetary reflectance (Source: Irish, 2000).

$$[A] \quad L_{\lambda} = (Gain_{\lambda} \times DN_{\lambda} + Bias_{\lambda})$$

$$[B] \quad \rho_{\lambda} = \frac{\pi \times d^2 \times (L_{\lambda})}{ESun_{\lambda} \times \sin(\theta)}$$

Where:

- Gain_λ = Gain response function for band λ
- DN_λ = the Digital Number or Digital Grey Level for band λ
- Bias_λ = Bias response function for band λ
- ρ_λ = Unitless planetary reflectance for band λ
- L_λ = Spectral radiance at the sensor's aperture for band λ
- d = Normalized Earth-Sun distance in astronomical units
- ESun_λ = Mean solar exo-atmospheric irradiances for the satellite sensor for band λ
- θ = Solar elevation angle in radians

3.3.4 Atmospheric Effects

According to Huang (2001), the conversion of Digital Numbers to at-satellite reflectances for Landsat imagery as described by Equation 3.1 [B] is highly beneficial since the method is physically based and can be readily implemented. Furthermore, without performing atmospheric corrections, substantial relative noise amongst clear and nearly cloud free images can be removed by converting DN to at-satellite reflectance, improving the quality of image mosaicing and land cover characterization of multi-temporal data. Huang (2001) indicates that results can be further improved by considering the impact of topography on illumination and view geometry.

To normalize multi-temporal imagery, radiometric correction models require *in situ* atmospheric measurements and radiative transfer code measurements (Chavez, 1996). This is, however, impractical and unacceptable in many instances as *in situ* measurements are not available, especially when working with historical data. Alternative, easy to use image based, cost-effective, robust and accurate, radiometric correction and calibration procedures are required.

In an effort to circumvent the required atmospheric measurements of radiative transfer code, Schott *et al* (1988) and many other authors have documented various radiometric scene normalization techniques that utilize ¹pseudoinvariant features such as water bodies, concrete, asphalt and rooftops to correct for atmospheric effects.

An example of a technique that utilizes pseudoinvariant dark-objects, such as fresh water bodies, is the dark-object subtraction (DOS) technique described by Chavez (1988). This simple image based technique removes the additive scattering component caused by path radiance. The DOS technique assumes that one or more pixels in the data set has a true value of zero, and that the scaling of DN values within each of the bands increases from the minimum dark-object reflectance that is greater than zero. The DOS technique linearly rescales all DN values by subtracting the dark-object reflectance value from all DN values, thereby forcing the reflectance value for dark-object features to zero (Chavez, 1988). This method does not, however, account for the multiplicative effect caused by atmospheric transmittance, which includes scattering and absorption of light.

Chavez (1996) argues that the DOS technique traditional methods of converting DNs to at-satellite reflectances, described by Equation 3.1 [A] and [B], may not correct for atmospheric effects adequately. Given that the electromagnetic energy measured by the sensor is influenced by the atmosphere, and is wavelength dependent, atmospheric scattering, absorption and refraction of light are both multiplicative and additive in nature across the different satellite bands and, as such, require a different approach.

¹ Pseudoinvariant features are characterized by near constant spectral reflectance characteristics over time.

To correct both the additive and multiplicative effects, Chavez (1996) developed a model based solely on the digital image measurements, which takes into account both additive and multiplicative components. This is known as the cosine of solar zenith angle (COST) model that converts DN values to at-satellite reflectances and, in addition, provides an image based atmospheric correction.

Equation 3.2 COST image-based atmospheric correction model (Chavez, 1996) for converting DNs to at-satellite reflectances. This model requires the calculation of the dark-object radiance for each band [A]. The COST model computes a unitless planetary reflectance for each band [B].

$$[A] \quad L_{haze_{\lambda,1\%}} = \frac{0.01 \times ESun_{\lambda} \times \sin^2(\theta)}{\pi \times d^2}$$

$$[B] \quad COST_{\lambda} = \frac{\pi \times d^2 \times (L_{sat_{\lambda}} - L_{haze_{\lambda,1\%}})}{ESun_{\lambda} \times \sin^2(\theta)}$$

Where: $L_{haze_{\lambda,1\%}}$ = Computed dark-object radiance for band λ (assumed to have a reflectance of 1%)
 $COST_{\lambda}$ = Unitless planetary reflectance for band λ
 $L_{sat_{\lambda}}$ = Spectral radiance at the sensor's aperture for band λ
 d = Normalized earth-sun distance in astronomical units from nautical
 $ESun_{\lambda}$ = Mean solar exo-atmospheric irradiances for the satellite sensor for band λ
 θ = Solar elevation angle in radians

3.4 Feature Extraction from Satellite Imagery

There are many ways of extracting information from satellite imagery. One of the simplest methods is the creation of false colour composite maps, which best enhance the feature of interest, and then digitising, from which manual or heads-up digitising is performed. This method was used extensively for mapping South Africa during the 1996 National Land Cover Project (Thompson, 1996).

There are many different classification techniques that can be applied to classify features. Kiefer and Lillesand (1994) and Thiam and Eastman (1997) provide good descriptions of these methods. These methods essentially apply different forms of distance measures between points situated in multidimensional space to assign group or class ownership.

There are several different techniques for automated classifications of satellite imagery into spectrally unique classes, that can be divided into two categories, namely supervised and unsupervised classifications. Essentially, supervised classification requires a set of training sites to define the spectral characteristics of the target feature. These rules are then applied to the entire image to isolate the target feature(s). Unsupervised classification techniques interpret the spectral characteristics

of the data and then divide the data into spectrally unique classes (Kiefer and Lillesand, 1994; Thiam and Eastman, 1997).

Associated with many of the classification methods are data reduction techniques. These are required to reduce the amount of data to be processed or data redundancy, as well as to increase computational efficiencies. Several data reduction techniques, such as Principal Component Analysis (PCA) and Tasseled Cap Transformations (TCT), can be used to reduce the dimensionality of the data while describing typically more than 95% of the variability (Thompson, 2003). It is not uncommon to apply data reduction techniques before applying classification procedures. One must, however, be aware of the fact that data reduction techniques, such as PCA, maximize the variance in the multi-dimensional data. While the dimensionality of the data may be considerably reduced, the smaller variations in the multidimensional data may be lost if one considers only the dominant components (Cheriyadat and Bruce, 2003).

More recently, the development of more sophisticated classification tools based on decision rules has provided an extension to the traditional supervised classification methodology. These are sometimes referred to as Knowledge Classification Algorithms and are based on a hierarchical set of rules and conditions to classify the data into different spectral classes (Erdas Inc, 1999). An example of a decision rule for classifying sugarcane would be: in an annual cutting cycle, at one point in the year, the crop will appear harvested or fallow, while for the period prior to this, the field should have a characteristic sugarcane colour signature. Other crops will not have the same spectral transition from sugarcane to fallow and back to sugarcane. Rules could be designed to facilitate extraction of sugarcane areas based on these spectral transitions. To operate effectively this technique requires a good understanding of the target features and their associated spectral characteristics.

A popular method for classifying data is that of unsupervised hierarchical classifications. According to Thompson (2002), the hierarchical clustering technique is based on repetitive iterations of the unsupervised clustering process. Those spectral classes that represent mixed information are re-classified to further break down the mixed (spectral) class structures. This procedure is repeated until a stage is reached when all output spectral clusters are associated with individual information classes that are no longer mixed.

There are many advantages to using the unsupervised hierarchical classification approach. Firstly, comprehensive set training information is not required, as is the case for traditional supervised classification procedures. Secondly, the iterative procedure allows the user to explore and subdivide the mixed spectral classes, which in turn assists in the separation of spectrally mixed classes (Thompson 2002, 2003).

3.5 Yield Estimation by Remote Sensing

Remote sensing has been used extensively in the field of crop forecasting. The ability of satellite remote sensors to measure the reflectance characteristics of vegetation surfaces over large areas in an unbiased manner, makes them invaluable in agricultural monitoring systems (Krishna Rao *et al*, 1999). The advantages of using remote sensing methods in conjunction with crop-weather models, is that remote sensing has the ability to measure the spatial variability of agricultural production that may be a result of factors such as: topography, soil conditions, nutrient deficiencies, lodging, pests or diseases (Baier, 1981).

Yield estimates require two key components, namely an estimate of the area cultivated to a particular crop and secondly an estimate of the crop yields (Rosema, 1981). Remote sensing techniques are frequently employed to map agricultural lands. Manual interpretation of the satellite imagery or classification techniques can be performed to map production areas. These techniques were briefly discussed in Section 2.4 *Feature Extraction from Satellite Imagery*.

Several methods can be applied to remote sensing data to estimate crop yields. These include vegetation indices (Noonan, 1999), estimates of leaf area indices and crop factor estimates (Doraiswamy *et al*, 2003a, 2003b; Rodriguez *et al*, 2003; Maas, 1988). In certain instances, these estimates are combined with crop-weather models to predict yields. Each of the different methods will be discussed.

3.5.1 Yield Estimation by Vegetation Indices

While remote sensing techniques cannot directly measure the crop yield, measurements of a crop's photosynthetic activity by means of vegetation indices can be used to monitor crop (phenological) development and estimate production. The advantage of using remote sensing in this regard, in relation to the crop-weather based models, is the ability of remotely sensed data to represent spatial variability.

Vegetation indices are based on the fact that healthy green canopies have very distinctive absorption and reflectance characteristics in the visible and near infrared radiation regions of the electromagnetic spectrum. The chlorophyll within the leaves strongly absorbs visible radiation, particularly in the blue and red regions of the electromagnetic spectrum, primarily for photosynthetic purposes. The near infrared wavelengths are, however, strongly scattered by vegetation, primarily as a result of the internal structure of most leaves. This strong contrast in the amounts of red and infrared energy reflected by vegetation surfaces has been the focus of many researchers in developing quantitative indices of vegetation condition by remote sensing (Thiam and Eastman, 1997).

According to Thiam and Eastman (1997), there are two different types of vegetation indices, namely slope and distance based vegetation indices. Slope based vegetation indices produce lines of differing gradients from the origin of a bispectral plot of the red against the infrared reflectance values for different crop conditions (see Figure 3.2). The most commonly used slope based vegetation index is the Normalised Difference Vegetation Index (NDVI). Distance based vegetation indices measure the degree of vegetation present by gauging the difference in reflectance to that of bare soil. Within a bispectral plot of the red against the infrared, the bare soil pixels of varying moisture levels within an image will tend to form a line known as the soil line. As the vegetation cover increases, the soil background becomes progressively obscured, with vegetated areas showing a tendency towards increasing perpendicular distance from the soil line. The Perpendicular Vegetation Index is an example of a distance based vegetation index and requires the slope and intercept of soil line to be defined before an image can be analysed. The most commonly used vegetation index is the NDVI.

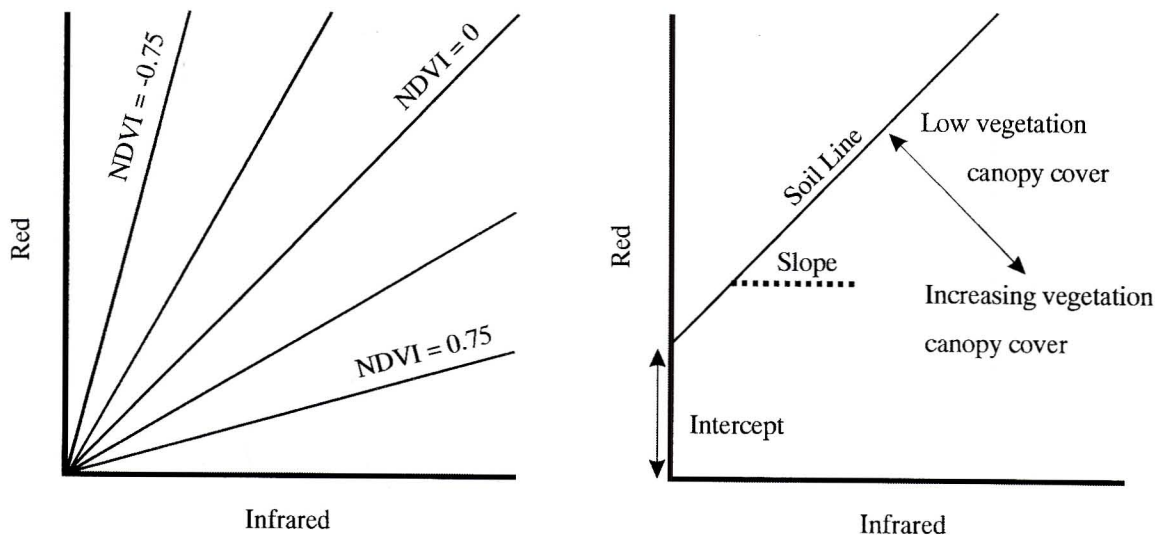


Figure 3.2 Bi-spectral plots of red against infrared for slope based vegetation indices on the left and distance based or orthogonal transformation vegetation indices on the right (Modified from: Thiam and Eastman, 1997, pp 13.2.)

Equation 3.3 The Normalised Difference Vegetation Index (NDVI). The different Landsat Thematic Mapper bands are denoted by the term TM.

$$NDVI = \frac{((\text{Near Infrared}) - (\text{Visible Red}))}{((\text{Near Infrared}) + (\text{Visible Red}))} = \frac{((TM4) - (TM3))}{((TM4) + (TM3))}$$

Noonan (1999) and Schmidt *et al* (2000) have shown that vegetation indices, and the NDVI (Equation 3.3) in particular, can be used to estimate sugarcane production. Two distinctly different approaches

made use of NDVI, namely a time step approach and a single date approach. Each of these methods will be expanded upon.

3.5.1.1 Yield Forecasts Using a NDVI Time Step Approach

The time step approach adopted by Schmidt *et al* (2000), made use of regularly acquired NDVI data for the area of interest, accumulated over the duration of the crop cycle or season. In essence, this approach regresses the total production against the accumulated photosynthetic vigour. This approach assumes that the total crop production can be expressed as a linear function of the accumulated NDVI or growth vigour for that season. Furthermore, the approach allows for yield prediction, given several different historical profiles of growth vigour and crop production. An advantage of this approach is that coarse resolution data can be employed. This in turn has the advantage of high temporal resolution, unlike the high resolution sensors that are generally more costly.

The approach used by Schmidt *et al* (2000) made use of 10-day synthesis or S-10 NDVI data sets to remove, as much as possible, the effects of cloud cover over the target areas. These S-10 data sets were accumulated over the growing season of the crop and regressed against the total production. This method produced desirable results in certain MSAs.

3.5.1.2 Yield Forecasts Using a NDVI Single Date Approach

The single date yield forecast approach applied by Noonan (1999) made use of a single NDVI image. This image was then divided into 25 different production classes, based on the spectral characteristics of the imagery. Using fieldwork and local knowledge of the area, yield characteristics were allocated to each NDVI production class from which a total production was calculated.

Furthermore, Noonan (1999) suggested that the Infrared Index (II) (see Equation 3.4) may have more potential than the NDVI for measuring the productivity levels of sugarcane, particularly in single date applications, given its sensitivity to changes in biomass and water stress.

Equation 3.4 The Infrared Index (II). The different Landsat Thematic Mapper bands are denoted by the term TM.

$$II = \frac{((\text{Mid Infrared}) - (\text{Near Infrared}))}{((\text{Mid Infrared}) + (\text{Near Infrared}))} = \frac{((\text{TM5}) - (\text{TM4}))}{((\text{TM5}) + (\text{TM4}))}$$

3.5.2 Combining Remote Sensing and Crop-Weather Models for Yield Estimation

Combining remote sensing and crop-weather models has been extensively used to monitor agricultural production for crops such as grain, sorghum, wheat and corn. Doraiswamy *et al* (2003b) states that the integration of remote sensing and crop models can be achieved by two distinct methods. The first method makes use of remote sensing to estimate the crop model initialisation parameters. The second method utilises remotely sensed time series data to calibrate the crop growth model. Each of these will be discussed briefly.

Examples of remotely sensed parameters that can be used to initialise and calibrate crop models include: light interception by the canopy and leaf area indices (LAI). Doraiswamy *et al* (2003a) provides an example of this method that used MODIS data to obtain LAIs that were then input into the Scattering by Arbitrarily Inclined Leaves (SAIL) model, to predict yields of soya bean and corn on a regional scale.

Another example of remotely sensed time series data to calibrate the crop growth model is described by Maas (1988), who successfully applied green leaf area indices derived from remote sensing to calibrate a simple crop model for grain sorghum. Maas (1988) adjusted the LAI modelled values to match the LAI estimates from remote sensing measurements made from the Landsat satellite. The remotely sensed LAIs were obtained by regression with NDVIs. The limitation with this approach is that the regression between LAI and NDVI is not constant for all locations in the same scene (Doraiswamy *et al*, 2003b). The simple model yield estimates, without remote sensing calibration, provided a 30% underestimation of the average yield. By including remote sensing, the results improved to a 2% overestimation of the average yield.

3.6 Remote Sensing in the South African Sugar Industry

Applications of remote sensing in sugarcane agriculture are relatively new and less developed when compared with cereal crops such as maize and wheat. The South African sugar industry has employed remote sensing technologies in sugarcane agriculture and has focused on three primary research areas, namely precision farming, estimation of the timing of harvest / standing crop throughout the milling season and yield forecasting. Each of these will be discussed separately in the context of the South African sugar industry.

3.6.1 Remote Sensing and Precision Farming

The research undertaken by ARC (2000a) utilised a Digital Multi-Spectral Videography (DMSV) sensor to investigate the potential benefits of this technology for precision agriculture in the sugar industry. The DMSV sensor system employed comprised four bands of wavelength 450 nm, 550 nm, 650 nm and 750 nm. This sensor was mounted on a fixed-wing microlite with a GPS system for rapid image geo-referencing and mosaicing. The DMSV sensor had a variable ground resolution of between 0.5 m and 3 m, depending on flying height. In this study, a 0.5 m resolution was chosen. Various image processing techniques, classification and principal component analysis, were explored to best explain features measured in the field (Schmidt *et al*, 2001; ARC, 2000a). The results of several experiments conducted are described in Table 3.1. Note that these results are based on the analysis of a single date DMSV image.

Table 3.1 The success with DMSV in distinguishing various crop factors or field conditions. A value of 1 indicates low success and a value of 5 indicates high success (Schmidt *et al*, 2001).

FACTOR	Success with DMSV to distinguish factor				
	1	2	3	4	5
Crop moisture stress	1	2	3	4	
Waterlogging	1	2	3	4	5
Sugarcane variety	1	2	3	4	
Crop age and ground cover	1	2	3	4	
Bare soil/surface conditions	1	2			
Early crop response to ripening	1				
Nutrient deficiency	1				
Field production potential	1				

3.6.2 Remote Sensing and Sugarcane Inventory Assessment

Remote sensing applications can play an important role in the management of sugarcane supply through the monitoring of the sugarcane areas harvested throughout the milling season. The proportion of the area harvested is important to the cane supply managers in planning and allocating delivery schedules to the growers. This in turn ensures rateable sugarcane supply to the mill. For example, if the proportion of the total mill area harvested half-way through the milling season is less than half the total area, the rate of sugarcane supply would need to be increased in order to complete the harvesting of the crop within that season.

Gers and Schmidt (2001) investigated the use of time step Spot 4 satellite imagery to monitor sugarcane areas harvested by smallholder growers in a selected area within the Umfolozi MSA. This was achieved by manipulation of the four satellite-measured spectral bands and subsequent classification of sugarcane into harvested and non-harvested areas. The results indicate that the satellite imagery classifications are able to distinguish between standing sugarcane and harvested plots.

3.6.3 Remote Sensing and Yield Forecasting in the South African Sugar Industry

According to Lumsden *et al.*, (2000): “*There is a need in the South African sugar industry to investigate improved techniques for forecasting seasonal sugarcane yields. An accurate and timely forecast of seasonal cane yield is of great value to the industry, and has the potential to result in substantial economic savings at national, Mill Supply Area (MSA) and individual farm scales. At national scale, forecasts could be used in the development of marketing and pricing strategies, in the early signing of export contracts and in the provision of forward cover for exchange rate fluctuations. At MSA scale, forecasts could be applied in the planning of mill operations such as the determination of mill opening and closing dates, haulage scheduling and in the determination of crushing and extraction rates. At farm scale, crop forecasts could be used in decisions relating to cash flows, in the planning of harvest and haulage scheduling and in crop husbandry decisions such as fertilizer applications and irrigation scheduling (Schmidt, 1998).*”

South African Sugar Association Experiment Station (SASEX) currently provide industrial crop yield forecasts that are derived from the modelling approach. Sugarcane yields are simulated on a regional basis with the intermediately complex CANESIM (water balance) sugar growth model. These regional forecasts are pooled to provide industry estimates (Bezuidenhout and Singels, 2001).

Schmidt *et al.* (2000) investigated the use of remote sensing for yield forecasting, using time step NDVI data, based on the NOAA AVHRR sensor data for the period 1988 to 1998. The methodology employed extracted ten-day maximum value composite NDVI images for nine target areas, each comprised of 3.3 km by 3.3 km blocks dominated by sugarcane. The synthesized ten-day NDVI composite values were analysed along with the production information for the target areas (ARC, 2000b). The results were favourable for the northern irrigated areas including Pongola, Komati and Malelane.

3.7 Current Sugarcane Research Applications Internationally

The Australian sugar industry has integrated remote sensing and Geographic Information System (GIS) tools to assist and improve sugarcane harvesting management. Markley *et al.* (2003) have made use of remote sensing to estimate the remaining areas harvested during the harvest season. These unharvested areas, combined with yield estimates for the areas already harvested, have been used to estimate the remaining crop. Their approach combines single date image analysis with multi date analysis. A change detection approach was employed that made use of vegetation indices to identify new areas harvested and, in cases where that sugarcane was stressed, a combination of the red and Short-Wave Infrared (SWIR) bands was employed. The difference in vegetation indices between stressed and harvested sugarcane was not significantly different, as is the case with healthy (unstressed) sugarcane

(Markley *et al*, 2003). Their approach also allowed fields to be subdivided or split, in the event that the field was not fully harvested.

3.8 Summary

The *Literature Review* begins by introducing the subject of remote sensing followed by applications of remote sensing in agriculture. Various characteristics of the satellite sensors such as the spatial, spectral and temporal resolution, as well as different types of satellite sensors, are explored. Various image processing techniques employed in agricultural applications including geometric, radiometric, solar elevation and earth-sun distance, as well as atmospheric corrections, are discussed.

The next section in this chapter discussed feature extraction from satellite imagery. These included: supervised, unsupervised, knowledge based, hierarchical, PCA and Tasseled Cap. Yield estimation was by means of a time step and single date approach using vegetation indices such as the NDVI.

The last section of this chapter reviewed the various applications of remote sensing in the South African sugar industry as well as internationally. South African application included precision farming, crop inventory assessment and yield forecasting. The Australian industry has made use of remote sensing to facilitate sugarcane supply management through the monitoring of fields harvested throughout the season.

4 MATERIALS AND METHODS

In this chapter, the methods relating to sugarcane area mapping by means of remote sensing, the relationships between spectral characteristics of the sugarcane and phenology, cultivar and yield, sugarcane inventory assessment throughout the milling season and yield estimation will be discussed. The remaining chapters will echo this format in order to relate the results, discussion and recommendations to the methods and materials employed.

4.1 Sugarcane Area Mapping by Remote Sensing

This section will begin with the acquisition of satellite imagery, followed by the selection of a suitable satellite sensor, processing of imagery, classification and validation procedures.

4.1.1 Acquisition of Satellite Imagery

The first step in the process of mapping sugarcane areas was the identification of a suitable high-resolution sensor that would adequately address the research requirements. Several important elements that were considered included spatial, temporal and spectral resolution, as well as the cost of the imagery. Ultimately, a balance between the cost, spectral and temporal resolution that would adequately address the research requirements was reached.

One of the primary concerns when selecting satellite data is the cost. Table 4.1 provides an indication of the costs, spatial, temporal and geographic extents of commonly used satellite sensors. Clearly, Landsat 7 ETM+ ranks very highly in terms of cost per unit area for its relatively high spectral resolution of 30 m. It should be noted that the costs provided in Table 4.1 represent the cost of the raw data only.

The processing costs for satellite imagery are not included in Table 4.1. Satellite image processing (such as geometric and ortho-rectification) typically cost an additional 30% of the raw imagery price. These costs are likely to be higher for the high-resolution data such as Ikonos, given that higher resolution elevation models are required for orthorectification. While the national elevation models provided by the Surveyor General of South Africa are 20 m contour intervals and are suitable for sensors such as Spot 2-4 and the Landsat, the higher resolution sensors such as Ikonos will require better resolution elevation data for more precise rectification. This is likely to raise the cost of data preparation for the very high-resolution sensors given the need for higher resolution digital elevation models, as well as the increased computational requirements.

Table 4.1 Cost in South African Rands of satellite data per square kilometre as well as the spatial, temporal and geographic extents of various satellite sensors. Unless otherwise stated, these prices refer to the cost of the raw data that requires further processing (Modified from Ferreira, 2003).

Sensor	Spatial Resolution	Temporal Resolution	Spatial Coverage	Cost per km ² (ZAR)
SPOT Veg. Index	1 km	daily	2250 x 2250 km	R 0.01
Landsat 7 ETM+	30 m	16 days	180 x 180 km	R 0.17
Landsat 7 Pan	15 m	16 days	180 x 180 km	R 0.17
Irs Pan	5.8 m	24 days	70 x 70 km	R 2.50
Spot 1,2,3 XS	20 m	26 days	60 x 60 km	R 4.72
Spot 1,2,3 Pan	10 m	26 days	60 x 60 km	R 4.72
Spot 4 Xi	20 m	26 days	60 x 60 km	R 4.72
Spot 4 Mono	10 m	26 days	60 x 60 km	R 4.72
Spot 5 Colour	10 m	26 days	60 x 60 km	R 8.98
Spot 5 Mono	5 m	26 days	60 x 60 km	R 8.98
Eros Pan	1.8 m	4 days	12.5 x 12.5 km	R 125.00
Ikonos Multispectral	4 m	2.9 days	11 x 11 km	R 247.00
Ikonos Pan	1 m	2.9 days	11 x 11 km	R 247.00
Digital Colour Ortho-photography	0.5 m to 2 m	On request	Variable	R 300.00
Digital Infrared Ortho-photography	0.5 m to 2 m	On request	Variable	R 300.00

4.1.2 Selection of the Landsat 7 ETM+ Sensor

The satellite chosen for this study was the Landsat 7 ETM+. While the spatial and spectral resolution of the sensor is slightly inferior to many of the competing satellites, such as Spot 4 and Spot 5 or even ASTER, the primary objective was to ensure the development of a methodology based on readily available, low cost commercial based satellites. Clearly, despite the decreasing costs of satellite imagery, Landsat data are highly competitive. Given that Landsat satellites are supported by NASA and also commercially, continuity of data is highly likely in the event of a satellite being decommissioned or satellite failure. This is critical in operational environments that rely on the satellite imagery. The favourable cost of the imagery, despite the slightly poorer spatial resolution, was the dominating factor that led to the choice of the Landsat 7 ETM+ for the research undertaken. More expensive satellite imagery, such as Spot, would have been used in the event that only one image was required. However, the approach adopted requires use of multi-temporal imagery in order to establish the status of the sugarcane crop at regular intervals throughout the growing season. This multiplicative effect of the more expensive satellite imagery made it prohibitive. Furthermore, it was hoped that by combining high temporal resolution data, the effects of the lower spatial resolution associated with the Landsat 7 ETM+ sensor could be overcome by using the combined spectral

profiles over time, to identify the small sugarcane fields. A time step spectral profile was believed to enhance the ability to identify or map sugarcane, given the limitations in the spatial resolution when compared with some of the other satellite sensors such as Spot.

Satellite imagery was obtained throughout the 2001-2002 growing season. A calendar of satellite image overpass dates for the area of interest was determined in order to assist in the operational planning of fieldwork at each overpass date. Fieldwork was conducted to obtain an independent set of data to be used for the validation process. Ultimately, five images were obtained, the dates of which are given in Table 4.2. A total of 698 random points were collected.

Table 4.2 Dates on which Landsat 7 ETM+ Satellite imagery was acquired in relation to the 2001-2002 milling season.

Event	Date	Days from beginning of 2001-2002 milling season	Days as % of season length	Season description
First Landsat ETM+ image	30-Oct-2001	-163		Mid-late previous season
Second Landsat ETM+ image	08-Apr-2002	-3	1%	Beginning of season
Mill Opening	11-Apr-2002	0	0%	Beginning of season
Third Landsat ETM+ image	13-Jul-2002	93	38%	Early-mid season
Fourth Landsat ETM+ image	17-Oct-2002	189	77%	Mid-late season
Fifth Landsat ETM+ image	18-Nov-2002	221	90%	Late season
Mill Closing	13-Dec-2002	246	100%	End of season

The spread of images was important. Weather dependent images needed to be spread over the growing season as evenly as possible, with at least the first image being taken prior to the beginning of the milling season. Given that the mills usually close in December, the period of vigorous sugarcane growth between December and the opening of the mill in April of the following year, would ensure that most fields harvested in the latter stages of the previous year would have well developed, full canopies. These fully developed canopies would assist in the detection of sugarcane fields, as the underlying soil reflectance tends to be masked by the foliage. This results in a clearer sugarcane reflectance that, in turn, makes its signature more distinct and hence more readily identifiable.

4.1.3 Processing of Satellite Imagery

In order to make quantitative measurements and comparisons between the images captured on different dates, normalisation was required to remove the effects of different earth sun distances and solar

elevation angles. To achieve this normalisation, the COST model described by Chavez (1996) was applied to the data. In addition to earth-sun distance and solar elevation corrections, the COST model includes an image-based atmospheric correction procedure. Given the unavailability of atmospheric radiative transfer code measurements to perform a full atmospheric correction, the COST model provided the best alternative.

4.1.3.1 Data Reduction Techniques

There are several data reduction techniques that can be applied to satellite data to improve both the computational efficiencies and discrimination of the features of interest. This is important, since the inclusion of all the data does not necessarily result in an optimal classification.

In studies of vegetated surfaces, the Tasseled Cap Transformation described by Kauth and Thomas (1976) is a very useful data reduction technique. This technique essentially uses the Gram-Schmidt orthogonalization process to compute three important bands, namely Wetness, Greenness and Brightness. These three bands describe most of the variability associated with the vegetation surfaces and have been widely used by Thompson (2002) for the mapping of sugarcane. Table 4.3 shows that while considering all five time step images, the Tasseled Cap transformed bands provide superior average separability of feature classes to that of the non-transformed satellite imagery, suggesting its use as an affective alternative for sugarcane area mapping.

Once the data were reduced by means of Tasseled Cap Transformations, further investigations were made to determine which, if any, of the Tasseled Cap bands could be omitted to further reduce the dimensionality, while not compromising on results. This was important given that two of the three images had a significant amount of cloud cover over them, and including these in the classification would complicate matters. Even if the cloud cover and shadows were removed from those images, the multitemporal stack of satellite imagery would have ambiguous (zero) data values over the cloud and shadow affected areas, which would further complicate the classification procedures. This was because the typical temporal profile associated with sugarcane production is different to other crops, and including a zero reflectance value or cloud cover value would complicate classification procedure.

A key objective was to omit cloudy images, in order to simplify the classification procedure, while at the same time not sacrificing important information that would facilitate the identification or classification of sugarcane areas. A useful tool for measuring the relative importance of different satellite bands or band combinations that can be used to separate out different spectral classes (e.g. sugarcane and wetlands), is the Jefferies-Matusita multi-variate distance measure (Erdas Inc, 1999; Thompson, 2003). The Jefferies-Matusita statistic provides, for a selected group of multi-spectral satellite bands, the optimum combination that can be employed to classify or separate out different land covers. In the context of this research, this statistic was employed to identify which band combination(s)

would best discriminate sugarcane from spectrally similar land covers. Furthermore, these statistics were also employed to evaluate the impact a reduced number of bands would have on the ability to separate sugarcane from spectrally similar classes - such as wetlands. The overall objective of employing this statistic was to determine the smallest number satellite bands that could be employed to classify sugarcane whilst maintaining a high level of accuracy. Table 4.3 summarizes these results for this exercise. A more technical description of Jefferies-Matusita statistic is described by Swain and Davis (1978) in Erdas Inc. (1999).

Preliminary investigations into the spectral characteristics of different land covers, for each time step image, revealed that certain land covers were spectrally similar to sugarcane (the investigations were conducted through both visual interpretation and unsupervised classifications of the imagery). The spectrally similar land covers included wetlands, natural grassland or veld, pineapples and dense natural bush. Sample areas of wetlands, veld, pineapples and dense natural bush as well as sugarcane fields at different stages of development were identified from each image. The ability to separate the spectra of different features (e.g. cane from wetlands) for the COST corrected satellite imagery as well as the Tasseled Cap transformed imagery, for different combinations (or dates) were evaluated using Jefferies-Matusita multi-variate distance measures. These results are shown in Table 4.3.

Table 4.3 essentially compares three different sets of information:

- COST corrected at-satellite reflectances for all images (ABCDE),
- The first three Tasseled Cap transformed bands for all images (ABCDE),
- The first three Tasseled Cap transformed bands for cloud free images only (CDE).

As previously stated, the aim of this exercise was to determine the smallest number of satellite bands that could be employed to classify sugarcane whilst maintaining a high level of accuracy. From Table 4.3 it can be seen that favourable average separabilities were obtained for the 6 and 9-band combinations for the Tasseled Cap transformed cloud free images, compared with the COST 30-band and 15-band Tasseled Cap band combinations. These statistics suggest that by using only the Tasseled Cap transformed bands for the cloud free images, the results should not be significantly compromised.

While the best minimum separability was lower for the cloud free Tasseled Cap images (images CDE) than the Tasseled Cap combination of all five images, it was believed that the high best average separability justified the choice of the 9-band Tasseled Cap combination. The complexities that would be introduced by the inclusion of the remaining two clouded images into the analysis further justified this choice, as the reflectance values of the clouds would interfere with the spectral temporal profile of the underlying vegetation. Similarly, if the cloudy areas were removed, the substituted zero values would have the same effect.

Table 4.3 Jefferies-Matusita multi-variate distance measures of separability for various combinations of spectral bands including the original COST corrected data and the Tasseled Cap transformed data. The letters “AB...” in the Image Stack represent time step satellite images in alphabetical order.

i n

Image Stack	Number of Bands	Best Average Separability	Best Minimum Separability	Band Combination
<i>Stack of COST normalized multi-spectral imagery</i>				
ABCDE	30	1329		1, 2, 3, ... 30
ABCDE	30		1184	1, 2, 3, ... 30
<i>All Tasseled Cap images stacked (Greenness, Wetness and Brightness)</i>				
ABCDE Tasseled Cap	15	1371		1, 2, 3, ... 15
ABCDE Tasseled Cap	15		971	1, 2, 3, ... 15
ABCDE Tasseled Cap	12	1359		1, 2, 4, 5, 6, 7, 8, 10, 11, 12, 13, 14
ABCDE Tasseled Cap	12		946	2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13
ABCDE Tasseled Cap	9	1337		1, 2, 4, 5, 6, 7, 8, 11, 14
ABCDE Tasseled Cap	9		849	2, 3, 7, 8, 9, 11, 12, 13, 14
ABCDE Tasseled Cap	6	1289		1, 2, 5, 9, 11, 14
ABCDE Tasseled Cap	6		694	2, 3, 8, 9, 11, 14
ABCDE Tasseled Cap	3	1134		9, 11, 14
ABCDE Tasseled Cap	3		360	9, 10, 14
<i>The three cloud free Tasseled Cap image stacks (Greenness, Wetness and Brightness)</i>				
CDE Tasseled Cap	9	1299		1, 2, 3, 4, 5, 6, 7, 8, 9
CDE Tasseled Cap	9		650	1, 2, 3, 4, 5, 6, 7, 8, 9
CDE Tasseled Cap	6	1253		1, 2, 4, 6, 7, 8
CDE Tasseled Cap	6		576	2, 3, 4, 7, 8, 9
CDE Tasseled Cap	3	1135		3, 5, 8
CDE Tasseled Cap	3		361	3, 4, 8

It should be noted that the coefficients used in the Tasseled Cap transformations were not the conventional coefficients but rather the revised coefficients described by Huang *et al* (2001) that are based on at-satellite reflectances. This was because the DN based transformations are based on measurements of different physical units. (Appendix B lists the revised coefficients used to compute the Tasseled Cap transformations from the Landsat 7 ETM+ at-satellite reflectances.)

4.1.4 Classification Procedures for Sugarcane Area Identification

The classification procedures performed on the satellite imagery were similar for small-scale and large-scale growers. They were, however, analysed separately. The approach adopted was that of hierarchical unsupervised classifications for sugarcane growing regions only. For the large-scale growers, the farm boundaries were used to exclude the non-sugarcane producing areas. These were available from the Umfolozi MGB. For the small-scale growers, broad-scale areas of sugarcane cultivation were identified and demarcated by visual interpretation of the satellite imagery, given the lack of formal boundaries within the tribal areas. By doing this, much of the spectral diversity associated with non-sugarcane growing areas was removed. This in turn simplified the classification procedure by reducing the spectral variability, thereby increasing the ability to resolve sugarcane from spectrally similar land types.

4.1.5 Validation Procedures for Sugarcane Area Identification

Fieldwork was conducted within a week of each image overpass. Standard data capture forms were created to record the land covers to the north, east, south and west of randomly selected Ground Control Points (GCPs) that were located by Differential Global Positioning System (DGPS) (see Figure 4.1). Digital pictures were captured in each of the four directions for future reference in the event of there being uncertainty about the true land cover. The classification schema described by Thompson (1996) formed the basis for the land cover classifications schema.

4.2 Analysis of Sugarcane Spectral Characteristics

An important component of this research was to investigate the relationships between the sugarcane crop and its spectral characteristics, given the lack of literature on this subject, particularly with respect to crop age (phenology), cultivar and yield for the Landsat sensor.

In order to investigate the relationships between the crop and spectral characteristics, reliable field records were collected for several large-scale grower farms. These records included information on sugarcane cultivar, start date, harvest date and yield on a field basis. Given the recent mapping at Umfolozi, by means of digital orthophotography, accurate field maps were available .

COST normalised reflectance values for each of the time step satellite images, as well as vegetation indices derived from each, were then extracted for each field, on a pixel basis, using the field boundary information. A 30 m (inside) buffer was applied to all field boundaries while extracting the spectral characteristics to reduce the contribution of edge effects to the final results (i.e. all pixels along the

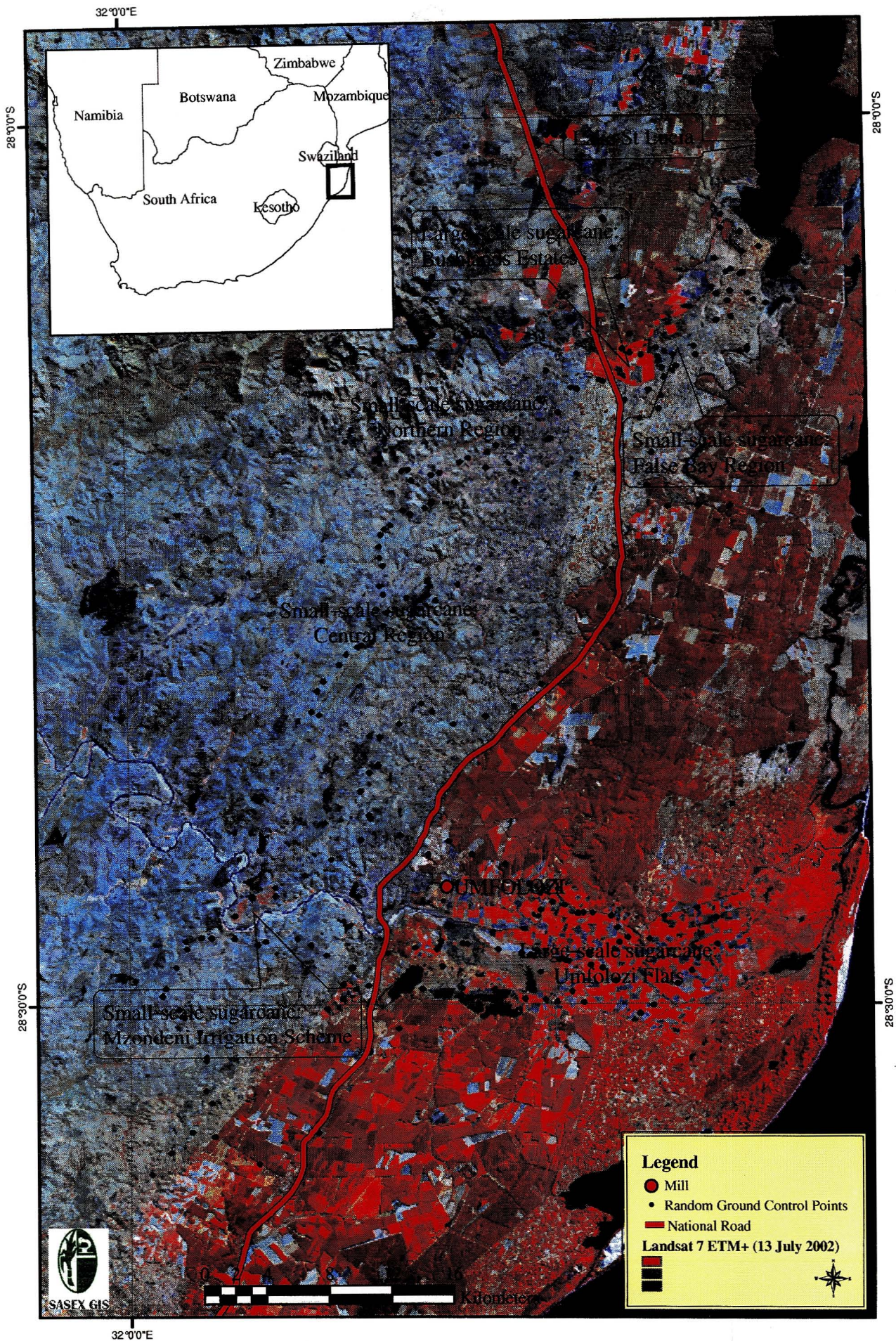


Figure 4.1 Landsat 7 TEM+ space map of the Umfolozi Mill Supply Area as well as the random Ground Control Points (GCPs) used to validate the sugarcane area mapping results. At each GCP, four land cover observations were made in the directions North, East, South and West.

field edge were excluded). This spectral information, as well as the field record and meteorological data, were then stored in a relational database. The data was then extracted by means of custom built queries to explore the relationships between the spectral characteristics of sugarcane: yield, cultivar and phenology.

The integrity of the information was carefully evaluated on a field basis. That is, visual inspections of the satellite imagery and corresponding field status were carefully compared. In all instances, where unmistakable errors were found, the data were deleted from the database of at-satellite reflectances to minimize errors. The main source of error was insufficiently precise harvest date information.

In many instances Principal Component Analyses (PCA) were used to reduce the data redundancy in evaluating the relationships, given the multi-collinearity effect associated with multi-spectral satellite data, especially for sugarcane growing fields. Several independent tests were conducted for sugarcane growing fields and, in most cases, above 95% of the total variance was accounted for by the first two factors. The details for each of the analyses are discussed below.

4.2.1 Relationship between Sugarcane Phenology and Spectral Characteristics

The three main phenological stages of sugarcane include pre-emergence, primary shoot emergence and tillering (Singels, 2003). Primary shoot emergence and tillering stages are of prime concern in the detection of sugarcane in remote sensing applications that rely on measurements of light reflected off the sugarcane canopy.

The development of the sugarcane ratoon canopy may be viewed as a process dependent on the emergence of tillers from the soil, and leaves from the whorl of each tiller. It was demonstrated by Inman-Bamber (1994) that the stalk population of sugarcane is highly correlated with thermal time when using a base temperature (T_b) of 16°C. Thermal time or growing degree days are calculated by adding together, on a daily basis, the units of temperature that exceed the base temperature. Days in which the daily maximum temperature is below the base temperature do not contribute.

As can be seen from Figure 4.2, the tiller emergence phenological stage includes a tillering stage from 0 to 500°C days, at which the stalk population peaks, followed by tiller senescence, between 500 and 1000°C days, when tillers die off, followed by a relatively stable stalk population after about 1600°C days. Most of the sucrose accumulation occurs at these latter stages prior to harvesting. The reason for the choice of cultivars (in Figure 4.2) was that NCo376 is widely considered as a benchmark cultivar, given its widespread cultivation for many years in South Africa and Swaziland. The cultivar N12 is more recent and possibly more representative of the newer cultivars. These two cultivars are therefore largely representative of sugarcane cultivars across the sugar industry.

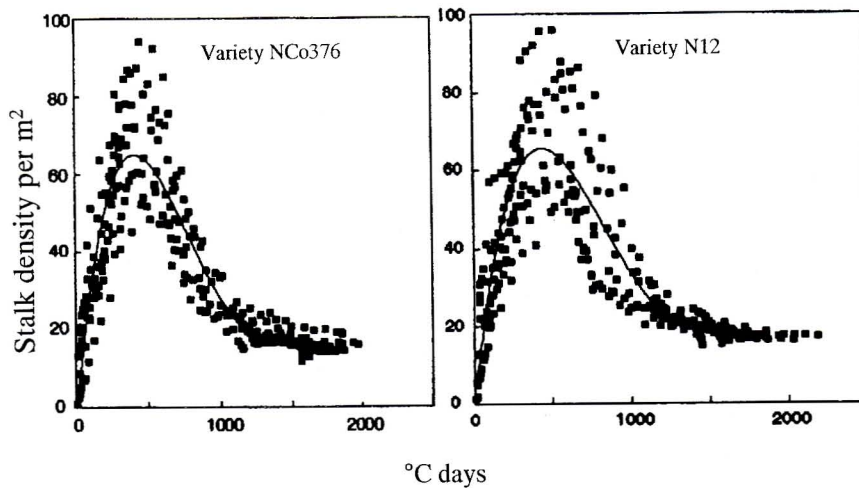


Figure 4.2 Stalk density against thermal time for ratooning sugarcane for cultivars NCo376 and N12. (Base Temperature =16°C days) (Source: Inman-Bamber, 1994).

It can be seen in Figure 4.2 that for the tiller emergence phenological stage, that is, from 70°C days to 1000°C days, large changes in the sugarcane stalk density take place over thermal time. Given these large changes in stalk population over a single phenological stage, a more descriptive phenological characterisation of tiller emergence was required to better account for the changes in stalk density, that may be measurable by means of remote sensing. Gers (2003a, 2003b) created pseudo phenological classes, based on stalk density and thermal age relationships illustrated in Figure 4.2, to better describe the phenological development of the sugarcane crop in relation to the changes in stalk density over time. The pseudo classes described in Table 4.4 were used to test whether or not the spectral characteristics were distinctive for each of these groups. Analysis of variance tests were conducted using the groups as treatment structures to determine whether or not the groups were spectrally significantly different. Following this, measures of group separation were made to determine their spectral separability. This would provide a practical measure of how accurately the groups could be identified, i.e. the probabilities of misclassifying a group.

Table 4.4 Groups of cumulative thermal time used to analyse field information (Modified from: Gers, 2003a, 2003b)

Thermal age group	Phenological classes based on thermal age ($T_b=16^\circ\text{C}$)	
	Cumulative thermal time range ($^\circ\text{C days}$)	Description
1	0 – 70	Primary shoot emergence
2	400 – 600	Tillering
3	750 – 1000	Tiller senescence
4	>1500	Tiller stabilisation

4.2.2 Relationship between Yield and Spectral Characteristics

Gers (2003a) investigated the relationship between the at-satellite reflectance values and yield for different thermal age groups. Thermal age and not calendar age was used to describe the crop age because of the seasonal effects on sugarcane growth. There is much scientific evidence that indicates that the use of thermal age, and in particular with a base of 16°C for sugarcane (Inman-Bamber, 1994) can be used to describe the growth of sugarcane independent of the seasonal temperature variations.

The at-satellite reflectances for thermal age groups 2, 3 and 4 (individually) as well as groups 2 to 4 (collectively/combined) were compared against production information. Group 1 was omitted since this group represented mainly fallow or bare ground. The NDVI and II indices were also included in the analysis.

In all cases, Correlation Matrix Principal Component analyses were conducted for the data comprising of field mean at-satellite reflectance values for Landsat 7 ETM+ bands 1 to 5 and 7 and yield data for groups 2, 3, 4 (individually) and groups 2 to 4 (collectively/combined) (see Table 4.4 for groups).

4.2.3 Relationship between Cultivar and Spectral Characteristics

The cultivar spectral characteristics for a selection of sugarcane fields in the study area were evaluated in terms of the at-satellite reflectances for the Landsat 7 ETM+ bands 1, 2, 3, 4, 5 and 7 for group 4. Variance-Covariance Principal Component Analyses were performed on the data to evaluate the trends. The five most abundant sugarcane cultivars were selected to ensure representative sampling. The areas planted to each of these cultivars are listed in Table 4.5. The analyses were conducted on pixel bases that were then averaged on a field basis, subject to the 30 m exclusion buffer.

The reflectance characteristics for each group could not be established in isolation given the lack of complete information on all cultivars for groups 2 and 3. Once again the first group was omitted since the analysis would focus on bare land and not the sugarcane canopy reflectances.

Table 4.5 Table showing the five most abundant sugarcane cultivars and their field areas used for evaluating the relationships between cultivar and spectral characteristics in the study area.

Sugarcane cultivar	Area (ha)	Number of fields
N19	154.6	25
N22	60.0	12
N27	50.5	11
N29	76.9	13
NCo376	77.9	12
Total Area	419.9	

4.3 Sugarcane Inventory Assessment Throughout the Milling Season

In order to evaluate the potential of remote sensing in determining the proportion of the total area harvested throughout the milling season, the initial methodology focused on the large-scale growers. The nature and scale of their operations made them an easier target to evaluate the methodology.

The methodology involved the use of the first three Tasseled Cap transformed satellite images for the large-scale grower fields only. These images were then classified into five spectrally unique classes ($p < 0.01$) by means of unsupervised classifications. From visual interpretation of the satellite imagery, these classes were assigned to different stages of sugarcane production, namely harvested, immature and mature sugarcane fields. Majority statistics were then extracted for each field and loaded into a relational database to facilitate the extraction and aggregation of statistics on a field level. Figure 4.3 illustrates this methodology.

Markley *et al* (2003) have utilised more detailed approaches for monitoring the field status. In particular, their approaches have made use of decision rules to subdivide or split fields in the event that they were only partially harvested. The approach adopted utilized the majority statistic, that is, the status of a field was decided by its dominant land type. It was believed that the errors of omission and commission introduced by this approach would balance each other out, given the scale of analysis.

To remove the influence of cloud cover on the results, all cloud-affected areas were masked out. That is, all clouded areas were assigned a pixel value of zero. It should be noted that the only images in which cloud cover masked out sugarcane fields were the first and second images. The cloud cover present in the remaining images did not interfere with the sugarcane growing areas.

To eliminate ‘double accounting’ of a harvested field in successive images, a cumulative raster mask, which represented harvested areas, was applied to each successive time step image. For example, the mask of harvested areas identified on the 8 April 2002 image was applied to the 13

July 2002 image. Similarly, the mask of harvested areas identified on the 8 April 2002 and 13 July 2002 images were applied to the 17 October 2002 image. Figure 4.3 illustrates the methodology employed for masking out of harvested areas in successive images. Given that all sugarcane is grown on a 12 month crop cycle at Umfolozi, the underlying assumption that each field can only be harvested once in the season was correct.

Table 4.6 Methodology employed to eliminate ‘double accounting’ of harvested fields by applying (cumulative) masks for removing harvested areas in successive time step images.

Event	Date	Mask Number	Applied Mask	Season Description
First Landsat ETM+ image	30-Oct-2001			Previous season
Second Landsat ETM+ image	08-Apr-2002	1		Beginning
Mill Opening	11-Apr-2002			Beginning
Third Landsat ETM+ image	13-Jul-2002	2	1	Early-mid season
Fourth Landsat ETM+ image	17-Oct-2002	3	1,2	Mid-late
Fifth Landsat ETM+ image	18-Nov-2002	4	1,2,3	Late season
Mill Closure	13-Dec-2002			End

In order to validate the results, the mill production figures were obtained for the 2001-2002 season, for both the small and large-scale growers. These statistics consisted of weekly percentages of the total crop crushed. This benchmarking exercise assumed that the yields were proportional to the area harvested. While this assumption is incorrect, the mill scheduling of allocation is based on the balance of sugarcane to be delivered. That is, the monthly allocations awarded to all growers in a manner that ensure equitable proportions of allocation on the balance of sugarcane to be delivered (de Lange, 2003). This process, in turn, translates into equitable proportions of areas harvested for the large and small-scale growers, where relative proportions of areas harvested across the MSA should be similar.

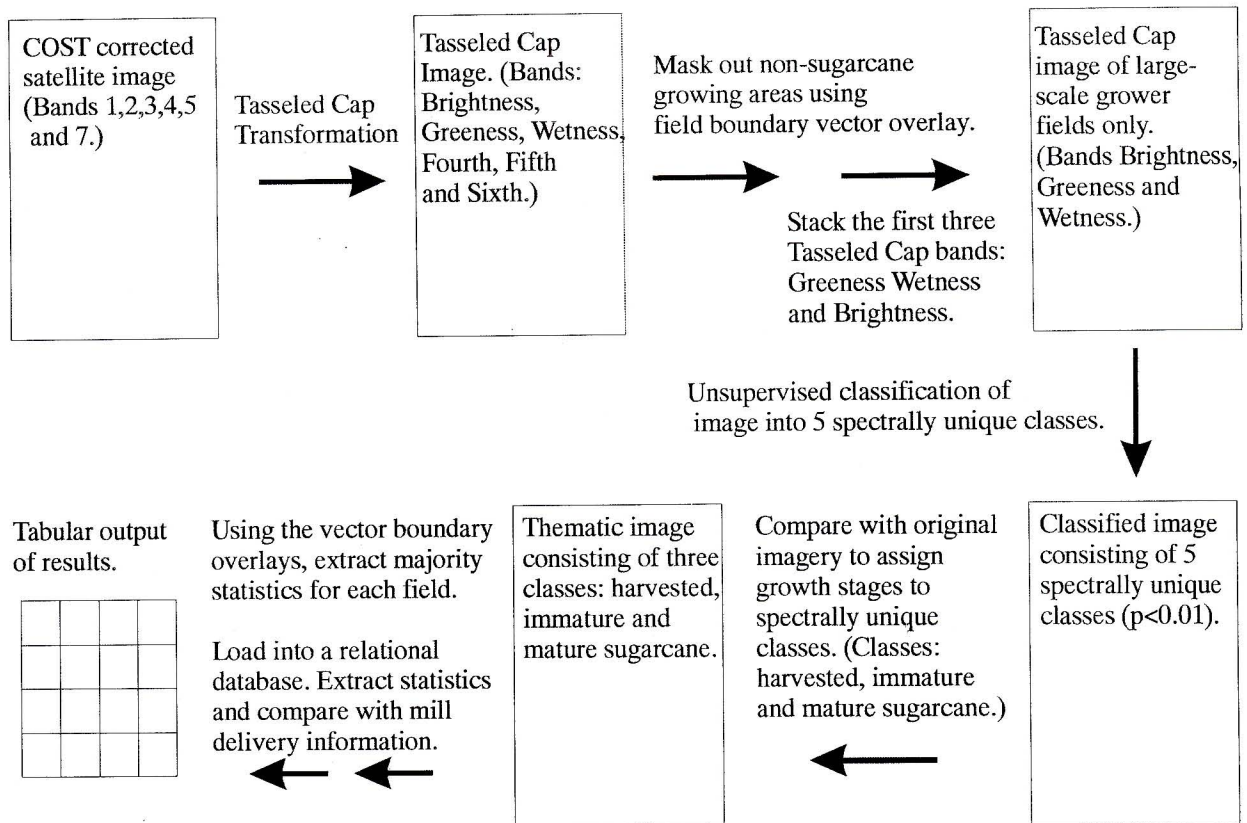


Figure 4.3 Flow chart illustrating the methodology employed to determine the proportion of the mill supply area harvested throughout the milling season.

4.4 Yield Prediction by Remote Sensing

This section will deal with the prediction of sugarcane yields on a MSA scale using different spatial resolution satellite imagery and analytical techniques. In all cases the methodology employed a time step approach similar to that of Schmidt *et al* (2000) in which time step vegetation indices were accumulated for sugarcane growing areas over different periods and correlated to annual production. That is, the area weighted cumulative vegetation indexes, which represented a measure of the cumulative growth vigour for the MSA, were used to predict the yields. Given the differences in temporal resolution for the Landsat and NOAA sensors, different periods over which the vegetation indices were accumulated were devised for each sensor in accordance with their respective temporal resolutions.

One of the aims of this approach was to determine the optimal number of images required to make a meaningful prediction of yield, given that that yield has been shown to be correlated with a cumulative vegetation index for other crops by Gordon and Brink (1995), Hobbs (1995) and Prince (1990) and for sugarcane by Schmidt *et al* (2000, 2001).

The research investigated the potential of applying this methodology using the Umfolozi MSA as a case study, for testing different windows of time or periods to predict annual yields. Several tests or scenarios, including those identified by Schmidt *et al* (2000) for the NOAA data, were used to investigate the optimal number of images required to meaningfully predict production. Ultimately, the fewer the number of images required, as well as their timing before the date of harvest, would be important in its industrial application. Ideally, one would like to predict with as few images as possible well in advance of the field's harvest. In the case of the mill operation, a forecast prior to the opening of the milling season before early April would be ideal, given that a smaller crop may require a delayed start to the milling season. Conversely, a bumper crop would require the season to start in early April or even late February. It should also be noted that this approach has a fundamental difference to that adopted by Schmidt *et al* (2000) in that the vegetation indices accumulated were area weighted by the relative proportions of sugarcane growing in the different climatic zones identified by Bezuidenhout and Gers (2002). This was done to ensure that the results were more representative of the production potentials in each of the zones.

The details for both the NOAA and Landsat time step approaches are discussed below. Please note that different scenarios and periods were used for the NOAA and Landsat data, given the differences in temporal resolution and history. The scenarios are independent of each other within the respective sections below.

4.4.1 Yield Prediction Using a NOAA NDVI Time Step Approach

NOAA NDVI data were obtained from the Agricultural Research Council Institute for Soil Climate and Water (ARC/ISCW) for the period 1985 to 2002. The data were processed by the ARC/ISCW and ten-day NDVI or S-10 synthesised images were created to minimise the likelihood of cloud cover masking the land cover. There were however two missing periods of data. The first period between 02-Dec-1990 and 03-Dec-1992 was missing on account of erroneous data extraction, and the second missing period between 02-Dec-1993 and 03-Jan-1995 was on account of NOAA satellite failures. The first missing period could not be obtained.

Bezuidenhout and Gers (2002) derived homogeneous climatic zones for the South African sugar industry taking into account rainfall, altitude, latitude and temperatures. The purpose for the climate zones was to delineate regions of uniform climatic potential for sugarcane growth modelling and yield prediction on an industrial scale.

Thompson (2002) identified sugarcane growing areas for the entire sugar industry by means of hierarchical unsupervised classifications on Tasseled Cap transformed Landsat 7 ETM+ imagery. Based on these sugarcane areas, 1 kilometre square pixels were identified in which more than 70% sugarcane was present. These sugarcane-dominated pixels are illustrated in Figure 4.4.

The methodology for extraction of NDVI statistics combined both the climate zones and sugarcane-dominated pixels described above. More specifically, NOAA NDVI statistics, including mean, median, maximum, minimum and standard deviation, were extracted for the sugarcane dominated pixel(s) per each climate zone, for each time step image. The resulting NDVI time series statistics per climate zone were then area weighted (i.e. according to the relative area contribution of that zone to the total MSA). These area weighted NDVI statistics were then combined into a single NDVI time series representative of the entire MSA. In order to predict a yield from the NDVI time series data, the ‘representative’ time series values were aggregated or accumulated over different periods, described in Table 4.7 and related to annual (mill) production. The aggregated time series included cumulative minimum, maximum, mean and median NDVI values.

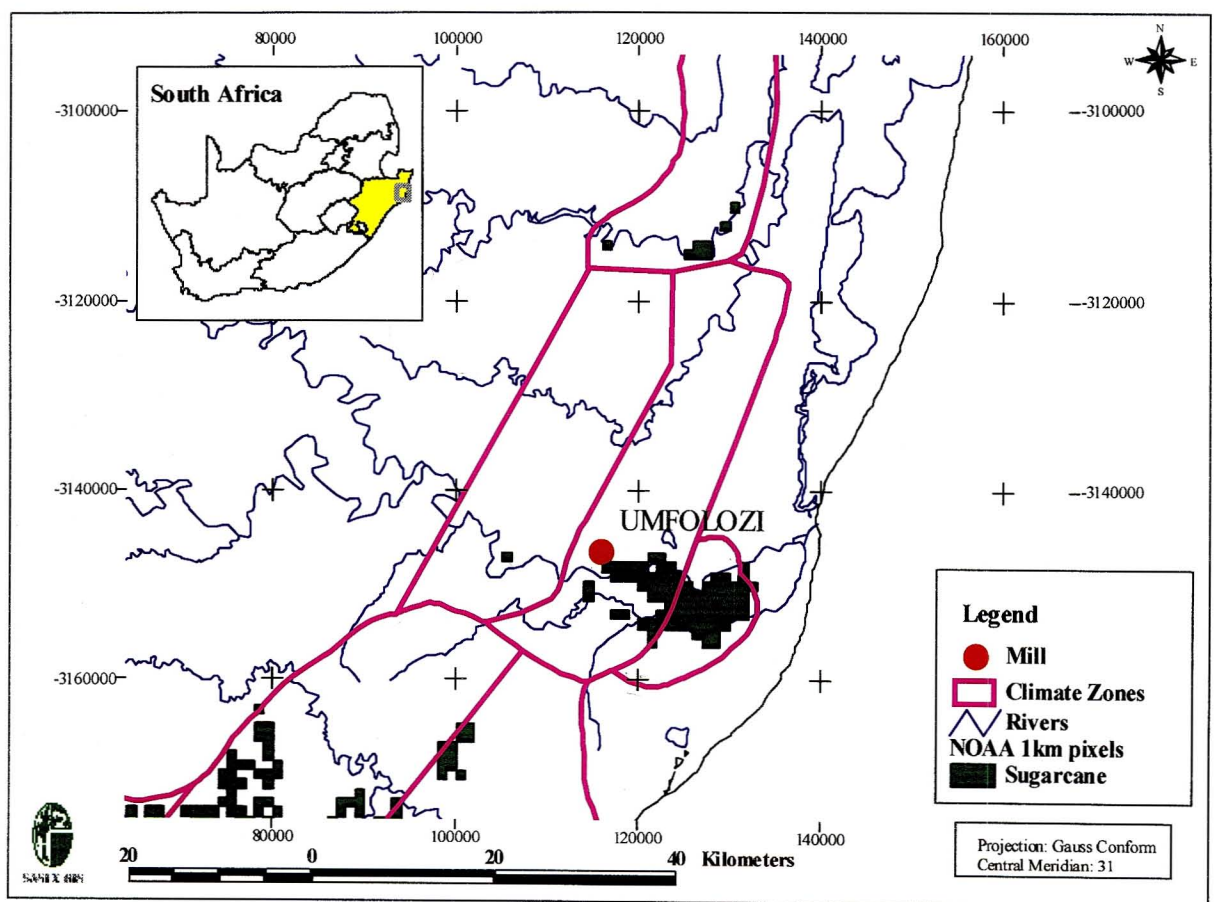


Figure 4.4 Map showing homogeneous climate zones for Umfolozi as well as the sugarcane dominated NOAA pixels. More than 70% of the area in each of these pixels was sugarcane.

Five different scenarios, including those identified by Schmidt *et al* (2000), representing different periods over which the time series NDVIs were accumulated to predict the mill production are described in Table 4.7 and illustrated in Figure 4.4. All accumulated vegetation index data were area weighted in accordance with the relative contribution of sugarcane in each of the different climatic zones. The area weighted NDVIs were accumulated over the different periods, each representing a different scenario, and then compared with the annual average yields for the MSA.

Table 4.7 Different scenarios and periods over which the area weighted time series NOAA NDVI data were accumulated and compared with mill supply yield data for the purposes of yield prediction.

Scenario	Period	Period of accumulation (months)
1	Current and previous growing seasons (December to December)	24
2	Current milling season and the wet season prior (October – April)	14
3	Wet season prior (October – April)	7
4	Current milling season (April – December)	8
5	Previous milling season	8

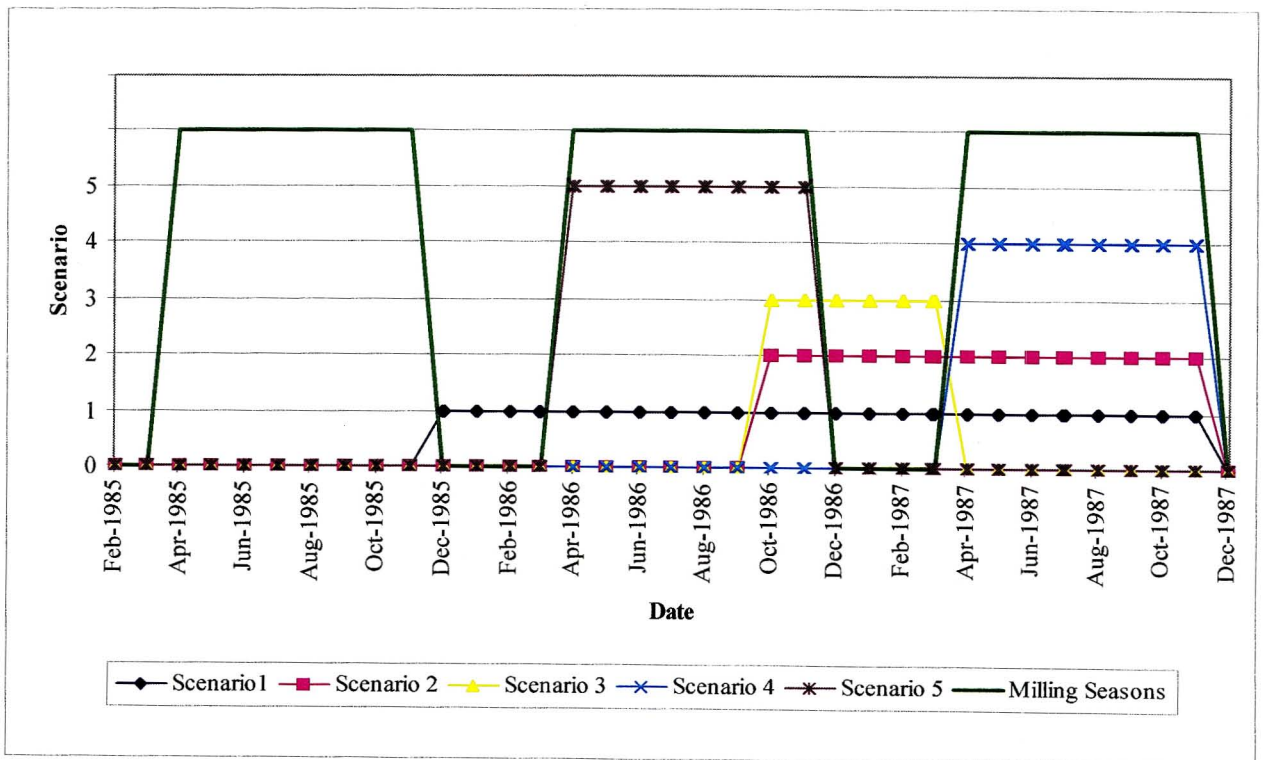


Figure 4.5 Graphic illustrating the different periods for five scenarios for the 1986-1987 growing season (i.e. April 1987 to December 1987). NDVI time series values were accumulated for the different scenarios and compared with 1986-1987 production.

The rationale behind scenario 1 was based on an incorrect assumption that the crop growth cycles were 24 months and was included for investigative purposes, given the 12-month crop cycles at Umfolozi. However, in the case of a 24-month crop, such as in the KwaZulu-Natal midlands, a 24-month crop harvested in December 1987 would have started growing or ratooned in December 1985. Hence, the

harvested in December 1987 would have started growing or ratooned in December 1985. Hence, the accumulated vegetation indices over this period were thought to be a possible predictor of sugarcane production.

The rationale behind scenario 2 was that the production of a season was related to the cumulative vegetation indices for that season as well the high summer growth period of the previous season. (The majority of sugarcane growth occurs in the hot and wet summer months between October and April.) The rationale behind scenario 3 was that the production of a season was related to the cumulative vegetation indices for the summer growth period of the previous season while scenario 4 based accumulated VIs for the current season only. The rationale of scenario 5 was based on the fact that any 12-month crop harvested in April started growing in April the year before. Furthermore, this approach only considers the contributions of the vegetation indices during the period of the previous milling season (7 months) and excludes the contribution of the vegetation index over the summer months (i.e. December of the previous season to April of the current season).

4.4.1.1 Handling of Missing Time Step Data

As previously mentioned there were two periods of missing data in the NOAA history of NDVI time series data. To remove the effects of missing data, the number of missing data values per scenario per year were calculated. Given the difficulties in patching this data, the initial analysis investigated only those values without missing information. This was made possible by the relatively long history of the NDVI time series data. In the event that results suggested the need for data patching, suitable methods would be investigated. The preliminary research therefore only evaluated all complete data to ascertain the potential of this methodology.

4.4.2 Yield Prediction Using a Landsat NDVI and Infrared Index Time Step Approach

The approach adopted was similar to that in 4.4.1 *Yield forecasting using a NOAA NDVI time step approach*. The difference in approach was that individual sugarcane fields rather than broad scale sugarcane producing areas were identified - as a result no area weighting of the NDVIs were required. Furthermore, II data were included in the analysis in addition to the NDVI data, following the recommendations of Noonan (1999), who suggested that the II are more sensitive to sugarcane production, particularly in single date applications.

Unfortunately, the history of satellite imagery was limited to the 2001-2002 season and, as a result, different scenarios comprised of different periods were required for the reduced dataset. The database constructed for the analysis of the spectral characteristics was used to extract the relevant information required to test

the various time step approaches. The possible scenarios are described in Table 4.8.

Scenarios 1 and 2 represent a single time step image. That is, a single image prior to the 2001-2002 milling season was used to predict its production. The rationale behind this scenario is that the majority of fields are harvested by November. Furthermore, the late season is often considered to be the time over which sugarcane growth is pronounced, as it is the period over which the summer rains occur and high temperatures facilitate stalk development. A single image prior to the opening of the milling season would therefore provide a good indication of the early stage sugarcane development for those fields harvested prior to November. The greatest benefit could be derived from successful prediction of yields from pre-season imagery. This is because there is ample time for the MGB to revise their LOMS estimate based on a pre-season remotely sensed estimate.

The rationale behind scenario 2 is similar to that of scenario 1. The difference, however, is that the benefits to the MGB in terms of LOMS estimates are less, given the close proximity to the opening of the milling. It may, however, be beneficial in the event that a below-normal crop is predicted and a delayed start of the season is required.

The rationale behind scenario 3 is based on the premise that the accumulated images represent the growth of sugarcane over periods of high growth. The benefits of this approach are less likely to influence changing of the LOMS, as could potentially be the case in scenario 2.

Scenario 4 is based on the premise that three NDVI or II images are required to accurately predict yields. The benefit of this scenario will be mainly for late season estimates and the scheduling of the remaining crop in relation to the milling capacity. Alternatively, this approach, if successful would provide a measure as to how many images over certain growth periods are required to meaningfully predict yields. Scenarios 5 and 6 would have similar benefits. It should be noted that scenarios 3 to 6 all assume that the contribution of growth late in the previous season are meaningful.

Scenarios 7 to 9 assume that the contribution of the previous season are less meaningful and focus incrementally on time step contributions of NDVI and II indices of the current milling season only. Once again, the benefits are limited to mid to late season estimates of the standing crop.

Finally, scenarios 1 to 9 represented all possible combinations of time step information that could be analysed with the available data. Any further analyses would require additional data not available at the time of the analysis.

Table 4.8 Different Scenarios that were used to predict the sugarcane yields based on Landsat 7 ETM+ derived Normalised Difference Vegetation Index and Infrared Indices.

Scenario	Description	Number of images accumulated	Images Accumulated
1	Single image mid-late previous milling season at which high growth occurred.	1	30 October 2001
2	Single image at the beginning of the current milling season.	1	8 April 2002
3	Image accumulated from mid-late previous milling season to the beginning of the current season.	2	30 October 2001 8 April 2002
4	Image accumulated from mid-late previous milling season to early-mid current milling season	3	30 October 2001 8 April 2002 13 July 2002
5	Image accumulated from mid-late previous milling season to mid-late current milling season.	4	30 October 2001 08 April 2002 13 July 2002 17 October 2002
6	Image accumulated from mid-late previous milling season to late current milling season. This will only apply to late season harvested fields.	5	30 October 2001 08 April 2002 13 July 2002 17 October 2002 18 November 2002
7	Image accumulated from the beginning of the current milling season to early-mid current milling season.	2	8 April 2002 13 July 2002
8	Image accumulated from the beginning of the current milling season to mid-late current milling season.	3	8 April 2002 13 July 2002 17 October 2002
9	Image accumulated from the beginning of the current milling season to late current milling season.	4	08 April 2002 13 July 2002 17 October 2002 18 November 2002

4.5 Summary

The chapter on *Materials and Methods* began by describing the methodology employed for sugarcane area mapping by means of remote sensing. This included the selection of the Landsat 7 ETM+ satellite as the most suitable sensor, as well as suitable dates for the acquisition of satellite imagery. In order to maximise the discrimination of sugarcane from spectrally similar land covers such as wetlands and pineapple fields, multivariate distance measures were used to identify the most suitable combinations of images and bands to distinguish sugarcane from non-sugarcane areas. Ultimately, three successive time step Tasseled Cap transformed images, consisting of only the first three bands, namely Brightness, Greenness and Wetness, were combined into a single image stack, and used to map the sugarcane areas. Unsupervised hierarchical classification procedures were conducted on the combined image stack, and ground control information was used to validate the results.

The next section in this chapter dealt with the analysis of sugarcane spectral characteristics. This involved the extraction of the at-satellite reflectances for several fields for which detailed agronomic records were available. The data were then analysed using various multi-variate analytical techniques including PCA to evaluate the relationships between the at-satellite reflectances and crops phenology, cultivar and yield. The multivariate techniques were required in order to remove the multi-colinearity effect, inherent in the satellite imagery.

The sugarcane inventory assessment throughout the milling season involved the Tasseled Cap transformation of the COST corrected satellite imagery. Existing field boundary information was then used to mask out all non-sugarcane areas. Unsupervised classifications were then conducted on all images, and through visual interpretation were assigned to a class of sugarcane production. These included harvested / fallow fields, immature sugarcane and mature sugarcane fields. Majority statistics were then determined for each field. To avoid double accounting of harvested fields, all fields that were identified as harvested were excluded from subsequent analyses. Statistics on the relative areas harvested were calculated for all images.

The yield forecasting was conducted using a time step approach for both NOAA and Landsat derived NDVIs. In the case of Landsat data, Infrared Indices were also included in the time step approach. Infrared Indices could not be included for the NOAA analysis as the original NOAA data from which the Infrared Index could be derived were not available (i.e. only the NOAA derived NDVI data were provided and not the multi-spectral bands from which the NDVIs were derived).

5 RESULTS AND DISCUSSION

The first section in the *Results and Discussion* will address sugarcane area mapping by remote sensing, followed by the study of the spectral characteristics of sugarcane with respect to phenology, yield and cultivar. The monitoring of the timing of harvest and yield prediction will follow.

5.1 Sugarcane Area Mapping by Remote Sensing

The results for the mapping of sugarcane areas by remote sensing are provided in Table 5.1, and are discussed separately for the small-scale and large-scale growers. The error of omission represents sugarcane areas that were excluded from the mapping exercise, while the error of commission represents non-cane areas incorrectly mapped as sugarcane. The Kappa Index of Agreement is often used to check for accuracy of classified satellite images against ground-truth data. This statistic varies between 0 and 1 and provides an estimate of the mapping accuracy. Values above 70% indicate that the results were not likely to have been as a result of chance, while values of below 30% suggest that results are likely to be chance (Anon, 2004b; Thompson, 2003).

Table 5.1 Summary results for the sugarcane area identification by remote sensing for the 2001-2002 season.

Statistic	Small-scale growers	Large-scale growers
Commission error (%)	36.8	23.9
Omission error (%)	36.8	23.9
Overall map accuracy (%)	63.2	76.1
90% confidence limits -low (%)	59.9	72.5
90% confidence limits - high (%)	66.5	79.6
Kappa Index of Agreement (%)	17.7	30.9
Satellite derived sugarcane area (ha)	9569.4	14311.5
MGB sugarcane area estimates (ha)	8928.0	[§] 13731.5

§ Large-scale grower field areas are based on the final results of the Umfolozi cartographic programme undertaken by the Umfolozi MGB in 2001.

5.1.1 Small-Scale Growers Mapping by Remote Sensing

In order to simplify the process of classifying the small-scale grower fields, the satellite imagery was broken down into two main growing regions. The first region included the south and central

regions located to the west of the N2 freeway, that runs in a north-south direction, while the second region consisted of the False Bay region to the east of the N2 freeway in the northern reaches of the MSA. The sugarcane spectral characteristic within each of these two regions was identified as similar, based on a combination of visual interpretation and hierarchical unsupervised classifications of the satellite imagery. These regions could have been broken down further into homogeneous bio-climatic zones based on the spectral characteristics of the vegetation. This, however, did not seem necessary, given the relative spectral homogeneity of the sugarcane within the two regions. The splitting of small-scale grower area into these two regions made the identification of sugarcane areas within each of these regions easier. That is, the spectral variation within the two regions appeared to be less than the variation between the regions.

The classification of the small-scale grower fields was extremely difficult owing to a number of factors. Two of the most important were the small size of the fields (typically around 1 hectare) combined with a high level of disaggregation. From a practical point of view, burnt patches of sugarcane and/or other land types were readily visible, but difficult to identify by the classification techniques. Much benefit from the imagery could be gained through visual interpretation rather than feature extraction by means of supervised or unsupervised techniques.

The following factors on the ground further complicated the mapping of small-scale growers:

- High levels of moisture stress, making the spectral identity less distinguishable,
- Confusion with wetlands, particularly when burnt,
- The hilly topography in the north-eastern sections of the MSA in which shadows occurred,
- The classification methodology is easier to implement for continuous land cover types rather than disparate/piecemeal agriculture given, that it is visually based.

Classification accuracy of between 59% and 66% was lower than expected. Surprisingly however was the very low Kappa Index of agreement of 17.69%. This statistic suggests that the results were less likely to be repeatable and more likely to have been as a result of chance.

5.1.2 Large-Scale Growers Mapping by Remote Sensing

The identification of large-scale grower sugarcane areas was far less difficult than that of the small-scale growers. One of the reasons for this was the average field size for the large-scale growers (2.92 ha) which was much larger than that of average small-scale grower field (1.07 ha). When one considers a pixel size of 30 m, there are approximately nine pixels that are used to represent each small-scale grower field of 1 ha. If a square small-scale grower field consists of 1 ha, it is represented by nine pixels in a three by three matrix, and only the centre pixel is likely to truly represent the spectral characteristics of sugarcane. This is because the eight surrounding are likely to be influenced by edge effects. Furthermore, the high level of geographic disaggregation of the small-scale grower fields

exacerbates the edge effect problem. In the case of the large-scale growers, their larger fields result in more pixels being truly representative of the sugarcane spectral characteristics. In addition, and probably more important, is the improved agronomic management of the large-scale grower fields. This, in conjunction with the ability to provide supplementary irrigation in most cases, results in a healthier, readily identifiable canopy of sugarcane. It should be noted that the non-irrigated commercial farms were far more difficult to map by comparison with the irrigated farms. Clearly factors influencing favourable growth conditions, such as nutritional status, water availability and field size, were key drivers in improving the ability to identify sugarcane from the surrounding land types.

The ability to map sugarcane varied between 72% and 79%. Once again the Kappa Index of agreement was low at 30.9%. The reason for this low value was not apparent; however, it is the opinion of the author that these results would be readily repeatable should another expert user follow the same methodology to map the sugarcane.

It should be noted that the most spectrally similar land covers to sugarcane were reeds and wetlands. Their spectral separability was further decreased by the fact that many, if not most, of the wetlands were burnt annually. This, in turn, created a temporal spectral profile very similar to sugarcane. In order to minimise the interference of wetlands, it is highly recommended that all known wetlands be masked out prior to the classification procedure. Similarly, pineapple fields in the northern reaches of the MSA, particularly in the Mkuzi area, despite being readily identifiable from the satellite imagery by visual interpretation, were difficult to separate out spectrally.

5.2 Analysis of Sugarcane Spectral Characteristics

The results of the investigations into the relationships between the at-satellite reflectances and sugarcane (phenology, yield and cultivar) are discussed below.

5.2.1 Relationship Between Sugarcane Phenology and Spectral Characteristics

The ANOVA results for at-satellite reflectance bands using the groups as treatment structures are listed in Table 5.2. It can be seen from these result that, with the exception of Band 2, all bands were significantly different at both the $p=0.05$ and $p=0.01$ levels. Thus at least two of the spectral bands were significant.

Table 5.2 Analysis of variance results for at-satellite reflectance bands using the thermal age groups as treatment structures (Source: Gers, 2003a).

Thermal age group	Band1	Band2	Band3	Band4	Band5	Band7
1	841.3	1079.3	1486.9	2458.3	3505.3	2866.0
2	445.6	649.4	704.6	2949.9	2460.1	1973.6
3	424.8	643.9	613.7	3395.1	2115.5	1793.3
4	623.5	930.3	840.0	5495.1	2568.5	1325.3
LSD (5%)	9.3	5.8	7.50	60.4	25.3	34.4
LSD (1%)	12.2	15.0	19.3	79.4	33.3	45.2

§ Least Significant Difference

While Analysis of Variance (ANOVA) results show a significant difference for at least two of the thermal age groups, a measure of group separation was required. A variance-covariance PCA was conducted in order to evaluate the group separation and results are shown in Figure 5.1. In the first factor that accounted for 76% of the variability, it can be seen in Figure 5.1 that groups 1 and 4 are well separated along Factor 1 (F1), while considerable overlap occurs between groups 2 and 3. Groups 2 and 3 overlap with groups 1 and 4. Factor 2, that accounts for 20% of the total variability, distinguishes group 1 from groups 2, 3 and 4 that overlap considerably with one another.

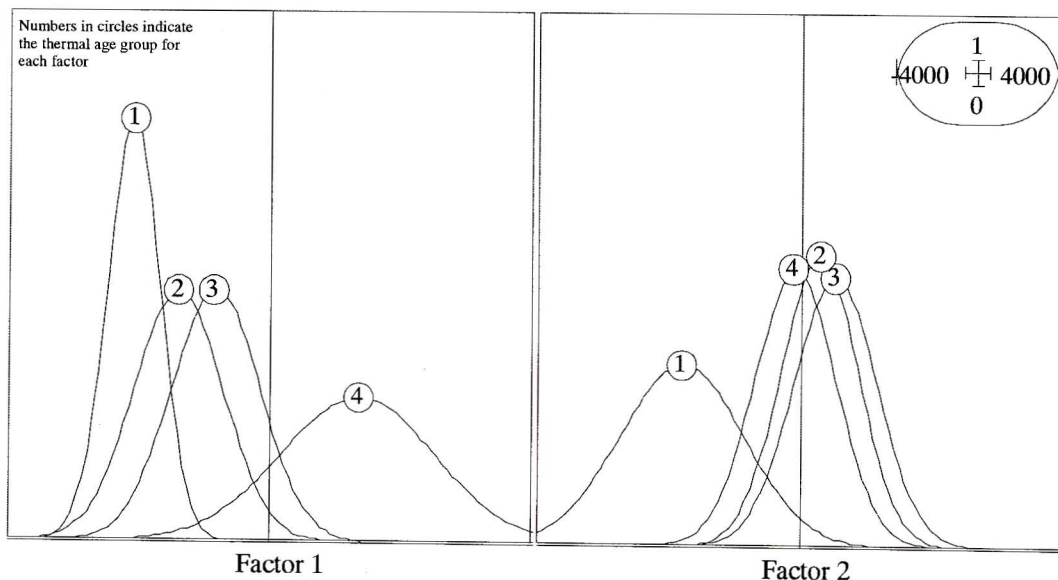


Figure 5.1 The four different thermal age groups against the first and second variance-covariance principal component factors (Source: Gers, 2003a).

In order to determine a probability matrix of misclassifying a particular thermal age group, the inter-group Mahalanobis distances were computed from Canonical Variate Analysis of the first three

variance-covariance principal component factors that accounted for more than 99% of the variability in the original data (see Table 5.3).

Table 5.3 Thermal age group classification probability matrix from which the probability of misclassifying a group *i* (column) into group *j* (row), can be obtained (Source: Gers, 2003b).

	Group 1	Group 2	Group 3	Group 4
Group 1	0.80	0.06	0.04	0.04
Group 2	0.09	0.51	0.32	0.14
Group 3	0.06	0.32	0.51	0.17
Group 4	0.05	0.11	0.13	0.65
Total	1.00	1.00	1.00	1.00

The probabilities provided in Table 5.3 should not be viewed as absolute values. The trends in the data are more important. In particular, groups 1 and 4 are readily separable from groups 2 and 3, which overlap each other.

5.2.2 Relationship Between Yield and Spectral Characteristics

Correlation matrix principal component analyses were performed on the yield and at-satellite reflectance values in order to evaluate the relationships between the variables. Analyses were conducted across all thermal age groups (groups 1 to 4) as well as for mature sugarcane only (group 4). As can be seen in Figure 5.2 [A] and [B], a negative result was obtained. A good positive result would show the yield arrow/vector extending close to the unity circumference line, preferably along the primary F1 axis or along the secondary F2 axis in either a positive or negative direction. Correlation of yield and spectral bands was weak along the primary axis (F1) that accounted for about 56% of the variability for both analyses (i.e. for groups 1-4 (A) and group 4 only (B)). Although the at-satellite reflectances of mature sugarcane indicated a better correlation with yield along the F2 axis (Figure 5.2 B), this was not meaningful, given the weak correlation along F1 and the low percentage variability (27%) accounted for by the second factor. The scatter plot in Figure 5.3 confirmed these conclusions. No meaningful relationship between the spectral characteristics for mature sugarcane and yield was evident.

It should also be noted that all fields were harvested on a 12-month cycle. Given that the period for the satellite imagery was one year, the majority of mature sugarcane fields in thermal group 4 were

represented only once for a particular image. As a result, between-year comparisons of yield and at-satellite reflectances could not be made. Yield predictions for mature sugarcane were therefore based on single-date comparisons of yield and at-satellite reflectances.

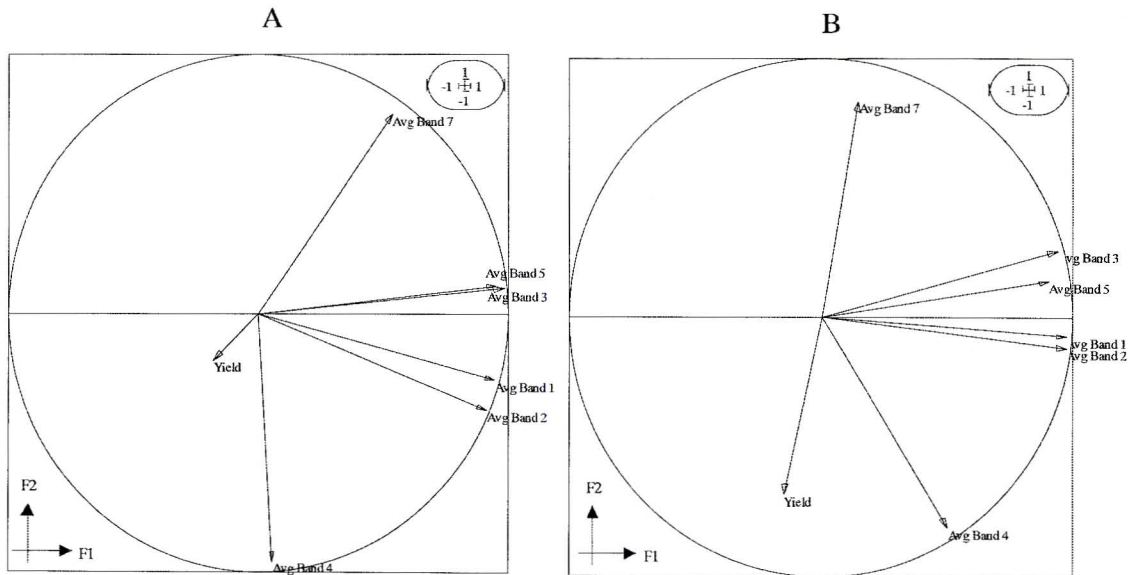


Figure 5.2 Correlation circles for the first two principal components of the average at-satellite reflectance and yield values for the five most abundant sugarcane cultivars. Correlation circle A represents all thermal age groups (1 to 4), and correlation circle B represents mature sugarcane fields (group 4 only).

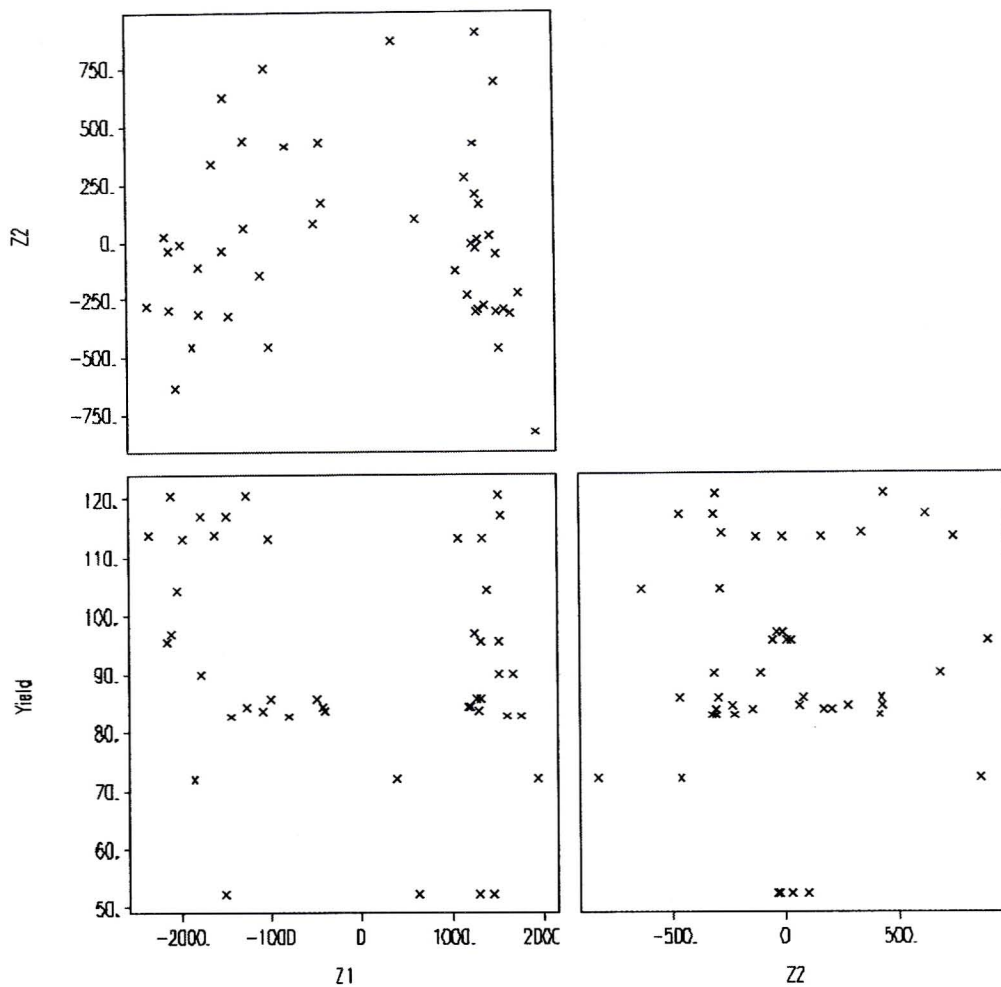


Figure 5.3 Plot of the first two variance-covariance principal component scores (Z_1 , Z_2) against yield for mature sugarcane (>1 500°C days, base temperature = 16°C).

5.2.3 Relationship Between Cultivar and Spectral Characteristics

The histogram plot of sugarcane cultivars against thermal group 4, that is mature sugarcane, is identical to that shown in Figure 5.4 with the exception that the first factor accounted for 81% of the total variability. Figure 5.4 clearly illustrates that no variety discrimination is possible on the basis of spectral characteristics for mature sugarcane.

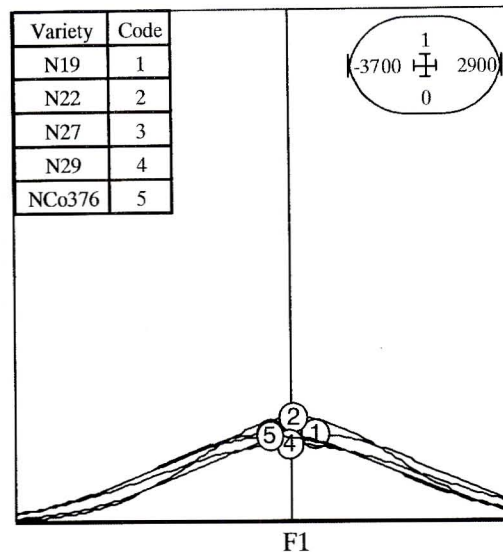


Figure 5.4 The five most abundant sugarcane cultivars for all thermal groups against the first variance-covariance principal component factor that accounted for more than 74.8% of the variability (Source: Gers, 2003a).

This may suggest that other factors, such as crop age, nutrient status and crop moisture conditions, may have a more profound influence on the spectral characteristics of sugarcane than physical vegetation characteristics such as foliage density, size, shape and angular distribution of the leaf structures for the different cultivars.

5.3 Sugarcane Inventory Assessment Throughout the Milling Season

The results of the assessment of the sugarcane inventory or areas harvested throughout the milling season are described in Tables 5.4 and 5.5. Included in the tables are the percentages of the mill's total crush to validate the results obtained by remote sensing. The only difference between the two tables is that the sugarcane area contributions from the Bushlands Estates are included in Table 5.4 and not Table 5.5. Bushlands Estates is a large commercial Estate in the Umfolozi MSA; however, it supplies its sugarcane to the Felixton Mill, hence its inclusion in the Umfolozi cartographic (mapping) programme. In order to evaluate the sensitivity of the system, a scenario with and without Bushlands Estates was included. Given that the relative percentage of the total area harvested should be similar across the MSA and to a lesser extent between MSAs, the results in the two tables (i.e. Tables 5.4 and 5.5) should be similar. Contrasting results in these two tables would raise questions about the reliability of the methodology. As can be seen in the tables, there was a very favourable agreement between the two results. This would suggest that the methodology employed was successful in accurately monitoring the relative areas harvested throughout the milling season.

The agreement between both scenarios as well as the validation Mill crush data was good. It should be noted that in both instances, the area identified as harvested, by means of remote sensing, is well above that of the area according to the Mill crush. This is partly because of seed sugarcane and/or fallow fields. Not all sugarcane harvested is sent to the mill to be crushed, but rather sold as seed for fields that are to be replanted. It should be noted that if one calculates the difference in offset at the beginning of the season, i.e. the difference between the Mill crush (%) of total and the cumulative area harvested, it can be seen that this offset is carried through the season.

The areas lost to cloud cover may include both harvested and green sugarcane. However, given the timing of this image in relation to the opening of the mill, the majority of the area lost is likely to be green sugarcane. This could, however, pose a more serious problem if cloud cover obscures a large portion of sugarcane fields in the latter satellite images. The threat of cloud cover masking out sugarcane fields remains a problem in most MSAs.

Table 5.4 Percentage of the total Mill Supply Area harvested at each time step image. The area lost to cloud cover as well as the mill crush totals are included to validate results. The area analysed includes Bushlands Estate that is within the Umfolozi Mill Supply Area but delivers its sugarcane to the Felixton Mill.

Land cover	Satellite derived areas in hectares on date			
	8-Apr-2002	13-Jul-2002	17-Oct-2002	18-Nov-2002
No data (ha)	1012.6	1599.4	7089.3	9175.3
Harvested (ha)	1619.9	5345.4	2734.4	1574.6
Immature (ha)	2201.9	2073.4	1182.5	1159.1
Mature (ha)	8905.8	4722.0	2734.0	1831.1
Total green (immature + mature) (ha)	11107.7	6795.5	3916.5	2990.3
Area lost to cloud (%)	7%	0%	0%	0%
% Area harvested	12%	39%	20%	11%
Cumulative area harvested (%)	12%	51%	71%	82%
Total area (ha)	13740.2	13740.2	13740.2	13740.2
<i>Mill validation information</i>				
Mill crush as % of total crush	0.49%	38.41%	78.62%	89.29%

Table 5.5 Percentage of the total Mill Supply Area harvested at each time step image. The area lost to cloud cover as well as the mill crush totals are included to validate results. The area analysed excludes Bushlands Estate that is within the Umfolozi Mill Supply Area but delivers its sugarcane to the Felixton Mill.

Land cover	Satellite derived areas in hectares on date			
	8-Apr-2002	13-Jul-2002	17-Oct-2002	18-Nov-2002
No data (ha)	728.0	981.7	5881.1	7701.8
Harvested (ha)	1011.9	4773.4	2384.6	1539.4
Immature (ha)	1994.7	1863.5	1083.7	1077.0
Mature (ha)	8165.1	4280.9	2550.3	1581.4
Total green (immature + mature) (ha)	10159.7	6144.5	3634.0	2658.4
Area lost to cloud (%)	6%	0%	0%	0%
% Area harvested	9%	40%	20%	13%
Cumulative area harvested	9%	49%	69%	82%
Total area (ha)	11899.6	11899.6	11899.6	11899.6
<i>Mill validation information</i>				
Mill crush as % of total crush	0.49%	38.41%	78.62%	89.29%

5.4 Yield Prediction by Remote Sensing

The yield prediction by remote sensing was conducted using broad scale NOAA NDVI time series data and high resolution Landsat 7 ETM+ data, both using the time step approach. The results are discussed below.

5.4.1 Yield Prediction Using a NOAA NDVI Time Step Approach

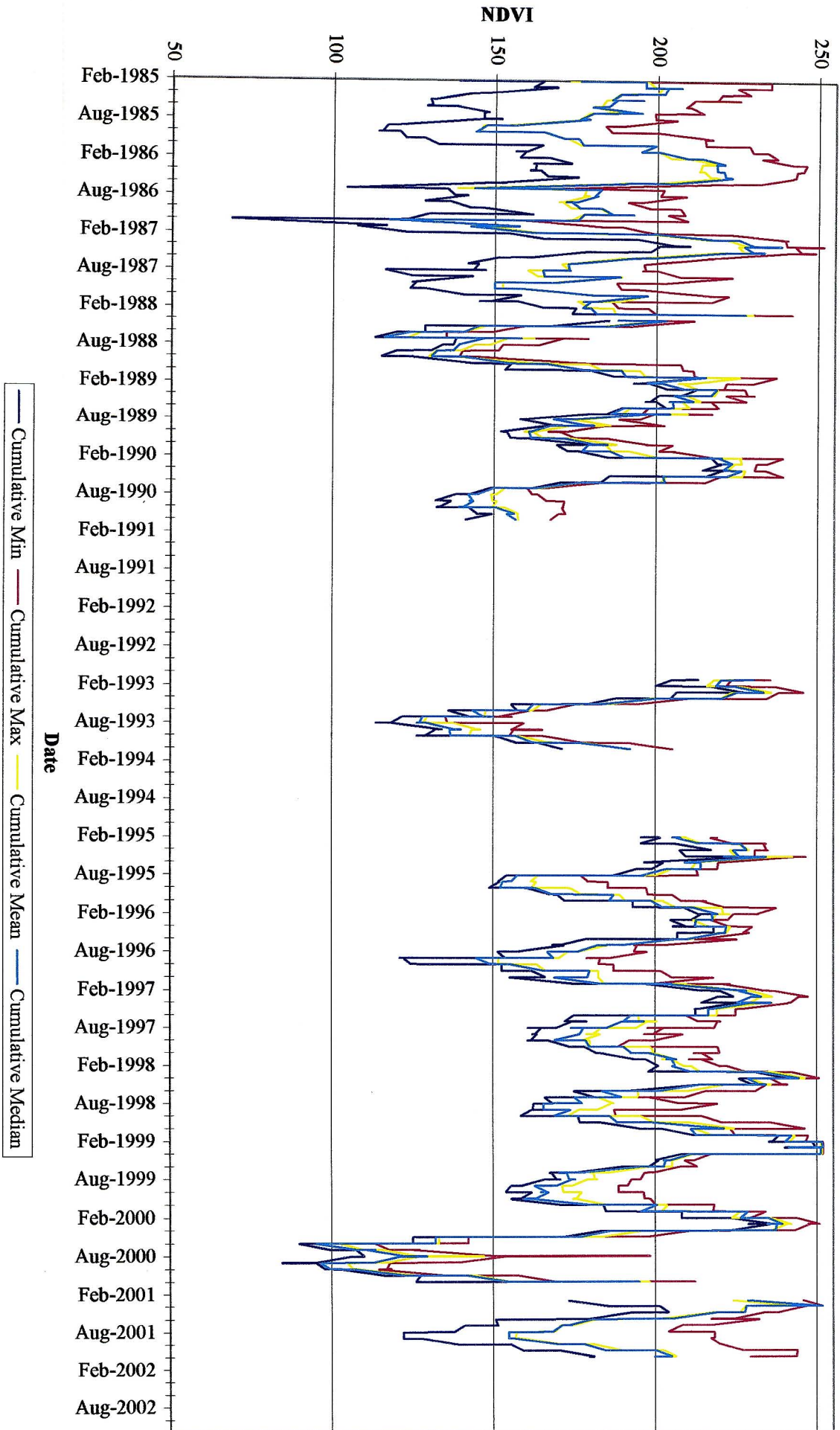
Figure 5.5 illustrates the time series graphs of NDVI for the Umfolozi MSA. The sinusoidal cyclicity was expected and is indicative of the seasonal growth patterns of the sugarcane crop. The NDVIs tend to peak between February and May and trough between August and November annually (see Figure 5.5). This is indicative of the seasonal growth trends in the warmer months and crop senescence in the drier colder winter months. These results show the same trends as the research conducted by Schmidt *et al* (2000).

Inman-Bamber (1994) showed that the development of sugarcane is closely correlated to the thermal time of base (T_b) 16°C . Using the automatic weather station data from Monzi, situated 28.45°S , 32.28°E , average monthly thermal times were calculated using a base of 16°C . Given the relatively short history of this data, long term mean climatic data were also obtained from the South African Atlas of Agrohydrology and Climatology (Schulze, 1997) for comparison. The average monthly thermal time derived from Schulze (1997) and the Monzi automatic weather station are illustrated in Figure 5.6 along with the monthly time series of NDVI.

It is interesting to note that there appears to be a two-month time lag between the NDVI response curves and the thermal unit curves. The NDVI maxima and minima seem to follow two months after the respective peaks of the thermal time curves. A possible explanation for this lag may be related to the growth and sucrose partitioning mechanisms within the sugarcane plant, and the physical manifestation of this growth partitioning in terms of crop growth and senescence. Research conducted by Glover (1971) illustrates this lag effect between sugarcane sucrose partitioning for both rainfall and minimum temperatures. In the case of temperatures, Glover (1971) noted that, for the Pongola MSA, which is in close proximity to the Umfolozi mill, a three-month time lag between the minimum monthly temperatures and sucrose % sugarcane existed. According to Smit (2003), the time lag trends are consistent with the current understanding of crop sucrose partitioning and plant growth or senescence when measuring crop characteristics by indirect measures.

Figure 5.5

Time series of NDVI for the Umfolozi Mill Supply Area. The time series were obtained by area weighting the NDVI statistics in each of the Umfolozi climatic zones.



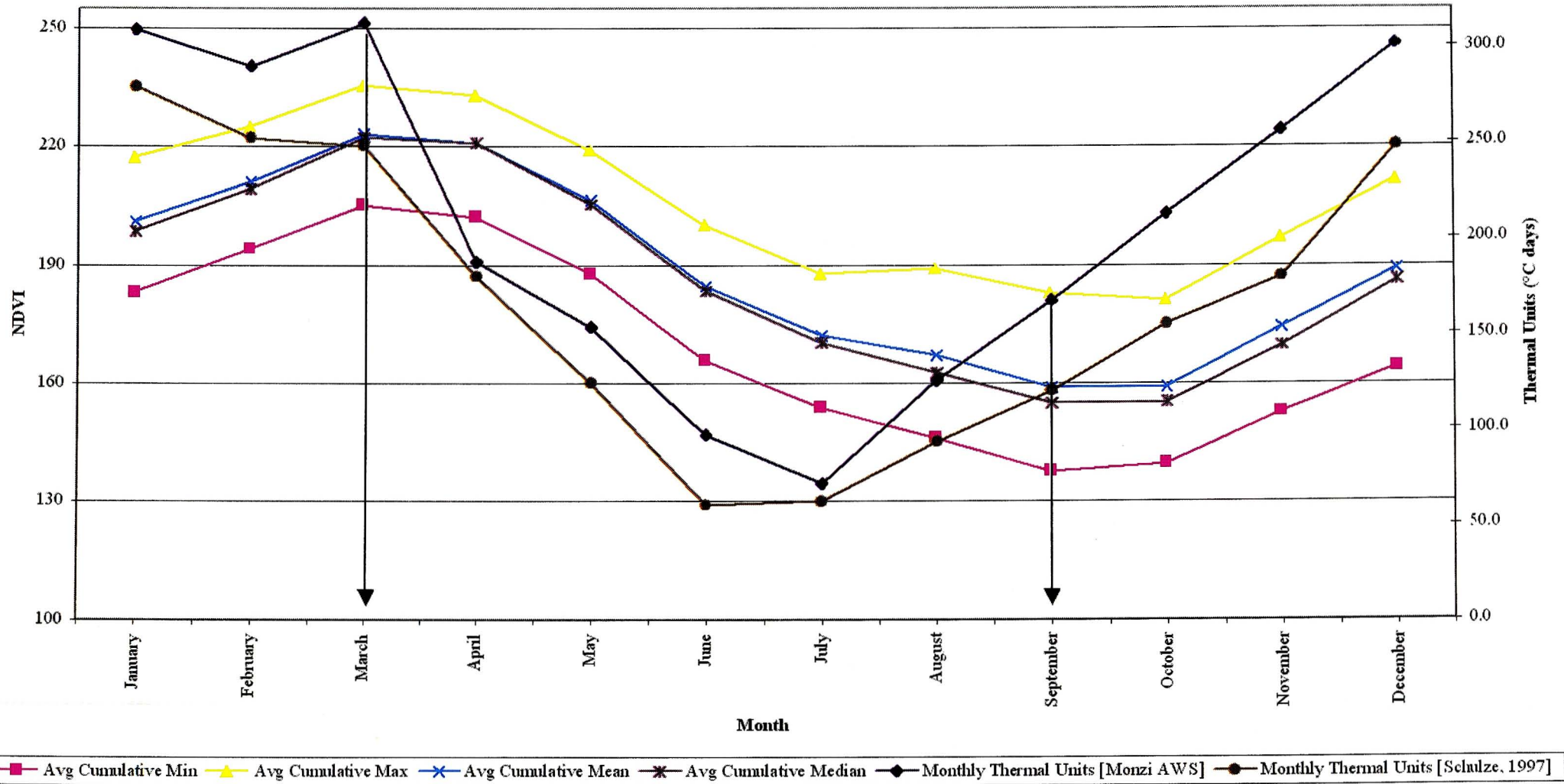


Figure 5.6 The Umfolozi Mill Supply Area average monthly NDVI values for the period Apr-1985 to Nov-2002.

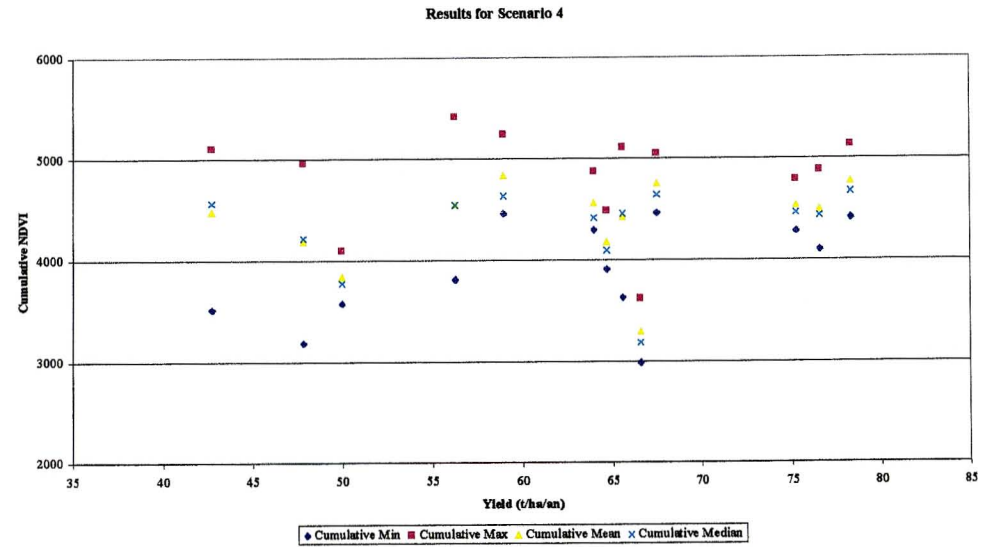
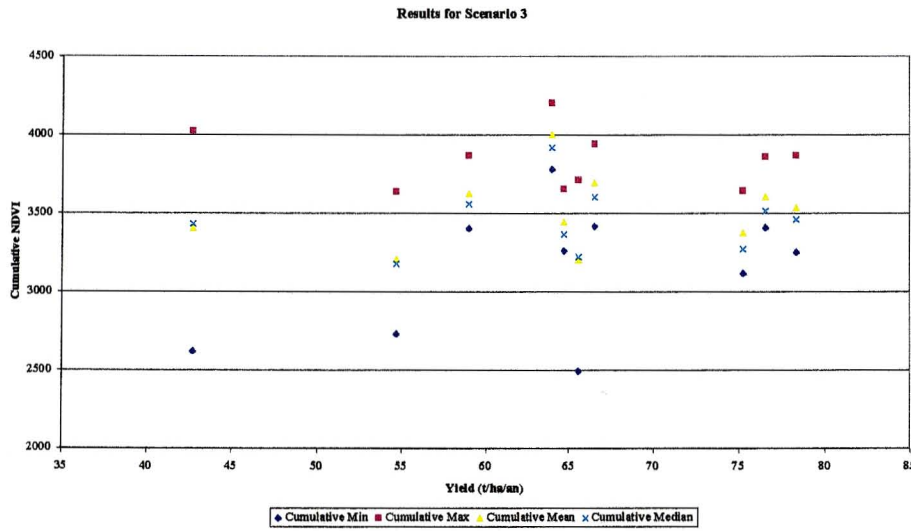
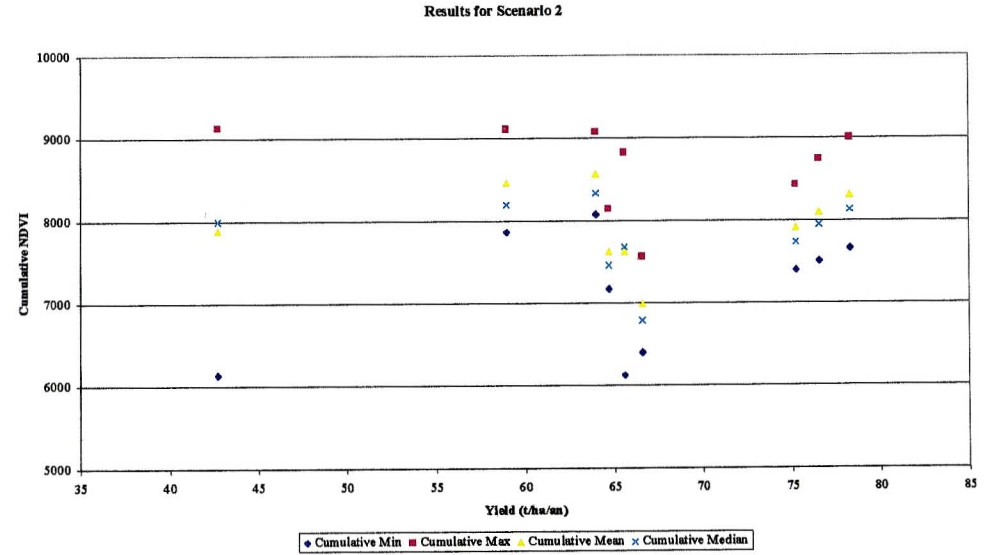
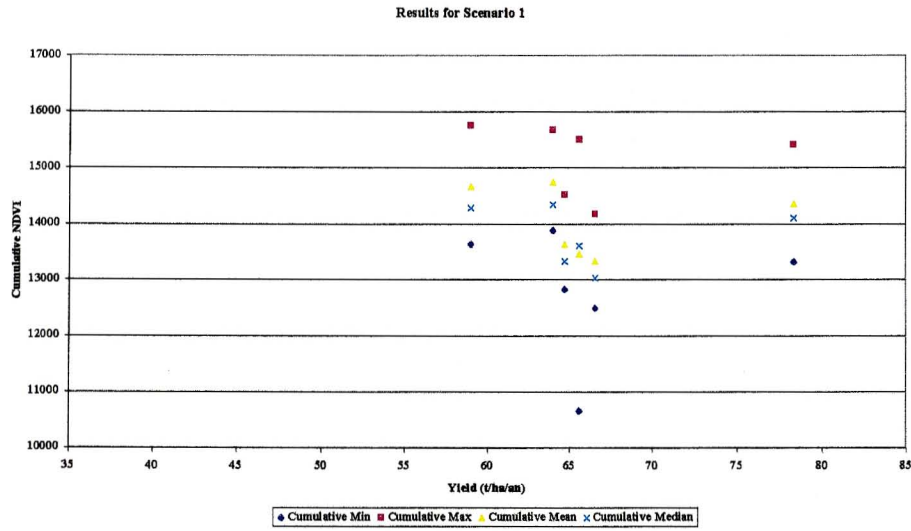


Figure 5.7 Results for the five different scenarios. NOAA NDVI time series values were accumulated over different periods for each scenario and plotted against the annual production for the respective seasons.

Results for Scenario 5

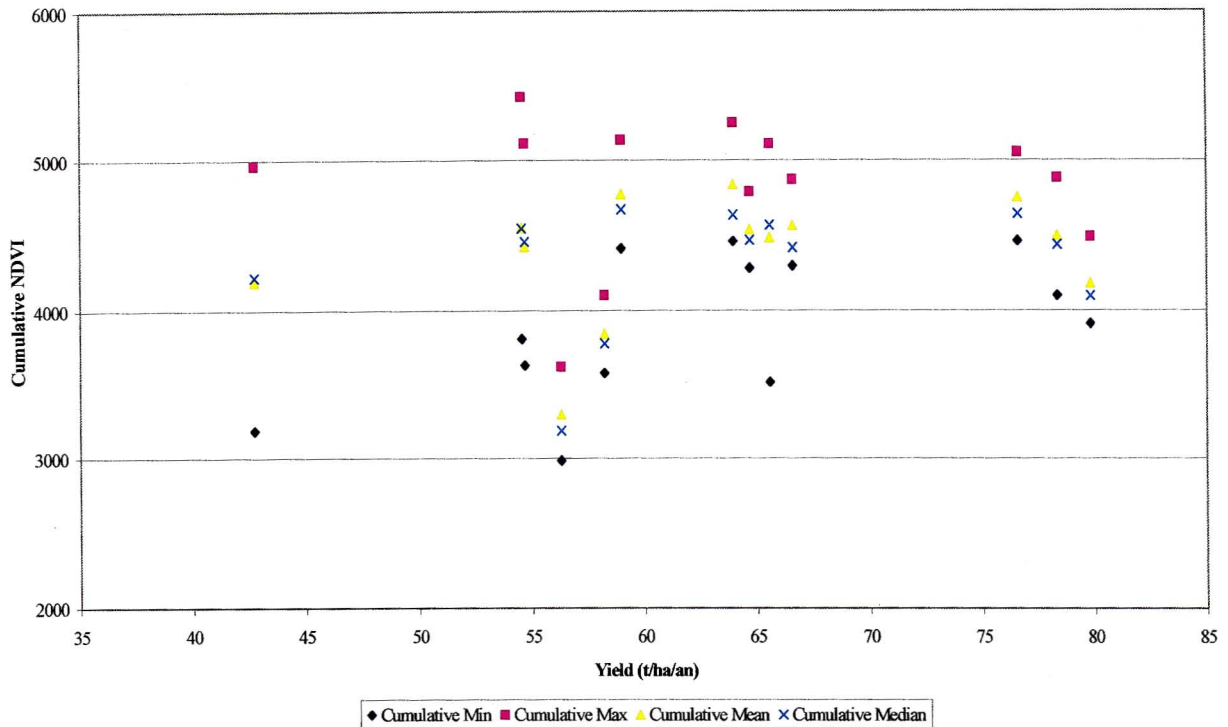


Figure 5.7 continued

5.4.1.1 Scenario Results

None of the results illustrated in Figure 5.7 show a positive correlation with annual production for the different scenarios. In all instances, the large variation in accumulated NOAA NDVIs over a particular yield range made it impossible to predict yields from the accumulated reflectances. For all scenarios, there appeared to be no linear correlation, given the very low R Square values. Furthermore, the data were not significant (see Table 5.6). As a consequence of these negative results, no additional investigation was made into the patching of the data to increase the number of data points.

Table 5.6 Summary of scenario results for yield against cumulative median NOAA NDVI.

Scenario	Vegetation Index	Observations	Mean MSA Yield (t/ha/an)	Standard Error (t/ha/an)	R Square (r ²)	Significance F	Level of Significance
Scenario 1	NDVI	6	66.3	7.1926	0.0007	0.96	3%
Scenario 2	NDVI	9	65.8	11.5903	0.0071	0.83	17%
Scenario 3	NDVI	10	64.7	11.4872	0.0036	0.87	13%
Scenario 4	NDVI	13	62.6	11.5217	0.0153	0.69	31%
Scenario 5	NDVI	13	63.1	10.859	0.047	0.48	52%
Median			64.7	11.4872	0.0071		
Mean			64.5	10.5302	0.0147		
Range			3.7	4.3977	0.0463		

5.4.2 Yield Prediction Using a Landsat NDVI and Infrared Index Time Step Approach

The results for the Landsat approach were mixed (see Table 5.7). Most of the results were highly statistically significant, but in most cases had very low R Square values. Scenario 2 produced the best results with a meaningful R Square of 0.52 ($p < 0.01$). The II index of scenario 6 had a high R square of 0.98 but had a low level of significance ($p < 0.11$). Furthermore, the number of observations in scenario 6 ($n=3$) were too few to make a meaningful or reliable estimate.

These results suggest that a single image at the beginning of the season can be used to predict the final production. It is, however, difficult to draw a meaningful conclusion from these results, as other factors such as climatic variability throughout the milling season, which may have influenced this result, have not been quantified. Given a different rainfall distribution over the 2001 season, it is possible that different results would have been obtained. In order to substantiate this result a larger historical archive of data are required. Given that the data were only available for one season, these results cannot be interpreted as conclusive.

It was interesting to note that in most of the scenarios, the II index graphs provided better R Square results than the NDVI results. This supports the work of Noonan (1999) who suggested that the II are better than the NDVI index for sugarcane applications. It was unfortunate that the II data could not be tested for the NOAA data as well. This was because only NDVI data were provided by the ARC/ISCW and not the individual bands from which the Infrared Index could be derived.

Table 5.7 Summary of scenario results for yield against cumulative mean Landsat NDVI and II.

Boldface text highlights the best results.

Scenario	Vegetation Index	Observations	Mean Yield (t/ha/an)	Standard Error (t/ha/an)	R Square (r ²)	Level of Significance
Scenario 1	NDVI	78	98.9	25.84	0.14	99%
Scenario 1	II	78	98.9	25.12	0.19	99%
Scenario 2	NDVI	87	98.2	18.37	0.52	99%
Scenario 2	II	87	98.2	18.47	0.51	99%
Scenario 3	NDVI	78	98.9	23.06	0.31	99%
Scenario 3	II	78	98.9	21.33	0.41	99%
Scenario 4	NDVI	39	95.2	24.73	0.24	99%
Scenario 4	II	39	95.2	22.48	0.38	99%
Scenario 5	NDVI	9	92.5	22.99	0.16	71%
Scenario 5	II	9	92.5	20.46	0.34	89%
Scenario 6	NDVI	3	82.7	23.52	0.70	62%
Scenario 6	II	3	82.7	6.78	0.98	89%
Scenario 7	NDVI	47	94	20.51	0.36	99%
Scenario 7	II	47	94	20.76	0.35	99%
Scenario 8	NDVI	19	93.5	17.45	0.01	34%
Scenario 8	II	19	93.5	15.38	0.23	96%
Scenario 9	NDVI	5	87.9	22.96	0.23	58%
Scenario 9	II	5	87.9	21.14	0.34	70%
Median			94	21.2	0.34	
Mean			93.5	20.6	0.36	
Range			16.2	19.1	0.96	

5.5 Summary

In this chapter, the results of the sugarcane area mapping by means of remote sensing are presented for both the small-scale and large-scale grower areas that were mapped separately. Tasseled Cap transformed images were employed in combination with an unsupervised hierarchical classification approach to map the sugarcane fields. The results show that the large-scale grower fields were easier to identify than the small-scale grower fields. The accuracy of the results was not as good as was originally anticipated. In particular, the small-scale grower accuracy assessment was low, as was the Kappa Index of agreement in both small and large-scale growers. Clearly, the spatial resolutions in conjunction with a suitable spectral and temporal resolution are important. The mapping exercise revealed that wetlands in particular, and to a lesser extent pineapples, were difficult to separate out spectrally from many of the sugarcane fields. However, pineapple fields were readily identifiable by visual interpretation of the satellite imagery. Generally speaking, the small-scale grower fields were more difficult to map than the large-scale grower fields because of their elevated levels of stress that were as a result of agronomic limitations, such as supplementary irrigation, to name but one factor. This, combined with the small field areas and the compounding problems of edge effects, are believed to be the main factors resulting in the low mapping accuracy.

The section on the analysis of sugarcane spectral characteristics investigated the potential for using the at-satellite reflectance values for the identification of the sugarcane phenology, yield and cultivar. The results suggest that three distinct phenological stages in the sugarcane growth pattern were identifiable from the at-satellite reflectances, namely pre-emergence (fallow or bare land), vigorously or actively growing sugarcane and finally maturing sugarcane. No relationships between yield and at-satellite reflectances were established. Nor were any relationships with cultivar and at-satellite reflectances established.

The section on sugarcane inventory assessment throughout the milling season showed that, by using unsupervised classifications on Tasseled Cap transformed images, for known sugarcane growing fields only, accurate estimates of the area harvested throughout the milling season can be obtained. The satellite image at the beginning of the season overestimated the actual area harvested. However, it is believed that this area was correct, as the harvested areas accounted for seed-sugarcane or alternatively fallow fields. All subsequent images were overestimated or offset by the initial overestimate.

The section on yield prediction by remote sensing revealed that neither NOAA nor the Landsat derived vegetation indices were able to meaningfully predict yields. In the case of the Landsat data, preliminary results for a one year period showed promise; however, the lack of adequate history to validate the results under different climatic conditions was limiting. The time step approach for crop yield estimation using NOAA derived NDVIs showed little potential.

6 RECOMMENDATIONS

The first section in the *Recommendations* will address sugarcane area mapping by remote sensing, followed by the study of the spectral characteristics of sugarcane with respect to phenology, yield and cultivar. The monitoring of the timing of harvest and yield prediction will follow.

6.1 Sugarcane Area Mapping by Remote Sensing

The requirement for sugarcane area mapping for any Mill Group Board within the South African sugar industry is that all sugarcane should be mapped within 1% of the true area (Gers, 2002). The results obtained for sugarcane area mapping by means of remote sensing for this study were not close to this value. In order to achieve a 1% mapping accuracy, digital orthophotography and/or differential global positioning systems have been employed in the South African sugar industry. According to Wooding (2001), the planimetric accuracy of field area measurements and scale are closely related for specified minimum mapping area. Wooding (2001) provides Equation 6.1 that, can be used to determine the appropriate pixel size, scale or spatial resolution required to map a minimum field size to a specified level of accuracy. Using Equation 6.1 it can be seen that in order to obtain a 1% accuracy on a 1.0 ha field (i.e. 100 x 100 metres), a typical small-scale grower field, one would require 0.50 metre pixel resolution. Based on this equation, it is highly unlikely that conventional high-resolution satellite imagery such as from Spot 4 and Landsat 7 will achieve a 1% mapping accuracy.

Equation 6.1 Equation describing the relationship between the orthophotograph pixel size, field area to be mapped and the desired level of accuracy (Modified from: Wooding, 2001).

$$P = \left[\frac{\sqrt{F}}{2} \right] \times \left[\frac{A}{100} \right]$$

Where: P = the pixel size expressed in meters (m),
F = the field area expressed in square meters (m²),
A = the desired accuracy expressed as a percentage (%).

At present the Ikonos and Quickbird satellites are capable of providing data of sufficiently high resolution to achieve the required levels of mapping accuracy. The costs of these data sources have historically been prohibitively expensive, in most agricultural applications where large-areas of low value commodities such as sugarcane are concerned. As the high-resolution data become more affordable, their adoption is likely to increase and compete with the more traditional methods of mapping sugarcane.

It should be noted that, despite the relatively low levels, 71% mapping accuracy on average for both the small and large-scale growers, much value could be gained from the map products and satellite imagery for the area. In particular, the rapid expansion of small-scale grower sugarcane in the tribal areas has made it difficult to maintain the cartographic integrity of map information, given the large geographic extent of the tribal areas and dispersed nature of their operations (Allsopp, 2002; Dalglish, 2002; Dlamini, 2002). To this effect, it is very costly and staff intensive to keep track of changes as they arise. The use of the satellite derived mapping, despite the relatively low level of accuracy, can add much value in identifying potential or likely areas of sugarcane expansion beyond the scope of areas already mapped by the Small-Scale Cane Development Officers. Thus, the mill Cane Development Officers will be able to identify from the satellite imagery new areas of sugarcane expansion that would then require more detailed mapping by DGPS or digital orthophotography, thereby increasing the effectiveness and efficient use of their time. This method would need to work in conjunction with the existing cartographic programme to facilitate the identification and mapping of new small-scale expansion.

It is highly recommended when using satellite imagery to map sugarcane areas, that local knowledge or understanding of the area and existing map information be harnessed before and during the analysis of the imagery for sugarcane mapping. In particular, if possible, it is recommended that the local knowledge and/or map information be used to mask out non-sugarcane features, in particular wetlands and pineapple lands. Digital elevation models may be employed to great effect to assist in the identification and delineation of wetland areas. Similarly, if non-sugarcane areas can be omitted, albeit through visual interpretation of the satellite imagery, it should be done so as to reduce the spectral variability analysed.

One of the limitations in optical remote sensing is the interference of clouds. Assuming that the Landsat sensor achieved the desired level of mapping accuracy, its methodology could not be employed throughout the entire sugar industry. In the sugar growing regions of Mpumalanga, clouds pose a serious limitation to the acquisition unobscured imagery. In such cases the only alternative besides airborne or aeroplane based sensors are SAR (Synthetic Aperture Radar) data. SAR is, however, still a relatively new, although rapidly developing, field of remote sensing. Furthermore, the resolution of most of the SAR data is too coarse for detailed mapping applications of small-scale grower fields.

6.2 Analysis of Sugarcane Spectral Characteristics

One of the most difficult aspects in the analysis of the spectral characteristics was obtaining accurate and reliable field information. Initially it was thought that the majority of the field information obtained from the growers participating in the Field Record System (FRS) was reliable. However, all data needed to be checked against the satellite imagery. In many cases, several fields were partially harvested, on account of seed-sugarcane or runaway fires. More often however, the dates at which the records reflected fields as being harvested were incorrect or insufficiently precise. The reason for these

discrepancies was that the harvesting of a field could take anything up to a week or more, in which case the grower may have put the date of harvest at the beginning or end of that period. Given that the spectral characteristics of a burnt field are significantly different to that of a mature sugarcane field, better and more precise information regarding the harvesting operations are required. In particular, the following items would be highly beneficial in further testing of this methodology:

- The date and time at which the field was burnt,
- The date on which the field harvesting operation was completed or the field was completely cleared of sugarcane.

6.2.1 Relationship Between Sugarcane Phenology and Spectral Characteristics

Despite the efforts to remove erroneous data from the database of at-satellite reflectances, it is believed that incorrect data were included in the analysis. There were many sugarcane fields which, through visual interpretation of the satellite imagery, looked questionable. However, there was no scientific evidence to justify their removal from the analysis of sugarcane phenology. It is the opinion of the author that the separation between thermal age group 4, and groups 2 and 3, would be further separated, given better field information.

The impacts of moisture stress were not included in the study. Further studies on sugarcane phenology would need to include the following information on a field level:

- Accurate digital field boundary information,
- Soil water depletion levels,
- Rainfall and irrigation water applied,
- Meteorological variables such as temperature, relative humidity and wind speed,
- Fertilizer information (crop nutrition),
- Detailed (agronomic) field records including harvesting operations,
- Suitable measurements of radiative transfer for atmospheric correction of the satellite imagery.

The proposed study would need to either measure, or alternatively simulate, the soil moisture conditions on a field basis to evaluate the impacts of crop moisture stress on the spectral characteristics over a range of nutritional conditions.

Having identified potential future research it should be noted that the results from the current research have many practical benefits and applications, especially if combined with the monitoring of the sugarcane inventory throughout the milling season.

6.2.2 Relationship Between Yield and Spectral Characteristics

The relationship between yield and the at-satellite characteristics showed no potential for yield prediction. Further research on the specific methodology employed is therefore not recommended. Alternative methods for yield prediction are discussed under Section 6.4 *Yield prediction by remote sensing*.

6.2.3 Relationship Between Cultivar and Spectral Characteristics

The analysis of the relationship between cultivar and the at-satellite reflectances showed that the Landsat sensors were not capable of differentiating between varieties. Given that research work conducted by ARC (2000b) showed that there were in fact spectral differences between different cultivars. This would suggest that either the spatial and/or spectral resolution of the Landsat 7 ETM+ sensor are insufficient for cultivar differentiation.

In terms of research priorities, the use of remote sensing for the identification of different cultivars is not of great importance to the sugar industry, especially given the alternative avenues for obtaining this information, such as Pest and Disease reports, and grower estimates. Until such time that a demand for this application in remote sensing is realised, no further research is recommended.

6.3 Sugarcane Inventory Assessment Throughout the Milling Season

The results for the sugarcane inventory assessment throughout the milling season were very promising; however, they relied on accurate field information that was captured by means of digital orthophotograph and DGPS mapping. The methodology was only tested on the large-scale grower fields.

Given the positive outcome of these results it is recommended that the methodology be applied to the small-scale grower fields as well. Furthermore, it would be interesting to see how different the results would be in the event that the satellite derived sugarcane areas for both the small and large-scale fields were used rather than the very accurate field areas.

6.4 Yield Prediction by Remote Sensing

The methodology of applying time step vegetation indices did not provide positive results. It is nevertheless recommended that alternative approaches be investigated, given the importance of crop forecasting on both a MSA and an industry-wide scale. These may include the derivation of crop parameters from remote sensing, such as LAI (Leaf Area Indices) that can be obtained from NDVIs (Choudhury, 1987). According to Norman *et al* (2003), the LAI is closely related to biomass for individual crops.

6.4.1 Yield Prediction Using a NOAA NDVI Time Step Approach

From the research results it would appear as though the resolution of the NOAA data are too coarse. In addition, the methodology time step approach has not been shown to be successful. Clearly, alternative approaches to this methodology should be investigated. The use of MODIS data to derive crop factors and/or LAIs in conjunction with crop models, has been successfully employed to predict yields in crops such as wheat, corn and soya beans (Doraiswamy *et al*, 2002, 2003a).

This alternative approach is highly recommended, given that the combined approach of crop-weather models in conjunction with remotely sensed derived indices for the sugarcane has not been investigated. Current research in other crops has shown much potential for this approach. It therefore remains to be investigated whether the same results can be realised for sugarcane.

6.4.2 Yield Prediction Using a Landsat NDVI and Infrared Index Time Step Approach

Mixed results were obtained with the time step approach using Landsat NDVI to predict yields. Ultimately, however, a single year's data was insufficient to establish a meaningful or reliable indicator of yield. In order to test the significance of climatic variations on the results, a longer history of satellite data is required. This would be particularly difficult to conduct at Umfolozi, given the lack of reliable and complete historical records for a large number of fields. It is not, however, recommended that this approach be pursued further, as the potential does not appear to be great. It would be more profitable to investigate the potential for integrating point source crop-weather based models to predict yields, and high resolution satellite imagery as a means of providing a measure of the spatial variability to this model. This approach is currently being investigated by the SASEX Agricultural Engineering Department.

7 CONCLUSION

This research was conducted in order to evaluate the potential of remote sensing technology in addressing many of the operational challenges facing the South African sugar industry, using the Umfolozi mill MSA for the case study. The format of the *Conclusion* will follow that of the research aims and objectives as stated in the *Introductory* chapter.

7.1 Mapping of Sugarcane Areas for Both the Large and Small-Scale Growers Using Satellite Imagery

The Umfolozi MSA was selected for the case study as the situation and challenges facing the mill were largely representative of other mills in the South African sugar industry. In particular, the problem exists of monitoring an increasing small-scale grower sector into marginal dryland areas, compounded by highly variable climatic conditions and a limited milling capacity.

The research conducted utilized multi-temporal Landsat 7 ETM+ imagery and an unsupervised hierarchical classification approach to map sugarcane areas. It was hoped that the use of the multi-temporal imagery would overcome, to a degree, the limitations associated with the larger spatial resolution of the Landsat sensor.

7.1.1 Quantifying the Mapping Errors

This research has shown that the use of Landsat 7 ETM+ satellite imagery cannot achieve the 1% level of mapping accuracy outlined in the recommended sugar industry mapping standards (Gers, 2002). It should be noted however, that it was never the objective of this research to test the potential for mapping sugarcane areas against the recommended mapping standard, but rather to evaluate the potential of this technique. Large-scale grower sugarcane was easier to map than the small-scale grower sugarcane, consequently, the mapping accuracies for the small-scale grower field areas were lower than for the large-scale growers. The principal reasons for these differences was believed to be a combination of small field areas (~1 ha on average) cultivated by the small-scale growers as well as agronomic factors such as the lack of irrigable water and crop nutrition.

It is likely that high-resolution satellite imagery such as Quickbird or Ikonos will not provide suitably accurate, that is 1% accurate, mapping of the small-scale grower fields on account of the large variability in spectral characteristics. A slight improvement in the mapping accuracy is, however, anticipated as result of the finer spatial resolution. These improvements in mapping accuracy are anticipated to be higher for the large-scale growers whose crops display a high degree of uniformity

because of their high level of agronomic management.

Despite the low mapping accuracies for both the large and small-scale growers sugarcane areas, 71% on average, much value can be gained from the image and map products of this research. In particular, the classified sugarcane areas can effectively be employed to facilitate the identification and location of horizontal expansion. The new sugarcane areas identified through this process would then require more detailed or accurate mapping. Given the vast geographic extent of the small-scale grower areas, as well as the dispersed nature of their operations, this methodology can greatly improve the effectiveness and efficiency of Small-Scale Development Officers, whose task it is to maintain and update the cartographic information for their growers. Similarly, much benefit can be realized simply through visual interpretation of the satellite imagery. Most mapping software packages will allow farm boundary information to be overlaid on top of satellite imagery. Through this method of visual interpretation, sugarcane fields are readily identifiable, especially when one compares imagery obtained at different dates in which a contrast of harvested or burnt sugarcane in one image and standing sugarcane in the second image is found. Furthermore, the characteristic sugarcane colour is readily distinguishable to the trained eye under favourable growing conditions, even the very small sugarcane plots.

7.2 Investigating the Relationship Between Phenology, Cultivar and Yield and the Spectral Characteristics of Sugarcane

This research has shown that Landsat 7 ETM+ data is not able to differentiate between various sugarcane cultivars. Furthermore, it has been shown that no meaningful correlation between the at-satellite reflectances and yields of sugarcane at different ages exists. Finally, this research has shown that various phenological stages of sugarcane growth are identifiable using Landsat 7 ETM + data.

7.3 Utilizing Existing Field Information to Determine the Percentage of the Total Mill Supply Area Harvested for Each Satellite Image Acquisition Date

The sugarcane inventory assessment throughout the milling season showed much potential. The agreement between the mill crush figures, which are in fact the best approximation of the areas harvested throughout the milling season, and the harvested areas measured by remote sensing was good. In this instance, the application of remote sensing information in conjunction with existing field boundary information made it possible to measure the true extent of harvested fields, which was previously not possible owing to the mechanisms employed.

7.4 Predicting Yields Based on Satellite Imagery

This research has shown that yield prediction by means of remote sensing using a time step approach in conjunction with Vegetation Indices has not been successful at Umfolozi. In particular, the broad-scale NOAA data showed poor correlations with annual production for a range of different scenarios. The higher resolution Landsat data showed some positive results; however, owing to the short period over which the data were analysed, the contribution of external factors such as climatic variation could not be meaningfully interpreted.

7.5 Concluding Remarks

In conclusion, remote sensing technologies alone are unlikely to deliver a meaningful advantage over the traditional methods employed in sugarcane supply management for the sugar industry. Clearly, the incorporation of information such as accurate field boundaries is required to facilitate more accurate and reliable results. The role of remote sensing, therefore, needs to be included and integrated within the existing structures and resources to deliver meaningful results.

This research has shown that Landsat 7 ETM+ data were successfully used to measure the age of sugarcane as well as to accurately measure the relative area of harvested cane throughout the milling season. By combining these two results, much potential can be realized in terms of sugarcane supply management. The ability to accurately determine the area harvested, as well as the age distribution of the remaining sugarcane throughout the milling season, is invaluable. This information can potentially assist in the scheduling of sugarcane supply through identification of outstanding sugarcane to be harvested.

It is unlikely that remote sensing applications will replace existing methods and procedures for sugarcane area mapping in the foreseeable future. However, in conjunction with existing methodologies and information sources, significant benefits can be realized. In particular, the use of remote sensing to facilitate the identification of small-scale grower expansion for more detailed mapping and the identification of the sugarcane inventory throughout the milling season.

Possibly the biggest global challenge facing the South African sugar industry has been the steady decline in the international or export price of sugar on world markets for approximately the past two decades. Given that approximately 50% of the sugar produced is exported at the low international prices, the profitability and sustainability of the sugar industry as a whole has and continues to be increasingly challenged (Anon, 2002). Innovation resulting in decreased operational costs and increased sucrose extraction as well as diversification into sugar by-products are critical to the industry's survival.

Remote sensing has the potential to increase operational efficiencies within the agricultural sector when incorporated with the existing approaches to sugarcane supply monitoring and management. This research has shown potential for remote sensing to improve the monitoring and management of sugarcane supply throughout the milling season. This thesis has demonstrated that the products derived from remote sensing can provide means for validating the information generated by the mill administrative structures. However, it is the opinion of the author that integration of reliable crop forecasts will add significant value to the sugarcane inventory monitoring. In this regard, there are many avenues that still need to be explored, including the derivation of crop growth parameters by means of remote sensing, such as the Leaf Area Index for yield forecasting; or incorporating crop-weather based models in conjunction with remote sensing data to extrapolate results.

Careful consideration of the cost benefit of remote sensing technology in the sphere of agricultural production must be made in the case of low value agricultural commodities such as sugarcane. Having said this, there are few alternatives to remote sensing that have the ability to provide unbiased information over large areas without incurring significant costs. Given the geographically dispersed nature of sugarcane production in the South African sugar industry, remote sensing can provide a cost effective means of measuring valuable information within and across MSAs. Furthermore, as the cost of satellite data decreases amid increasing global competition between the international space agencies and service providers, improved and less expensive data are likely to increase the scope and affordability of remote sensing applications in a variety of agricultural disciplines.

Remote sensing technology is unlikely to be the panacea for the South African sugar industry's sugarcane supply management or yield forecasting. However, integrated within the existing structures and resources, remote sensing technology is likely to improve decision making by providing alternative, unbiased measures, which can be used to validate and reduce the uncertainty inherent in information derived from the existing structures. Ultimately the cost benefit of this technology at a MSA level will depend on the value these unbiased estimates add to the existing information. The success of remote sensing at a MSA level will rely on the management's ability to support and promote these technologies throughout the stages of development, implementation and rollout. Key components of this will include education as well as continued investment, support and development of human capital, software and hardware resources. Without this continued support at a management level, remote sensing at a MSA level is unlikely to succeed.

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APPENDICES

Appendix A Metadata for Raw Satellite Imagery.

This appendix describes the metadata and image acquisition details of the raw satellite data used in this research. Raw imagery were ordered by private consultants on behalf of SASEX from Satellite Applications Centre archives at Pretoria, with the following parameters:

Parameter	Values
Path-Row Number	167-79
Shift	50% South
Dates	30 October 2001 8 April 2002 13 July 2002 17 October 2002 18 November 2002
Processing Level	1G (Level 4) Path orientated
Resampling Method	Cubic Convolution
Format	Landsat-7 Fast Format
Media	CD-Rom
Bands	All bands

Appendix B Tasseled Cap Coefficients for Landsat 7 ETM+ At-Satellite Reflectance (Source: Huang *et al*, 2001).

Index	Band 1	Band 2	Band 3	Band 4	Band 5	Band 7
Brightness	0.3561	0.3972	0.3904	0.6966	0.2286	0.1596
Greenness	-0.3344	-0.3544	-0.4556	0.6966	-0.0242	-0.2630
Wetness	0.2626	0.2141	0.0926	0.0656	-0.7629	-0.5388
Fourth	0.0805	-0.0498	0.1950	-0.1327	0.5752	-0.7775
Fifth	-0.7252	-0.0202	0.6683	0.0631	-0.1494	-0.0274
Sixth	0.4000	-0.8172	0.3832	0.0602	-0.1095	0.0985