

**LAND DEGRADATION
IN THE LIMPOPO PROVINCE, SOUTH AFRICA**

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I declare that this research report is my own unaided work. It is being submitted in partial fulfilment for the degree of Master of Science at the University of the Witwatersrand. It has not been submitted before for any degree or examination at any other university.

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Contents

1	ABSTRACT	1
2	INTRODUCTION	2
2.1	STUDY OBJECTIVES.....	9
2.2	STUDY AREA.....	10
3	MATERIALS AND METHODS.....	11
3.1	CHOICE OF STUDY AREA	11
3.2	NORMALIZED DIFFERENCE VEGETATION INDEX DATA.....	12
3.3	NDVI AND RAINFALL TRENDS.....	15
3.4	RAIN-USE EFFICIENCY CURVES AND IDENTIFICATION OF OUTLIERS	16
3.5	LAND-COVER CHARACTERISTICS OF MAPPED DEGRADED AREAS	17
3.6	VALIDATION	17
4	RESULTS.....	18
4.1	NDVI AND RAINFALL TRENDS.....	18
4.2	RAIN-USE EFFICIENCY CURVES.....	20
4.3	LAND-COVER CHARACTERISTICS OF MAPPED DEGRADED AREAS	23
5	VALIDATION AND DISCUSSION	23
6	CONCLUSION	28
7	ACKNOWLEDGEMENTS	29
8	APPENDICES.....	31
8.1	APPENDIX 1: LITERATURE REVIEW.....	31
8.1.1	<i>Historical background.....</i>	<i>33</i>
8.1.2	<i>Towards a definition of desertification.....</i>	<i>33</i>
8.1.3	<i>Desertification research using remote sensing technology.....</i>	<i>35</i>
9	REFERENCES	42

List of Figures

Figure 1 Map showing the location of the study area. White areas represent privately owned land used for commercial agriculture or conservation purposes.	10
Figure 2: Yearly average maximum composite NDVI images (1985-2004).....	14
Figure 3: Long-term (1985-2004) average maximum composite NDVI image (NDVI _{avemax}) used in the degradation analysis. (A) Swartruggens Mountain Bushveld, (B) Indigenous and plantation forestry, (C) Commercial cultivation and riparian vegetation along water courses, (D) Areas of low NDVI values, (E) Swaziland Sour Bushveld vegetation type on dark coloured basalt-derived soils with low NDVI values, (F) Mosaic of subsistence cultivation and communal rangeland, (G) Mining area showing low NDVI values.....	15
Figure 4: (a) Second order polynomial regression to test the significance of the curvi-linear trend in yearly cumulative NDVI values; ‘x’ denotes the two anomalous data points excluded from the analysis, and (b) trend in yearly mean NDVI and mean rainfall values for all pixels in Limpopo Province between the years 1984-2004.....	19
Figure 5: Non-linear regressions using a fitted Gompertz logistic function between long-term average maximum NDVI and (a) mean annual precipitation, and (b) growth days index. The fitted functions are given above each graph.....	21
Figure 6: Map of studentized residuals depicting observed deviation from the predicted Gompertz rain-use efficiency model established in the regression of average maximum NDVI and mean annual precipitation. Negative standard deviations (red) depict areas where rain-use efficiency is lower than it should be, while positive standard deviations (green) depict areas that have higher rain-use efficiency.	22
Figure 7: Maps of degradation based on thresholds of (a) 0.75 standard deviations, (b) one standard deviation, and (c) two standard deviations, less than the predicted model.....	23
Figure 8: Independent validation datasets: (a) the ‘degraded’ land-cover class of the National Land-cover 2000 project, mapped from Landsat satellite imagery taken in 2001/2002, and (b) the degradation indices from the 1999 National Review of Land Degradation constructed per municipal district through perception-based surveys with field technicians and extension officers.	25

List of Tables

Table 1: Synthesis of remote sensing research on desertification with summary characteristics of study scale, data used, index used and temporal period.....	6
Table 2: Land-cover characteristics of mapped degraded areas. A threshold of one standard deviation was used to define the degraded area, and the land-cover classes were aggregated from those used in CSIR and ARC (2004).....	23

1 ABSTRACT

An estimated 91 % of South Africa's total land area is considered dryland and susceptible to desertification. In response, South Africa has prepared a National Action Programme to combat land degradation, and this requires assessment and monitoring to be conducted in a systematic, cost effective, objective, timely and geographically-accurate way. Despite a perception-based assessment of land degradation conducted in 1999, and a land-cover mapping exercise conducted for 2000/2001, there are few national scientifically rigorous degradation monitoring activities being undertaken, due largely to a lack of objective, quantitative methods for use in large-scale assessments. This study therefore tests a satellite-derived index of degradation for the Limpopo Province in South Africa, which is perceived to be one of the most degraded provinces in the country. The long-term average maximum normalized difference vegetation index (NDVI), calculated from a time series (1985-2004) of NOAA AVHRR satellite images, as a proxy for vegetation productivity, was related to water balance datasets of mean annual precipitation (MAP) and growth days index (GDI), using both linear and non-linear functions. Although the linear regressions were highly significant ($p < 0.005$), a non-linear four parameter Gompertz curve was shown to fit the data more accurately. The curve explained only a little of the variance in the data in the relationship between NDVI and GDI, and so GDI was excluded from further analysis. All pixels that fell below a range of threshold standard deviations less than the fitted curve were deemed to represent degraded areas, where productivity was less than the predicted value. The results were compared qualitatively to existing spatial datasets. A large proportion of the degraded areas that were mapped using the approach outlined above occurred on areas of untransformed savanna and dryland cultivation. However the optical properties of dark igneous derived soils with high proportions of smectitic minerals and therefore low reflectance, were shown to lower NDVI values substantially. Overall, there was an acceptable agreement between the mapped degradation and the validation datasets. While further refinement of the methodology is necessary, including a rigorous field-based resource condition assessment for validation

purposes, and research into the biophysical effects on the NDVI values, the methodology shows promise for regional assessment in South Africa.

KEYWORDS: Land degradation; Desertification; Rain-use efficiency; Remote Sensing; NDVI; Limpopo Province.

2 INTRODUCTION

Approximately 91 % of South Africa is potentially susceptible to desertification (Hoffman and Ashwell, 2001). Recognising this, and that a large proportion of the population are dependent for their livelihoods on the services derived from dryland ecosystems, South Africa ratified the United Nations Convention to Combat Desertification in Those Countries Experiencing Serious Drought and/or Desertification, Particularly in Africa (UNCCD) in 1997, and has prepared a National Action Programme (NAP) Combating Land Degradation to Alleviate Rural Poverty (Department of Environmental Affairs and Tourism, 2004). The NAP requires that monitoring and evaluation of the status of land degradation and implementation of the NAP takes place. However, there is a lack of objective methods for assessing desertification and land degradation in South Africa, and little research has been conducted on appropriate methods for this on a national scale.

Several studies on the extent and rate of desertification in South Africa have been conducted in the last 50 years. These include Acocks (1953), United Nations Environment Programme (UNEP) (1997) World Atlas of Desertification, the baseline land degradation study conducted by Hoffman et al. (1999), the two land-cover mapping exercises (conducted in 1995 and 2001/2002 by the Council for Scientific and Industrial Research and the Institute for Soil, Climate and Water) containing classifications for degradation, and the Southern African Millennium Assessment that included a regional study of degradation (Scholes and Biggs, 2004). There are, however, several drawbacks to these studies. Nicholson et al. (1998) pointed out that the UNEP study resulted in a map of desertification severity that was extrapolated from risk factors, and thus included little information on the actual status of desertification. The result is that the levels of desertification were over-exaggerated. The

UNEP study alarmingly concluded that approximately 60 % of South Africa was degraded. The Hoffman et al. (1999) study used the knowledge and perceptions of extension officers and resource conservation technicians to assess the extent of soil and vegetation degradation at a fairly coarse, magisterial district scale. It was therefore perception-based and semi-quantitative, and therefore not built on objective measurements, and so the authors identified areas most severely affected only in a relative sense. Finally, the land-cover mapping exercises mentioned above mapped degradation using image brightness values on a snapshot satellite image. They cannot therefore be representative of a persistent decrease in productivity.

There is an extensive international literature on desertification and vegetation monitoring research using remote sensing techniques. Several authors have provided summaries of these (Hoffman et al., 1999; Food and Agriculture Organization, 2003 unpublished report; Archer, 2004; Yang et al., 2005). A tabular synthesis of selected published studies is provided in Table 1. Trends in research have involved a shift from a manual, visual approach to the interpretation of images, in both aerial photography and satellite imagery, to a more model-based approach involving indicators and proxy variables, measurable over large areas and over longer periods. It is evident that recently, there have been several studies conducted at a large scale, nationally and sub-continentially, and using a longer time series of data. Most of the studies have used vegetation indices such as the normalized difference vegetation index (NDVI) as the basis for assessment, although other indices have been used.

Mackay and Zietsman (1996) assessed rangeland condition in the Ceres Karoo region of the Western Cape by comparing field survey data with the soil adjusted vegetation index (SAVI). Tanser and Palmer (1999) conducted a localised degradation assessment in South Africa using Landsat Thematic Mapper imagery, by comparing the NDVI with the moving standard deviation index (MSDI), which they describe as a measurement of landscape heterogeneity, a key determinant of degradation status. With the exception of the most arid site within a single ecosystem, the NDVI and MSDI resulted in similar conclusions in terms of degradation. Tested across five different ecosystems, the MSDI performed consistently while NDVI produced erroneous results in the arid and semi-arid ecosystems. Their conclusion was that the MSDI is a powerful adjunct to the NDVI. Lambin and Strahler's (1994) study in west

Africa using a similar measurement termed the 'spatial structure indicator' found that the NDVI and spatial structure indicator were slightly redundant as indicators of land cover change, but that the indicator measured over a long term, may be able to detect anthropogenic processes of change. Liu and Kogan (1996) used the NDVI and the vegetation condition index (VCI) derived from NOAA AVHRR data, to map a time series of potential drought areas on a continental and regional scale for South America. Threshold values for the NDVI and VCI were set, as determined by previous studies, and pixels with values below the thresholds were defined as drought areas. This is the basic concept on which this study for the Limpopo province was built. Milich and Weiss (2000) tested the interannual coefficient of variation of the mean growing season maximum monthly NDVI composites for 1980-1994, calculated from the AVHRR satellite.

Several local scale studies of degradation and vegetation change using remote sensing have been conducted in South Africa (for example Jarman and Bosch, 1973; Viljoen et al., 1993; Makhanya, 1993; Palmer and van Rooyen, 1998; Tanser and Palmer, 1999; Wessels et al., 2004; Archer, 2004). Few studies have looked at larger provincial, national or regional scales of degradation, and even fewer have used long-term satellite derived biological productivity as an indicator of degradation, as has been done extensively in West Africa (e.g. Herrmann et al., 2005; Olsson et al., 2005; Budde et al., 2004; Li et al., 2004; Diouf and Lambin, 2001; Milich and Weiss, 2000; Prince et al., 1998; Nicholson, 1998; Tucker and Nicholson, 1998), in sub-Saharan Africa (Sannier et al., 1998, Prince, 2002); in the Middle East (Weiss et al., 2001; Weiss, 1998; Evans and Geerken, 2004; Geerken and Ilaiwi, 2004; Al-Bakri and Taylor, 2003), and in South America (Liu and Kogan, 1996).

Two recent studies, Wessels et al. (2004) and Archer (2004), however, have used productivity indicators to assess vegetation condition. Wessels et al. (2004) showed that moderate resolution NDVI data, integrated seasonally for 1985 to 2003, could be used to detect degraded areas. Their study, conducted in the Limpopo Province of South Africa, revealed that for various land capability units with uniform soil, climate and vegetation, the productivity of degraded areas was consistently lower than nondegraded areas relative to rainfall. Further, degraded areas were no less stable or resilient than nondegraded ones. Archer

(2004) used a 14-year time series of NDVI data, corrected for rainfall, to study the effects of grazing practices on vegetation cover in the Karoo. The study revealed that once the climate signal in the form of rainfall was removed from the NDVI data, some grazing strategies lead to consistently lower vegetation cover values than others.

There are drawbacks to using vegetation indices. As Archer (2004) mentions, vegetation indices are affected by a range of biophysical factors. Vegetation indices that attempt to circumvent the problems with the NDVI have been developed. Examples include the SAVI, which was developed for use in sparsely vegetated areas (Huete, 1988), the Modified Soil Adjusted Vegetation Index (MSAVI)(Qi et al., 1994), and the Enhanced Vegetation Index (EVI) (Huete et al., 2002). The limitation with these however is that they are more complex in that they require the use of user defined constants and scaling factors, which would vary over and be difficult to determine for a large study area. There is therefore no long-term time series of data for these indices. There is evidence that the NDVI performs suitably in sparsely vegetated areas. Jacobberger-Jellison (1994), for example, showed that the SAVI and the Leaf Vegetation Index did not perform more reliably than the NDVI in a sparsely vegetated area, in the Tombouctou region in Mali. The NDVI is seemingly the most widely used index for large-scale studies of vegetation productivity.

More particularly, the effects of precipitation on NDVI values have received considerable attention of late (e.g. Herrmann et al., 2005; Olsson et al., 2005; Archer, 2004; Wessels et al., 2004; Evans and Geerken, 2004; Geerken and Ilaiwi, 2004; Li et al., 2004; Prince, 2002; Diouf and Lambin, 2001; Milich and Weiss, 2000; Nicholson et al., 1998; Tucker and Nicholson, 1998; Bastin et al., 1995; Nicholson et al., 1990). This study explores this relationship using a satellite-derived index of rain-use efficiency (RUE). RUE is the ratio of net primary production (NPP) to rainfall, and a decrease in this efficiency occurs in association with land degradation (Diouf and Lambin, 2001). Several authors have conducted studies using the concept of rain-use efficiency (RUE) of vegetation. RUE is thought to be an important indicator of the functioning of rangeland ecosystems (Snyman, 1998).

Table 1: Synthesis of remote sensing research on desertification with summary characteristics of study scale, data used, index used and temporal period

Study	Location	Scale of study	Data used	Index / method	Time period
Masoud and Koike (in press)	Egypt	Local	Landsat TM/ETM	Vegetation indices, Tasseled cap, image differencing	1987-2003, 3 images
Chikhaoui et al. (2005)	Morocco	Local (catchment)	ASTER	Spectral index (“Land degradation Index”), band ratios	Snapshot
Herrmann et al. (2005)	Sahel	Sub-continental	NOAA AVHRR	Long-term average & monthly NDVI in relation to rainfall, trends in residuals	1982-2003
Khan et al. (2005)	Pakistan	Local	Indian IRS	Vegetation indices and ratios of signals	Snapshot of a season
Olsson et al. (2005)	Sahel	Sub-continental	NOAA AVHRR	Seasonal integrated NDVI trend per pixel in relation to rainfall	1982-1999
Archer (2004)	South Africa, Karoo	Local	NOAA AVHRR	Seasonal integrated NDVI in relation to rainfall (“Detrended NDVI”)	1984-1997
Budde et al. (2004)	Senegal	National	NOAA AVHRR, SPOT 4	Integrated NDVI, local variance analysis, trends in residuals	7 years
Evans and Geerken (2004)	Syria	National	NOAA AVHRR	Accumulated annual maximum NDVI, rain-use efficiency, residual analysis	1981-1996
Geerken and Ilaiwi (2004)	Syria	National	NOAA AVHRR, Landsat TM, Indian IRS	Accumulated annual maximum NDVI, rain-use efficiency, residual analysis	1981-1996
Li et al. (2004)	Senegal	National	NOAA AVHRR	Integrated NDVI, rain-use efficiency stratified per vegetation type, Standard error of estimate, residual analysis	1982-1997
Tappan et al. (2004)	Senegal	Sample sites over country	Landsat ETM	Land-cover change per vegetation unit	
Tong et al. (2004)	China	Local (catchment)	Landsat TM	Land-cover mapping and “Steppe Degradation Index” with ancillary data	1985 and 1999
Wessels et al. (2004)	Limpopo Province, South Africa	Local-provincial	NOAA AVHRR	Cumulative NDVI scaled per land capability stratification and related to rainfall	Long-term (1985-2003)
Al-Bakri and Taylor (2003)	Jordan	National	NOAA AVHRR	Long-term Average NDVI, Vegetation condition index	1981-1997
Ries and Marzolf (2003)	Spain	Local	Aerial	Visual interpretation	1995-1998

Study	Location	Scale of study	Data used	Index / method	Time period
Collado et al. (2002)	Argentina	Provincial	photographs Landsat TM	Image differencing of 2 images	1982 & 1992
Gupta et al. (2002)	China (Mekong River)	Local (catchment)	SPOT XS	Visual interpretation	
Wu and Ci (2002)	China	Provincial	Landsat TM	Land-cover mapping and ancillary data	50 years
Diouf and Lambin (2001)	Senegal	Local	NOAA AVHRR	Rain-use efficiency using integrated NDVI	10 years
Rasmussen et al. (2001)	Burkina Faso	Provincial	Aerial photography, SPOT XS	Albedo analysis of 5 images	1986-1996
Weiss et al. (2001)	Saudi Arabia	Regional	NOAA AVHRR	Coefficient of variation of interannual NDVI	12 years
Borak et al. (2000)	Sun-Saharan Africa	Local test sites	NOAA AVHRR, Landsat TM and MSS, SPOT XS	Spatial and temporal metrics of land-cover change, image differencing	
Milich and Weiss (2000)	Sahel	Sub-continental	NOAA AVHRR	Coefficient of variation of interannual NDVI	1980-1994
Kiguli et al. (1999)	South Africa, Peddie District	Local	Landsat TM	NDVI versus Moving Standard Deviation Index	
Tanser and Palmer (1999)	South Africa	Local test sites, 5 biomes	Landsat TM	NDVI versus Moving Standard Deviation Index using fence-line contrasts	Snapshot in 1994
Hill et al. (1998)	Greece, Crete	Local	Landsat TM	Spectral unmixing of bands	1984-1996
Maselli et al. (1998)	Italy, Tuscany	Local	Landsat TM, NOAA AVHRR	Regressions of bands – high resolution versus low resolution	Snapshot in 1990
Nicholson et al (1998)	Sahel	Sub-continental	NOAA AVHRR	Integrated NDVI and rainfall regressions	1980-1995
Palmer and van Rooyen (1998)	South Africa, Kalahari	Local	Landsat TM	Change vector analysis between 2 bands, NDVI	1989 and 1994
Sannier et al. (1998)	Etosha National Park, Namibia; Zambia	National	NOAA AVHRR	NDVI stratified per vegetation type, vegetation productivity indicator	10 years
Tucker and Nicholson (1998)	Sahel	Sub-continental	NOAA AVHRR	NDVI related to rainfall	1980-1996
Weiss (1998)	Saudi Arabia	Provincial	NOAA AVHRR, Landsat TM & MSS, SPOT XS	Coefficient of variation of interannual NDVI	12 years
Liu and Kogan (1996)	South America	Sub-continental	NOAA/NESDIS	Vegetation indices (NDVI, Vegetation	1981-1987

Study	Location	Scale of study	Data used	Index / method	Time period
			AVHRR	condition index) related to rainfall, threshold mapping	
Mackay and Zietsman (1996)	South Africa, Karoo	Local	Landsat TM	Soil adjusted vegetation index, fence line contrasts	Snapshot 1992
Tripathy et al. (1996)	India	Local	Landsat MSS, Indian IRS	Albedo, NDVI time series, visual interpretation, image differencing	1984-1991
Bastin et al. (1995)	Australia	Local	NOAA AVHRR, Landsat MSS	Rain-use efficiency, grazing gradient method	Snapshot
Jacobberger-Jellison (1994)	Sahel, Mali	Local	Landsat TM	Albedo versus vegetation indices (NDVI, Soil Adjusted Vegetation Index, Leaf Vegetation Index)	1986-1988
Lambin and Strahler (1994)	Africa	Sub-continental	NOAA AVHRR	NDVI, surface temperature, moving spatial mean	1987-1989
Ringrose and Matheson (1994)	Sahel	Sub-continental	Landsat MSS	Visual mapping	Snapshot 1986
Hill (1993)	Greece	Local	Landsat TM	Linear spectral mixture analysis, image differencing	1985 and 1990
Makhanya (1993)	South Africa, Limpopo	Local	Aerial photography, SPOT XS	Visual interpretation, image differencing	2 dates
Marsh et al. (1992)	Sahel	Local	NOAA AVHRR, SPOT XS	NDVI, high resolution versus low resolution	1989 several images
Nicholson et al. (1990)	Sahel and East Africa	Sub-continental	NOAA AVHRR	Rain-use efficiency per vegetation type	1982-1985

Diouf and Lambin (2001) assessed dryland land cover modification in Senegal by using a combination of remote sensing and field-based measurements to compute RUE. They found that NDVI alone did not reveal trends in degradation, but that RUE was the most likely indicator to reveal trends in land cover modification. Other research (Prince et al., 1998; Nicholson et al. 1998; Herrmann et al., 2005) conducted in the Sahel, has used NDVI as a proxy variable for NPP in the computation of RUE, and all studies agree that there has been no reduction in productivity of the area. Herrmann et al. (2005) show that there has in fact been a recent greening over a large area of the Sahel, largely due a recovery in rainfall from the great Sahelian drought that started in the early 1970s and continued for several decades thereafter.

Prince's (2002) research in Zimbabwe, Mozambique and the surrounds, proposes the use of RUE as a useful indicator of degradation using a carbon cycle model that utilises satellite imagery to estimate net primary productivity (NPP). However, a shortcoming of using RUE in the measurement of desertification is that RUE is applicable only when rainfall is the major limiting factor in productivity. This occurs in dry areas, while in areas with higher rainfall, and areas with low rainfall, factors other than rainfall determine productivity (Prince, 2002). Further, the nature of the relationship between NDVI and precipitation is variable. Several authors have found good correlations between the variables, using different accumulation periods of rainfall to maximize the correlation with NDVI (Nicholson et al., 1990; Yang et al., 1997; Evans and Geerken, 2004; Herrmann et al., 2005). Herrmann et al. (2005) found that monthly maximum NDVI in the Sahel was correlated best with rainfall accumulated over a period of three months while Evans and Geerken (2004) found that accumulation periods of between four and six months preceding the maximum monthly NDVI value resulted in optimum correlations. Nicholson et al. (1990) showed that the rain-use efficiency curve is linear in the Sahel and log-linear in East Africa, where rainfall is higher. This study follows recent trends in research and uses a rain-use efficiency index for mapping degradation.

2.1 Study objectives

The aim of this study is to develop and test a method for monitoring and assessing land degradation. Specifically, the objectives are to:

- Investigate the relationships between NDVI, a proxy for vegetation productivity, and two water balance indices: mean annual precipitation and growth days index;
- Using the fitted rain-use efficiency curves, identify areas where the water use and growth efficiency is lower than predicted, which are assumed to represent degraded areas; and
- Assess the agreement between the resulting degradation map and existing degradation maps for the region.

2.2 Study Area

The Limpopo Province is situated in northern South Africa (Figure 1), and covers an area of approximately 123 910 km². The province is characterised by a diverse topography, ranging from 120 m above sea level in the eastern lowlands to over 2000 m in the central highlands of the Waterberg complex and the Drakensberg Escarpment. The northern and north-western plains stretch to the Limpopo River.

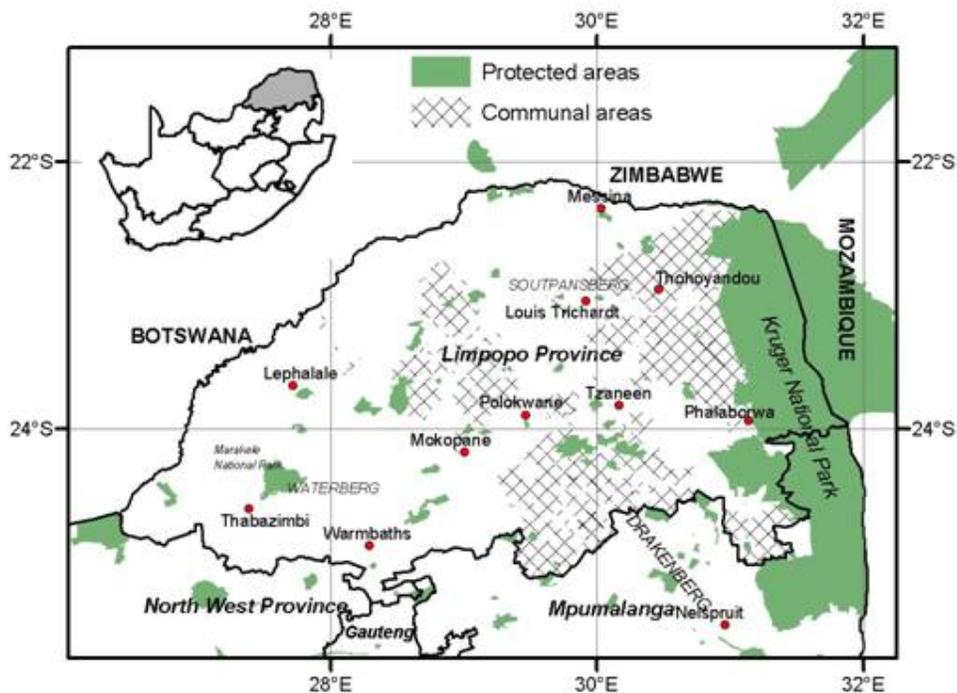


Figure 1 Map showing the location of the study area. White areas represent privately owned land used for commercial agriculture or conservation purposes.

Limpopo experiences summer rainfall, which varies with altitude. The northern and north-western parts are arid, as defined in the UNCCD (United Nations, 1994), and are susceptible to frequent drought (Limpopo DFED, 2003), while southern parts of the province are semi-arid. Small areas along the escarpment fall into the dry sub-humid and humid categories. The majority of the province receives less than 500 mm rainfall per annum while the higher-lying Drakensberg Escarpment stretching northwards to the Soutpansberg Mountains receives more than 1000 mm per annum in some places (Schulze, 1997).

The biogeographical diversity has resulted in a diverse array of habitat types and land uses. Dry woodlands and bushveld, which cover most of the province, makes way for moister highland grasslands, mist-belt and afro-montane forests in the higher lying areas. Commercial agriculture occurs scattered throughout the province, but is centralised mainly in the southern area, while subsistence agriculture is extensive throughout the communal lands.

The province comprises a diverse array of production systems including urban, cultivation, livestock, forestry, mining, natural vegetation and conservation. Approximately 73 % remains in its natural state (much of which is used for grazing), while 27 % has been transformed by other land uses, notably cultivation, of which six per cent is commercial and six per cent is subsistence.

The major river systems in Limpopo are the Mokoko, Lephallale, Mogolakwena, Sand, Luvuvhu, Letaba and Olifants. The province is bordered in the north by the Limpopo River.

The population of Limpopo was estimated at 5.2 million in 2001 with an average population density of 42.5 people per km² (Statistics South Africa, 2003). This however varies considerably with the former communal homeland areas of Venda, Gazankulu and Lebowa having over 100 people per km².

3 MATERIALS AND METHODS

3.1 *Choice of study area*

The Limpopo province is thought to be one of the most degraded provinces in South Africa, particularly in the communal areas (Hoffman and Ashwell, 2001). The soils in the province are highly susceptible to erosion, and sheet and gully erosion are prevalent throughout croplands

and grazing lands (National Botanical Institute, 1999). Vegetation degradation is also a serious problem. Loss of plant cover and bush encroachment are problematic in the east and west of the provinces respectively. Communal areas are affected mainly by deforestation and change in species composition. It is estimated that 14 % of the province is infested with alien plants (National Botanical Institute, 1999).

Wessels et al. (2004) have successfully demonstrated in communal areas in Limpopo Province that medium resolution satellite-derived NDVI data can be used to detect areas of degradation. They showed that the productivity of degraded areas was lower than in non-degraded areas. The Limpopo Province therefore presents appropriate conditions for the development of indicators of desertification.

3.2 *Normalized Difference Vegetation Index data*

Advanced Very High Resolution Radiometer (AVHRR) images (1.1 km resolution) captured by the National Oceanic and Atmospheric Administration (NOAA) satellites were used as the source of the NDVI data. While there are other NDVI satellite data available with improved sensor technology and improved resolution, for example the MODIS data at a 250 m spatial resolution, the NOAA satellites have been operational for over two decades and therefore offer an unrivalled time series (Herrmann et al., 2005).

The NDVI was used in this study as a proxy for green leaf mass. The NDVI is a normalized index derived from reflectance measurements in the red and infrared portions of the electromagnetic spectrum, and is calculated using the following equation:

$$\text{NDVI} = (\text{NIR} - \text{RED}) / (\text{NIR} + \text{RED})$$

where *RED* = Red reflectance value and *NIR* = near infra-red reflectance value.

It is sensitive to the presence, density and condition of vegetation and is correlated with absorbed photosynthetically active radiation and primary production (Herrmann et al., 2005). The Council for Scientific and Industrial Research's Satellite Application Centre acquired the NOAA AVHRR time series (from 1985/1986 to 2003/2004), directly from the satellite. The Institute of Soil, Climate and Water at the Agricultural Research Centre processed and calibrated the daily to correct for sensor degradation and satellite changes (Rao and Chen,

1995, 1996). A complete time series of growing season images for 1994 were unavailable due to the failure of AVHRR-16 on board the NOAA13 satellite. The daily images were geometrically corrected using orbital parameters and 300 ground control image subsets.

The daily NDVI images were used to calculate decadal (10-day) maximum composite NDVI images following the method used by Holben (1996). In this method, the maximum NDVI value for each pixel for each 10-day period was used to create a 10-day maximum value composite (MVC) image, resulting in 36 images per year. This procedure minimizes atmospheric effects, although on examination of the MVC images, several of them were covered by clouds, particularly those in the wet season when cloud cover is more prevalent.

To further minimise the seasonal and climatic effects on the NDVI time series, smoothing of the time series was conducted by calculating the moving mean for each MVC image. The following equation was used to calculate the smoothed decadal images:

$$NDVI(t) = (NDVI(t-1) + NDVI(t) + NDVI(t+1))/3$$

where t = MVC image x in month y .

For display purposes, and in order to assess the inter-annual variation present in the time series, the yearly average of the smoothed MVC images (July to June of each year) was calculated. The yearly average NDVI images are presented in Figure 2. In general, there appears to be a trend of increasing NDVI values over the study period, particularly from 1995 onwards. Years that stand out as anomalous include 1998/1999 and 1993/1994, which appear to have markedly lower NDVI values, and 1994/1995, 1998/1999 and 1999/2000, which have higher NDVI values. The spatial effects of vegetation types and land-cover on NDVI values can be seen on most of the images. The “C”-shaped green areas representing high NDVI values reflect the distribution of the Swartruggens Mountain Bushveld and the Pretoriuskop Sour Bushveld vegetation types, occurring in higher-lying areas and with large areas of indigenous and plantation forests. The Swaziland Sour Bushveld vegetation type, underlain by basalts, and running north to south along the eastern border of the province in the Kruger National Park, reflects low NDVI values, often lower than most of the province. Further interpretation of the overall trends in NDVI values is presented in 4.1.

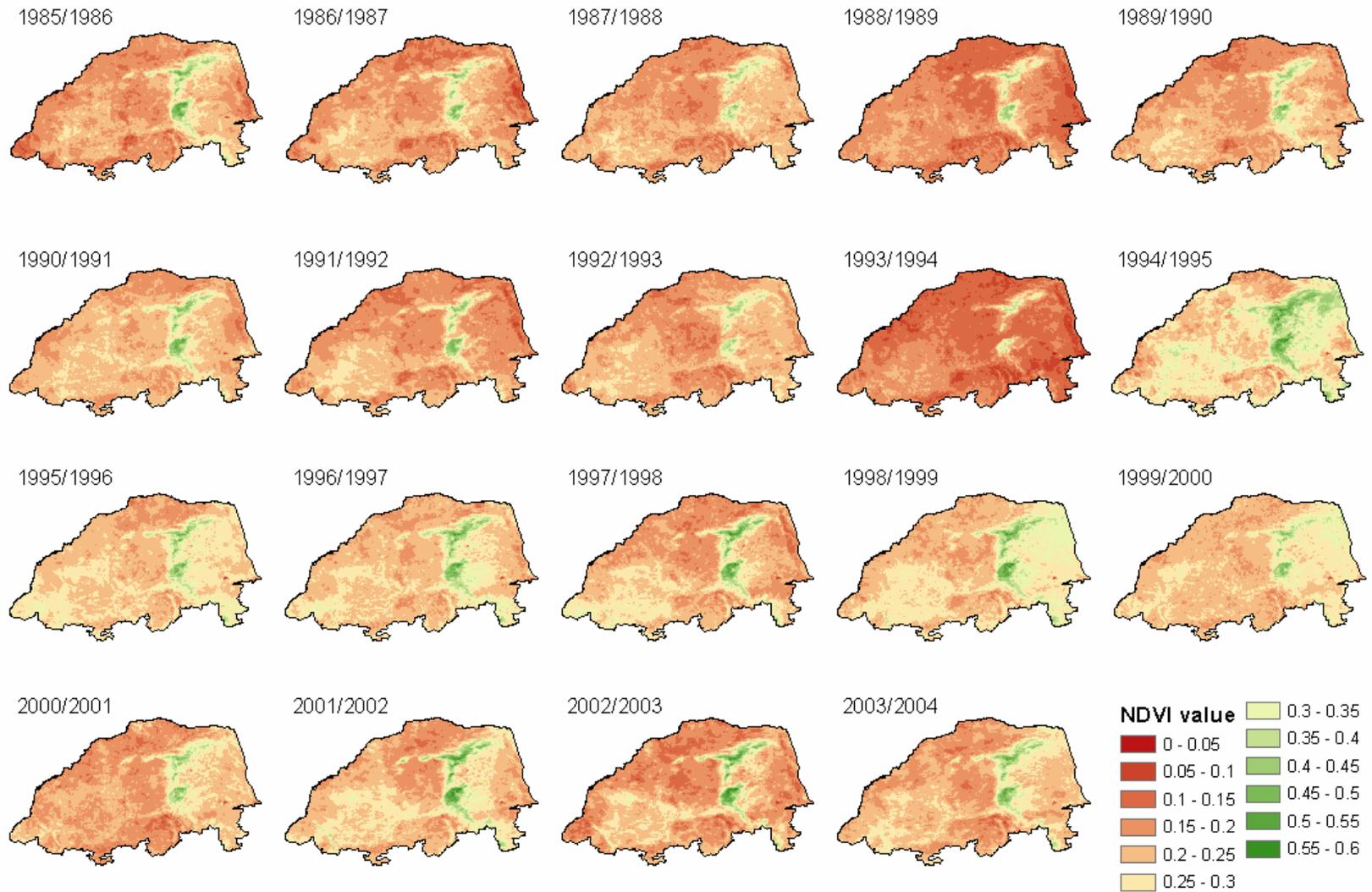


Figure 2: Yearly average maximum composite NDVI images (1985-2004)

A long-term average image ($NDVI_{avemax}$) was then calculated from the yearly images for use in the degradation analysis. The 1993/1994 and 1994/1995 data occurred outside the range of normal variability and were omitted from this calculation. This image is presented in Figure 3. The spatial patterns of NDVI values are further accentuated in this image. The “C”-shaped area of high NDVI is clearly visible (A and B on map), as are the high NDVI values reflecting riparian vegetation and commercial cultivation along watercourses in the western areas of the Province (C). The southern central, central and northern central areas show low NDVI values (D), while the Swaziland Sour Bushveld vegetation type occurring on dark coloured basalt-derived soils is clearly visible (E). Also visible is the landscape mosaic of subsistence cultivation and communal rangeland (F), and the mine located at G.

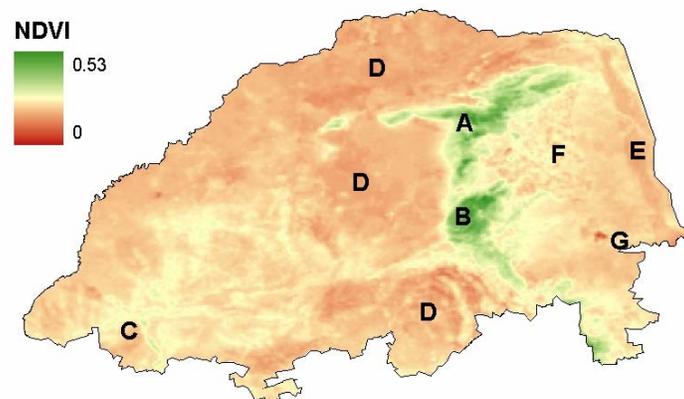


Figure 3: Long-term (1985-2004) average maximum composite NDVI image ($NDVI_{avemax}$) used in the degradation analysis. (A) Swartruggens Mountain Bushveld, (B) Indigenous and plantation forestry, (C) Commercial cultivation and riparian vegetation along water courses, (D) Areas of low NDVI values, (E) Swaziland Sour Bushveld vegetation type on dark coloured basalt-derived soils with low NDVI values, (F) Mosaic of subsistence cultivation and communal rangeland, (G) Mining area showing low NDVI values.

3.3 *NDVI and rainfall trends*

Significant trends in NDVI values over the time series would indicate the potential influence of factors such as rainfall, differences in sensor calibration or human-induced changes in

vegetation productivity. Given that four satellites (NOAA9, 11, 14 and 16) with different sensors were used in the study period, it is likely that NDVI values will differ across the study period. In order to investigate the stationarity in the data and determine if there were any trends in the NDVI values over the study period, a time series of yearly average NDVIs for all pixels in the province was plotted, and a simple linear function was fitted to the data to determine the slope of the trend. A non-linear function was also fitted excluding the 1993/1994 and 1994/1995 anomalies in an attempt to improve the variance accounted for (Figure 4). This plot should be read in conjunction with the images presented in Figure 2.

The potential effects of rainfall on the NDVI values were investigated by correlating yearly average rainfall with yearly average NDVI for all pixels in the province. These rainfall data were derived from gridded rainfall surfaces that were interpolated from rainfall data captured by between 350 and 450 rainfall stations across the province by the Institute of Soil, Climate and Water at the Agricultural Research Council.

3.4 Rain-use efficiency curves and identification of outliers

The relationships between $NDVI_{avemax}$ and mean annual precipitation (MAP) were examined through regression analysis. A Gompertz logistic curve (often used to describe growth) was fitted to the data and a non-linear regression analysis was carried out between $NDVI_{avemax}$ and MAP. The Gompertz model used to describe the asymmetrical logistic relationship contained four parameters as follows:

$$NDVI = a + b * \exp(-\exp(-c(MAP-d)))$$

where 'a' is the lower asymptote, 'b' is the upper asymptote, 'c' is the MAP level of maximum NDVI increase, and 'd' is the rate of increase. Because the data number of points fed into the regression was large (n = 88 120), a four parameter model and the associated degrees of freedom did not invalidate the fitting of this curve.

The fitted curve allowed for the identification of outliers, which are theoretically those falling outside the range of normal variability and are therefore potentially caused by human activities. Outliers above the curve represent those sites that are greener than they should be, for example, irrigated lands and riparian zones, while outliers below the curve represent sites

that are not as green as they should be, i.e. the degraded areas. Different thresholds of variation from the fitted curve (using 0.75, one and two standard deviations, calculated as studentized residual values for each data point) were experimentally chosen to represent the cut-off's below which points were classified as outliers. These represent probability levels of 77 %, 84.13 % and 97.72 % for standard deviations of 0.75, one and two respectively.

The same procedure was carried out for the relationship between $NDVI_{avemax}$ and the growth days index (GDI) to investigate whether GDI was a better predictor of $NDVI_{avemax}$ than MAP. The GDI was calculated using the following equation (Ellery et al., 1991):

$$GDI = \sum_{i=1}^{12} (\text{Rainfall}_i / \text{Evaporation}_i) * \text{days}$$

where 'i' is months and rainfall/evaporation > 1.

3.5 *Land-cover characteristics of mapped degraded areas*

In order to begin to understand how land-cover and land-use may affect degradation, a descriptive analysis of the distribution of mapped degradation in relation to different land-cover and use classes was undertaken. The latest land-cover dataset for South Africa (CSIR and ARC, 2004) was summarized from a 25 m spatial resolution, to a one kilometre resolution in order to correspond with the NDVI data. The land-cover category of each square kilometre grid cell was determined by summarizing the modal land-cover category of all 25 square kilometre grid cells falling within it, of which there could be up to 16.

For the degraded area, mapped using a threshold of one standard deviation, the proportional area under various land-cover and land-use classes was calculated.

3.6 *Validation*

Although a detailed ground-truthing exercise, measuring amongst other variables, land-cover, geology and soil type, landform, state of the soil surface (capping, pedestal and gully erosion, presence/absence of debris) and vegetation condition (dominance and desirability of the woody and herbaceous layers), is desirable to validate this degradation classification, it was not possible to conduct one for this study. Consequently, existing independent datasets were used to validate the results qualitatively. The National Land-cover 2000 dataset, which

includes several classes for degraded land, was compared to the derived classification. The dataset was resampled to a one kilometre spatial resolution to correspond with that of the NDVI data. Confusion matrices and a Kappa Index of Agreement (KIA) between the surfaces were then calculated. Also, the district level degradation indices from Hoffman et al. (1999) were compared visually with the derived degradation dataset.

4 RESULTS

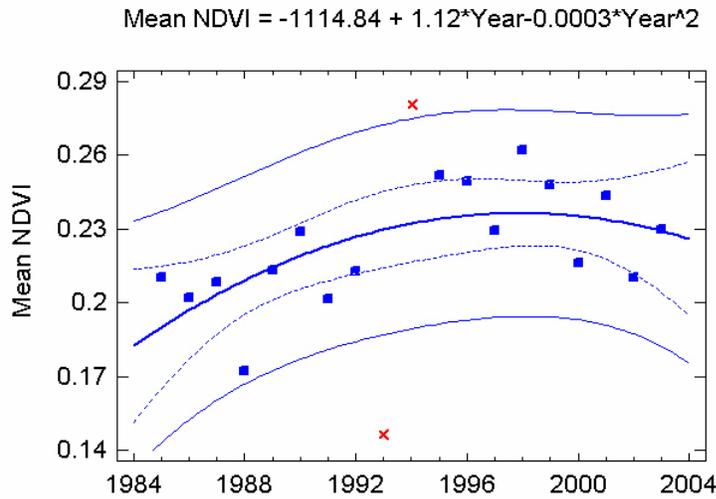
4.1 *NDVI and rainfall trends*

A time series plot of yearly average NDVI values for all pixels in the province is presented in Figure 4a. The patterns described here should be read in conjunction with the description of the yearly images given section 3.2. It is evident that the NDVI values after 1995, although decreasing, are higher than those prior to 1993. There are two anomalies in the time series, namely 1993/1994 and 1994/1995, denoted by the crosses on the graph. These resulted from the malfunction experienced with the satellite sensor in 1994, resulting in images being available for only part of each growing season. Averages are therefore not representative of the entire growing season, but only the latter and former parts of them for 1993/1994 and 1994/1995 respectively. The data from these anomalies were excluded in the degradation analysis, but have been included here for illustrative purposes. A linear regression including these anomalies revealed that there was not a significant increasing overall linear trend in the data. Having excluded the two anomalies, however, there was a significant increasing linear trend in the data ($p < 0.05$). A curved trend in NDVI values was also significant ($p < 0.05$), and explained more of the variability than did a linear model.

These significant trends illustrate possible influence of an external factor such as rainfall or changes in sensor calibration and sensitivity over the study period. A correlation analysis showed a moderately strong relationship between mean NDVI and mean annual rainfall ($r = 0.54$), and that an increase or decrease in rainfall in general elicited a similar response in NDVI values over the time series (Figure 4b). Interestingly, anomalous rainfall years including the dry conditions experienced in 1991/1992, and the floods in 1995/1996 and 1999/2000 did not elicit such drastic responses in NDVI. This picture shows that the stationarity in the NDVI

data series may be low; however, it is likely that rainfall alone is not a sufficient factor influencing NDVI values as it doesn't explain the elevated values after 1995. It is likely that the increasing sensitivity of the sensors or atmospheric effects in this period influenced the higher NDVI values.

(a)



(b)

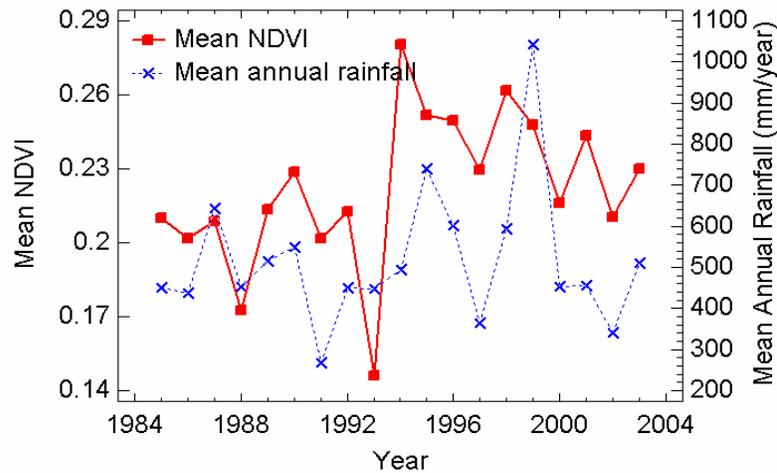
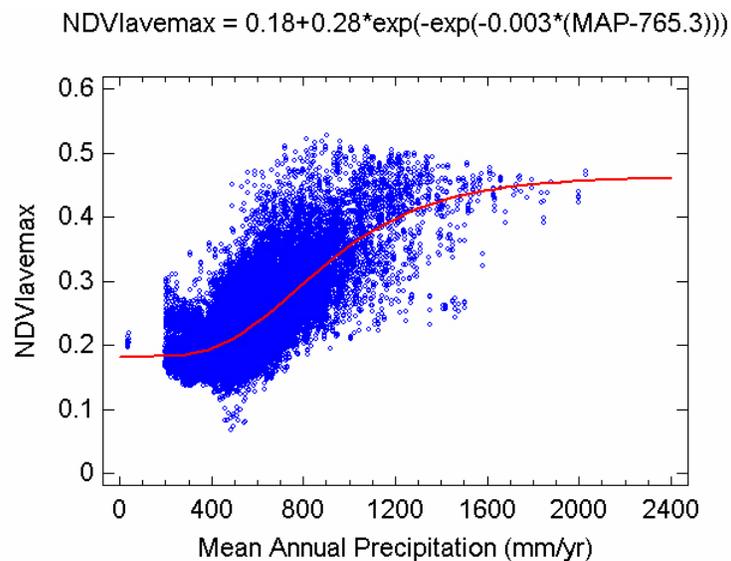


Figure 4: (a) Second order polynomial regression to test the significance of the curvi-linear trend in yearly cumulative NDVI values; ‘x’ denotes the two anomalous data points excluded from the analysis, and (b) trend in yearly mean NDVI and mean rainfall values for all pixels in Limpopo Province between the years 1984-2004.

4.2 Rain-use efficiency curves

The correlation coefficients between $NDVI_{avemax}$ and MAP, and $NDVI_{avemax}$ and GDI were 0.73 (53.29 %) and 0.5 (25 %) respectively, indicating moderately strong relationships between NDVI and both variables. Linear regressions revealed statistically significant relationships between $NDVI_{avemax}$ and MAP and GDI respectively ($p < 0.005$ for both). Considering that the distribution of the data suggest non-linearity, and the literature (e.g. Le Houerou, 1984; Li et al., 2004; Hein, 2006) shows there should be both an upper saturation level above which further inputs of rainfall have limited effect on productivity, and a lower level below which productivity doesn't decrease, it was felt that a sigmoidal curve would represent the relationship more accurately. Plots of fitted Gompertz logistic curve models regressing $NDVI_{avemax}$ to MAP and GDI respectively are given in Figure 5. These non-linear regressions explained 55.64 % and 25.76 % of the variation in NDVI respectively, marginally higher than those of the linear relationships. Because GDI was found to be a poor predictor of $NDVI_{avemax}$ in this case, the analysis using GDI was not taken further.

(a)



(b)

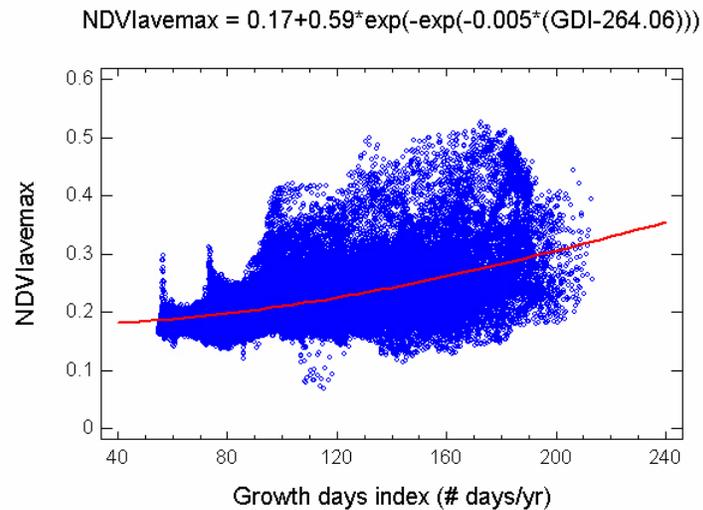


Figure 5: Non-linear regressions using a fitted Gompertz logistic function between long-term average maximum NDVI and (a) mean annual precipitation, and (b) growth days index. The fitted functions are given above each graph.

Although the regressions could be improved substantially by excluding the residuals from the analysis, the purpose of this exercise was to identify the residuals and map those greater than defined thresholds of standard deviation away from the predicted values given by the fitted model (indicated in red on the regression plots in Figure 5). These are theoretically the pixels representing degraded areas, having a lower rain-use efficiency, or growth efficiency than should be the case. A map of the calculated studentized residuals is presented in Figure 6. Negative residuals, falling below the fitted curve and denoted by red areas, represent those areas where degradation may be taking place. Noteworthy are the dark red areas in the southern central area of the province, in the northern central areas, and the strip stretching along the eastern border.

Classifications of residuals based on different thresholds of deviation from the predicted model are shown in Figure 7. One standard deviation lower than the predicted model appeared to be the optimal threshold, when compared to the validation data sets, as 0.75 and two standard deviations map too much and too little area as degraded, respectively.

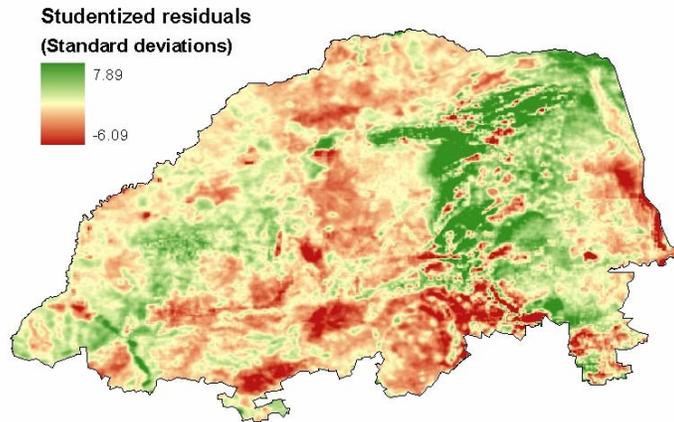


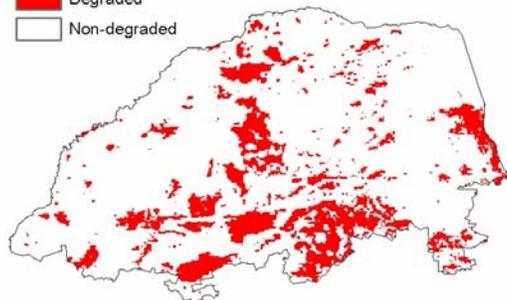
Figure 6: Map of studentized residuals depicting observed deviation from the predicted Gompertz rain-use efficiency model established in the regression of average maximum NDVI and mean annual precipitation. Negative standard deviations (red) depict areas where rain-use efficiency is lower than it should be, while positive standard deviations (green) depict areas that have higher rain-use efficiency.

(a)

(b)

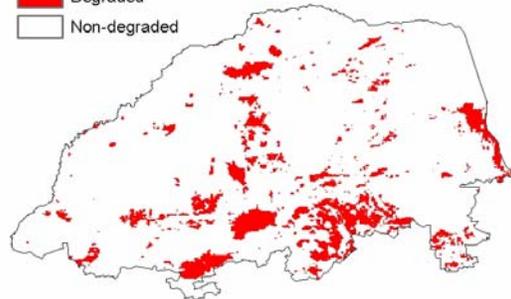
Threshold: 0.75 standard deviations

■ Degraded
□ Non-degraded



Threshold: 1 standard deviation

■ Degraded
□ Non-degraded



(c)

Threshold: 2 standard deviations

■ Degraded
□ Non-degraded

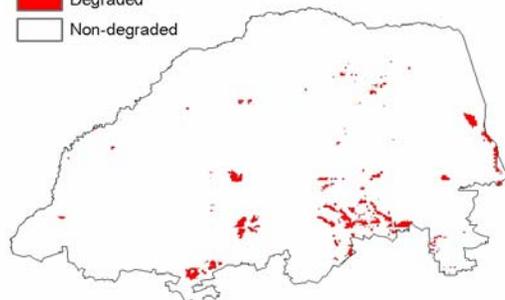


Figure 7: Maps of degradation based on thresholds of (a) 0.75 standard deviations, (b) one standard deviation, and (c) two standard deviations, less than the predicted model

4.3 *Land-cover characteristics of mapped degraded areas*

Much of the area mapped as degraded (57.85 %) is untransformed land used primarily for the grazing of domestic animals. It is comprised mainly of savanna vegetation, and grassland to a lesser extent (Table 2). Approximately 13.23 % of degraded are taken up by commercial and subsistence dryland cultivation. Both commercial irrigation areas and forestry plantations contribute substantially to the degraded areas.

Table 2: Land-cover characteristics of mapped degraded areas. A threshold of one standard deviation was used to define the degraded area, and the land-cover classes were aggregated from those used in CSIR and ARC (2004).

Land-cover class	% of mapped degraded area
Thicket and bushland	32.90
Grassland	10.84
Cultivation: commercial, irrigated	8.85
Cultivation: commercial, dryland	8.57
Woodland	8.11
Forest plantations	7.52
Shrubland	5.99
Cultivation: subsistence, dryland	5.54
Other ^a	5.30
Erosion and bare soil	4.95
Wetlands	1.42

Note: Figures do not add up to 100 due to rounding

^a this class includes waterbodies and urban areas

5 VALIDATION AND DISCUSSION

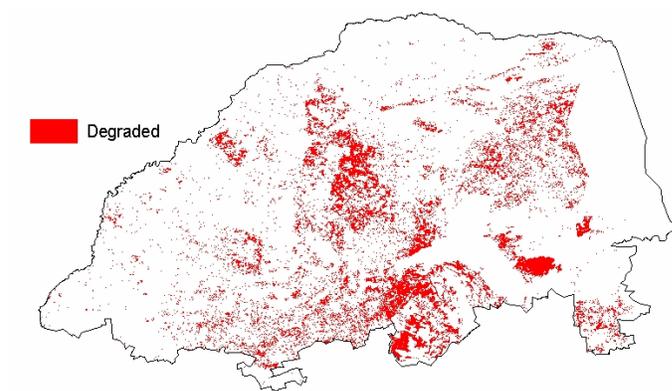
While there are several studies that provide independent datasets for validation purposes, the methods used in these studies differ substantially, rendering comparison difficult. The National Land-cover 2000 project mapped land-cover across South Africa using an automated unsupervised classification technique on Landsat imagery from 2001 and 2002. The result is a

land-cover map of South Africa at a 30 m² pixel resolution and with a minimum mapping unit of 100 m². The classification included several classes for degradation, which were mapped using pixel brightness only. Although independent field workers conducted a ground-truthing exercise, there was no rigorous degradation assessment using standard soil and vegetation condition indicators included in this. A further drawback of this dataset is that its definition precludes the possibility of other land-cover classes such as cultivated areas being degraded, which according to Hoffman et al. (1999) in many dryland cultivation areas of the province is exactly the case. The assessment of the degraded class can therefore not be considered scientifically rigorous.

The second dataset is the National Review of Land Degradation published in 1999 (Hoffman et al., 1999). While this is the first comprehensive analysis of land degradation across the country, the assessment was conducted through perception-based surveys with extension officers and resource technicians. This resulted in indices of soil, vegetation and combined degradation for each municipal district. The indices are therefore based on perceptions and semi-quantitative measurements, and are therefore only applicable in a relative sense. Further, because indices are averaged for districts, the exact locations of degradation within each district are not known. The results of both these studies are presented in Figure 8.

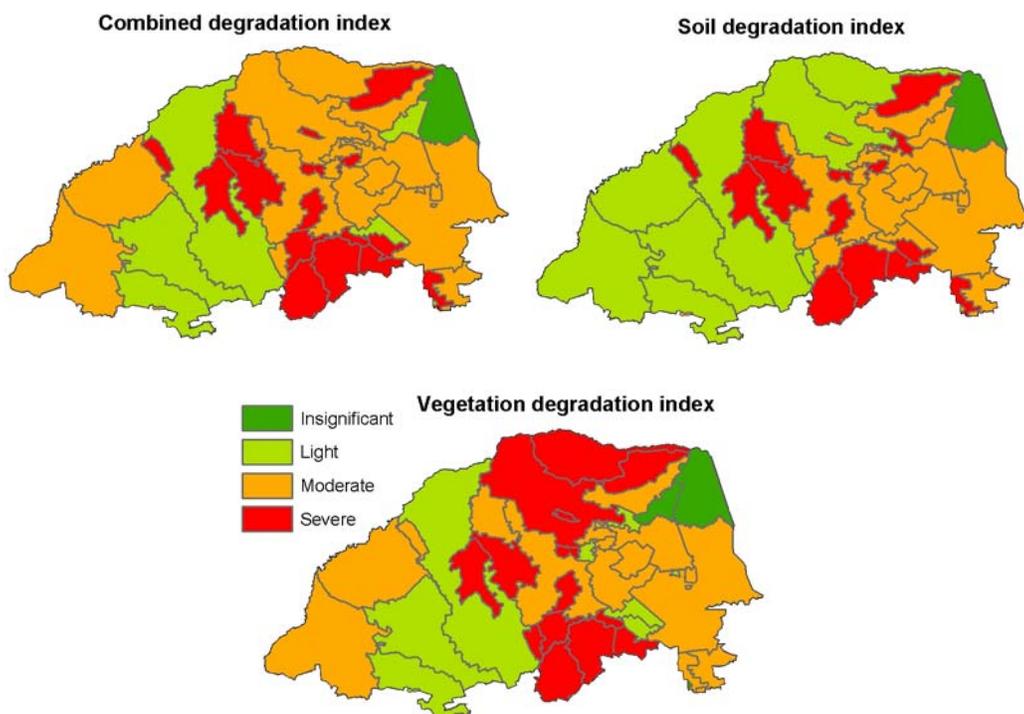
While there is reasonable similarity between the NLC2000 degraded classification and the district degradation data, notably in the southern and central regions of the province, the similarity between the NLC2000 classification and the Vegetation Degradation Index (VDI) is less convincing, particularly in the northern districts. This indicates that there may be an underestimation of the area of degradation in the NLC2000 dataset, or alternatively an overestimation in the VDI dataset.

(a)



Source: Extracted from the National Land-cover 2000 map, provided by the Council for Scientific and Industrial Research

(b)



Source: Hoffman et al. (1999)

Figure 8: Independent validation datasets: (a) the ‘degraded’ land-cover class of the National Land-cover 2000 project, mapped from Landsat satellite imagery taken in 2001/2002, and (b) the degradation indices from the 1999 National Review of Land Degradation constructed per

municipal district through perception-based surveys with field technicians and extension officers.

The agreement between the mapped degraded areas in this study and the NLC2000 dataset is low and variable. The Kappa Index of Agreement was found to vary between 9.89 and 12 % depending on the threshold used to map degraded areas. This low level of agreement was expected, as the NLC2000 data were mapped degradation at a far higher spatial resolution, thereby increasing the number of pixels classified as degraded through the detection of smaller patches of degradation. The statistics are therefore not reliable in measuring agreement between the data sets in this case.

While there is general agreement in the communal areas particularly in the southern central and central regions of the province, where degradation is known to be prevalent (Hoffman and Ashwell, 2001; CSIR and ARC, 2004), and in surface mining areas devoid of vegetation, there is considerable disagreement elsewhere. For example, unlike the other datasets, this study has mapped many dryland cultivation areas (both subsistence and commercial), as degraded. Dryland areas are dependent on rainfall, and therefore generally stand fallow in the dry season. This results in lower long-term average NDVI values, with pixels falling below the rain-use efficiency curve.

It is evident that soil reflectance has affected NDVI values substantially. Several of the areas with particularly low NDVI values and thus classified as degraded coincide with dark coloured soils with a high percentage of smectitic clay minerals, that are derived from basic igneous substrates. Notable is the area in the Kruger National Park along the eastern boundary of the province that is underlain by basalt, as well as the two areas coinciding with the dryland cultivated areas in the southern central area of the province, underlain by basalts and gabbros. Several of the mapped degraded areas also coincide with dolerite intrusions. The effects of soil optical properties on vegetation indices, and NDVI in particular, has received considerable attention in the literature (e.g. Rondeaux et al., 1996; Gilabert et al., 2002). NDVI is known to be sensitive to soil background, and several adjusted vegetation indices have been developed to minimize this effect (Pearson and Miller, 1972; Richardson and Wiegand, 1977; Huete,

1988; Baret and Guyot, 1991; Qi et al., 1994; Rondeaux et al., 1996; Gilabert et al., 2002). The results of this study therefore confirm those in the literature. The critical question for mapping land degradation in this area is how can the effects of background soil properties be minimized. The limitation of the adjusted vegetation indices is that they are more complex than NDVI in that they require the use of user defined constants and scaling factors, which would vary over and be difficult to determine for a large study area. The next logical step for this study therefore would be to mask out those areas defined as degraded that coincide with the dark coloured substrates. Alternatively, correction of the NDVI values during pre-processing based on a derived algorithm could be used to correct for soil background effects. Further research into this is necessary.

A final explanation of these expected differences is that the NLC2000 map was mapped using a snapshot of satellite imagery in 2001 and 2002, and considering the variability of vegetation productivity in semi-arid areas, may not be representative of consistent conditions in the long-term. This contrasts with much of the recent research, such as Milich and Weiss (2000), who investigated variability in vegetation productivity over a 15 year time period in the Sahel using coefficient of variation of NDVI images, which has investigated longer-term trends instead.

There is reasonable agreement with the 'severe' degradation classes of Hoffman et al. (1999) for degraded land in communal areas in the southern and central regions of the province, as well as agreement with the 'light' and 'insignificant' classes. However, it is inappropriate to compare a boolean map of degradation with one representing different classes of severity. Comparing Figure 6 depicting the studentized residuals, with the Hoffman et al. (1999) indices, shows a compelling similarity, with the exception of cultivated areas just west of the central regions.

The results of this study provide some important insights for future research using satellite-derived indices for desertification, specifically the productivity-rainfall relationship-type index. Many similar studies to this have fitted a linear regression curve to the relationship (for example Herrmann et al., 2005; Li et al., 2004), and while this may be applicable for certain areas where rainfall is the primary limiting factor for productivity, such as in semi-arid

areas, in areas where there is a wide range in rainfall, as is the case in Limpopo, a saturation level occurs above which further inputs of rainfall have limited or no effect on NDVI values (Li et al., 2004). At these high rainfall levels, productivity becomes limited by nutrient availability rather than water (Hein, 2006). Several recent studies (Hein, 2006; O'Connor et al., 2001; Wylie et al., 1992) also showed that a linear curve is not able to account for relatively low vegetation production at high rainfall levels. The same is true at low rainfall levels, where more water is lost through evaporation, leaving less plant available water, the RUE decreases (Hein, 2006; Le Houerou, 1984). The current study therefore confirms the applicability of the sigmoidal curve in this case. However, further work is required to understand how RUE varies with rainfall, and how this relationship varies over time on a pixel by pixel basis. This would allow for the identification of trends in RUE, which would add depth to this study.

Although a sigmoidal function provides a better fit to the data than does a linear one, the low percentage of variance accounted for by the fitted curves point to factors other than rainfall influencing vegetation productivity. These may include vegetation type, land-cover, soil and geology, and soil moisture. Hein (2006) using RUE, used 'effective' rainfall instead of total rainfall in his calculation as it is a better indicator for the amount of rain available to plants, particularly in semi-arid environments that are subject to a high annual rainfall variability. 'Effective' rainfall is the total rainfall corrected for water loss due to run-off and evaporation. Perhaps this would be a better predictor for NDVI in some parts of the province. It is also suggested that stratification of the study area occur prior to the analysis, in order to normalize for geology, terrain-type, vegetation type and other factors that may influence productivity (cf. Prince and Tucker, 1986; Bastin et al., 1995; Sannier et al., 1998; Al-Bakri and Taylor, 2003; Li et al., 2004; Budde et al., 2004, Wessels et al., 2004).

6 CONCLUSION

It is clear that there is potential for using a satellite-derived index of productivity to assess land degradation in the Limpopo Province of South Africa. For the method to be used on a national scale, further research is required to account for the relationship between NDVI response and

rainfall, and to understand how this relationship varies according to the eco-climatic conditions across the country. Further research is also required to understand other biophysical factors such as geology influencing NDVI values. It will be prudent for further research in this regard to be undertaken using higher resolution imagery such as MODIS, which is reported to have improved measurement capabilities through improved sensor technology, although the unavailability of precipitation and other biophysical data at this scale may prove to be a hindrance.

This study, and other remotely sensed or opinion-based studies confirm the necessity of having a rigorous, objective, appropriate-resolution in situ dataset against which various degradation indices can be validated. Existing degradation datasets are inadequate because (1) they were not compiled using rigorous resource assessment methods using accepted degradation indicators, and (2) the resolution, type of data and methodologies render it difficult to make a quantitative comparison.

Given the sizeable land degradation challenges faced by South Africa, it is hoped that the extensive body of research undertaken internationally will be evaluated and adapted for use locally.

7 ACKNOWLEDGEMENTS

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8 APPENDICES

8.1 *Appendix 1: Literature review*

The long-term productivity of South Africa and the well-being of a large proportion of the population of which are non-urban dwellers (DEAT 2003), and who depend largely on the services derived from ecosystems, are threatened by degradation and desertification.

South Africa became a signatory to the United Nations Convention to Combat Desertification (UNCCD) in January 1995, and ratified it in September 1997. In terms of the UNCCD, and in furtherance of a long history of concern for maintaining the productivity of the land in South Africa, South Africa has prepared a National Action Programme (NAP) for Combating Land Degradation to Alleviate Rural Poverty (Department of Environmental Affairs and Tourism, 2004).

These initiatives are particularly appropriate in South Africa when considering the definition of desertification. The UNCCD defines desertification as: *'land degradation in arid, semi-arid and sub-humid areas'* (United Nations, 1994), which effectively covers 91% of South Africa, and therefore implies that the vast proportion of the country is potentially susceptible to some form of desertification. Furthermore, implicit in the definition of land degradation, which is defined as: *'reduction or loss, in arid, semi-arid and dry sub-humid areas, of the biological or economic productivity and complexity of rainfed cropland, irrigation cropland, or range, pasture, forest and woodlands resulting from land uses or from a combination of processes, including processes arising from human activities and habitation patterns, such as: (i) soil erosion caused by wind and/or water; (ii) deterioration of the physical, chemical and biological or economic properties of soil; and (iii) long-term loss of natural vegetation;'* (United Nations, 1994), is the emphasis that human life depends on the continuing capacity of biological processes to provide goods and services (White *et al.* 2000). The long-term productivity of developing countries like South Africa, of which approximately 45% of the population are non-urban dwellers (DEAT 2003), and who therefore depend largely on the services derived from ecosystems, is consequently threatened. Indeed, White *et*

al. (2000) surmises that water scarcity and soil degradation are contributing factors to the 16 % reduced yields in food production in Africa.

As will be illustrated in the literature review below, there are a lack of objective methods for assessing desertification and land degradation. Several large-scale studies have been conducted for South Africa, most notably Acocks (1953), United Nations Environment Programme (UNEP) (1997) World Atlas of Desertification, and recently the land degradation study conducted by Hoffman *et al.* (1999). There are drawbacks to these studies. Nicholson *et al.* (1998) points out that the UNEP study resulted in a map of desertification severity that was extrapolated from risk factors, and thus included little information on the actual status of desertification. The result is that the levels of desertification were over-exaggerated. The UNEP study concluded that approximately 60 % of South Africa was degraded. The Hoffmann *et al.* (1999) study was perception-based, and therefore not built on quantitative, objective measurements, and so areas most severely affected only in a relative sense, were identified. Several localised studies using satellite imagery have been conducted for South Africa (for example Jarman and Bosch (1973), Viljoen *et al.* 1993, Tanser and Palmer (1999), Wessels *et al.* (2004)), but there exists no comprehensive scientific regional study of desertification for Southern Africa. Monitoring for the purposes of the NAP will need to be conducted in a systematic, cost effective, objective, timely and geographically accurate way. In fact the NAP and associated strategies have been developed based on the baseline information provided in Hoffman *et al.* (1999), and no update on the status of desertification exists for the country to guide strategy development and implementation of the NAP. South Africa therefore has no idea whether there has been an improvement or deterioration in the status of desertification. This project sets out to test a method for monitoring and assessment based on remote sensing.

The following questions have emanated from a review of past literature:

- What is the extent of desertification in the Limpopo Province of South Africa?
- Are the communal rangelands and dryland cultivation areas the primary locations of degradation?

- Can a satellite-based measure of long-term productivity be used to rapidly identify and monitor areas of potential desertification and degradation in the Limpopo Province.

8.1.1 Historical background

Since the promulgation of the UNCCD in 1994, land degradation has become a central issue in conservation and development (van Lynden and Mantel, 2001), especially in Africa. Even prior to this, the United Nations Conference on Desertification (UNCOD) was held in Nairobi in 1977, and emanated from, amongst other dryland concerns, the severe Sahelian drought (1968-1974) and subsequent food crisis of the early 1970's (Hoffman et al. 1999). Although apparently unsuccessful in achieving its objectives (Hoffman et al. 1999), this was the first multi-national political initiative to combat desertification.

South Africa, although not officially represented at UNCOD, has been dealing with issues of land degradation for over a century (Hoffman et al. 1999). Early accounts of degradation in the Karoo date back to 1873 while other reports were presented to Parliament in 1877 and 1879 (Hoffman et al. 1999). After a report on droughts, rainfall and soil erosion in 1914 by the Senate Select Committee, the Drought Investigation Commission published a report in 1923, which focused primarily on the impact of land use practices on rainfall efficiency, particularly the effects of kraaling and overstocking on vegetation cover and soil erosion. Thereafter, the Desert Encroachment Committee, established in 1948, and which was heavily influenced by Acocks (1953) work, produced the expanding Karoo hypothesis, which has dominated the land degradation debate in South Africa for almost half a century (Hoffman et al. 1999). There has been a great deal of research on this topic, with the consequent neglect of other aspects of desertification.

8.1.2 Towards a definition of desertification

There are many definitions of and concepts related to desertification. The UNCCD defines desertification as: '*land degradation in arid, semi-arid and dry sub-humid areas resulting from various factors, including climatic variations and human activities*' (United Nations, 1994). Land degradation is the '*reduction or loss, in arid, semi-arid and dry sub-humid areas, of the*

biological or economic productivity and complexity of rainfed cropland, irrigation cropland, or range, pasture, forest and woodlands resulting from land uses or from a combination of processes, including processes arising from human activities and habitation patterns, such as: (i) soil erosion caused by wind and/or water; (ii) deterioration of the physical, chemical and biological or economic properties of soil; and (iii) long-term loss of natural vegetation' (United Nations, 1994). An earlier definition of desertification by UNEP (1984) referred to desertification as being caused solely by humans, but as above, the official definition takes the effects of climatic variability into account. Some definitions mention specific causes such as alien infestation, overgrazing, deforestation, fuel-wood collection, while others include systems ecological concepts such as productivity and ecosystem resilience. As Rasmussen et al. (2001) and Zha and Gao (1997) point out, it is evident that desertification is a complex process, with various causes and processes involved, and definitions vary as to how broadly they define the concept. Many authors use narrower definitions, relating to their field of expertise. Rasmussen et al. (2001) uses the following examples: geomorphologists may focus on erosion processes, soil scientists on physical and chemical degradation, ecologists on ecosystem productivity and botanists on species composition. This seems to be the case in China, where the assessment of overall nationwide desertification has been difficult due to the complexities of desertification definition, types, causes and degrees in China (Yang et al., 2005). Consequently many studies, with narrow definitions, have been conducted in isolation of one another.

There has also been a focus on the long-term irreversibility of desertification and the scale at which it occurs. Prince (2002) believes that due to the large number of definitions, research has resulted in contradictory observations on the nature of desertification, and specifically with regard to its relationship with causative factors. The consequence of this is that studies are not appropriately designed, and do not therefore result in the advancement of understanding of the subject. He therefore proposes a hierarchical conceptualisation and definition of the process of desertification, which is based on both spatial and temporal scale. He suggests that the land cover dynamics of desertification occur at the spatial and temporal scales of $1^{\circ} \times 1^{\circ}$ and 20-50 years respectively, at which the active influences may be markets for staple foods, population

density and rainfall. Coarser scale processes which determine variables that set the boundaries for desertification are variables like regional climate, land tenure and long-term government policies. Vegetation dynamics and human land management, which are the most frequently investigated processes in degradation and desertification studies, occur at the finest scale. Prince's definition therefore implies that desertification occurs at scales larger than that of natural fluctuations in rainfall and vegetation productivity, and human land management practises.

Although 91 % of South Africa (Hoffman et al. 1999) is potentially susceptible to some form of desertification, the National Action Programme (DEAT, 2004) refers to land degradation and does not include the concept of desertification. It commendably views land degradation in multiple contexts: socio-economic, environmental and cultural, and it takes a holistic approach to reversing degradation, including many of the causes and processes in its strategy.

8.1.3 Desertification research using remote sensing technology

Internationally, there is a vast body of literature relating to desertification and land degradation, and the assessment and measurement thereof. Until recently, few regional or national inventories have been conducted in Southern Africa. Some larger scale assessments were conducted and maps produced for South Africa, such as those discussed above and detailed in Hoffman et al.'s degradation review (1999). The emphasis of past research seems to have shifted from the assessment of areas of localized importance, using field-based range condition assessment techniques, such as the Ecological Index Method (Vorster, 1982), the Key Species method (Trollope, 1990), the grazing index method (Du Toit, 1995), to an ecosystem approach using medium resolution, and increasingly higher resolution, satellite remote sensing techniques for large scale and regional assessment (for example UNEP, 1997; White et al., 2002; Borak, et al., 2000; Tucker and Nicholson, 1998; Milich and Weiss, 2000; Prince, 2002; Evans and Geerken, 2004; Scholes and Biggs, 2004; Wessels et al., 2004; Li et al., 2004; Budde et al., 2004; Herrmann et al., 2005). The move toward a more systems approach has been precipitated by the need for comprehensive and integrated policies and

strategies at national and regional level, for example the National Action Plans required by the UNCCD, and presumably the deepened understanding of scale issues in desertification.

South Africa has had a long history of monitoring vegetation using satellite imagery. Jarman & Bosch (1973) assessed the value of using satellite imagery in measuring vegetation change in the arid parts of South Africa and concluded that the Karoo had moved a further 70 km north-eastward. Many localized studies on degradation have used remote sensing, in particular aerial photography. Talbot's (1947) study on soil erosion in the Cape Province is an example of the use of aerial photography. Makhanya (1993) used a combination of aerial photography and SPOT XS images to map the extent of settlements and land degradation in a localised area of communal land in a former homeland of Mpumalanga, using mainly manual and visual interpretation techniques. These results agree with results obtained elsewhere in South Africa, where SPOT XS imagery was used to classify land cover in the former homeland areas of the former north-eastern Transvaal (Viljoen et al. 1993). Other studies include: Makhanya (1993), Viljoen et al. (1993), Mackay and Zietsman (1996), Tanser and Palmer (1999), Kiguli et al. (1999) and Thompson and Fairbanks (1999), Wessels et al. (2004), Scholes and Biggs (2004), and CSIR and ARC (2005).

Elsewhere, Fadul et al. (1999) studied gully erosion in Sudan, while Jurio and van Zuidam (1998) compared various image processing techniques using Landsat TM, Spot panchromatic and aerial photographs to map bare soil in a known desertified area of Argentina. They found that a merging of the Landsat and Spot panchromatic satellite imagery in a Brovey Transformation to be the most useful for identifying degraded areas and their degree, land features, and vegetation features.

Trends in remote sensing have involved a shift from a manual, visual approach to the interpretation of images, in both aerial photography and satellite imagery, for example Thompson (1996), to a more model-based approach involving indicators and proxy variables, measurable over large areas. The National Land Cover Database (Thompson 1996) for South Africa, and the latest update the National Land-cover 2000 dataset, were created by classifying land cover and land use using Landsat 5 satellite imagery, and included several categories for degradation. For the former dataset, land class units were mapped visually for the entire

country by manually digitising hardcopy satellite maps, while for the latter automated image classification techniques were used. The vast majority of recent and current assessments and research however, is focused on the use of indicators and proxy variables. The latest study to evaluate remote sensing techniques for assessing land degradation is Wessels et al. (2004). This study looked at the applicability of using coarse-scaled satellite imagery to identify degraded areas in certain zones of land capability in the Limpopo Province. It concluded that coarse scale NDVI data was suitable for identifying degraded areas in most of the land capability units tested. The Wessels et al. (2004) study laid a solid foundation for desertification assessment in the Limpopo Province, and this study builds on that foundation for an assessment of the entire province. Scholes and Biggs (2004) as part of a southern African regional assessment of ecosystem services, mapped degradation using NOAA AVHRR NDVI data from 1998 to 2002, and related the NDVI values to a water balance index called growth days.

Valid desertification indicators should be expected to have some of the following properties (Mabbutt 1986, DEAT 1998, Lambin and Strahler 1994):

- Be specific to desertification pressures alone;
- Be sensitive to change in desertification status;
- Contain significant information content that has biological meaning;
- Be readily observable and quantifiable;
- Be widely applicable;
- Be suitable for repeated update;

Mabbutt (1986) is positive about the use of these indicators for extrapolation mapping, a method for which was formulated by the Food and Agriculture Organisation (FAO) in 1984. This method presents indicators, some of which are collected in the field and calibrated for more generalised mapping from satellite imagery and aerial photography, for the status, rate and risk of desertification by the following processes:

- Vegetation cover degradation; and
- Soil degradation including water and wind erosion, salinization crusting and compaction, and organic matter reduction (Mabbutt 1986).

Mackay and Zietsman (1996) assessed rangeland condition in the Ceres Karoo region of the Western Cape by comparing field survey data with the soil adjusted vegetation index (SAVI). Tanser and Palmer (1999) conducted a localised degradation assessment in South Africa using Landsat Thematic Mapper imagery, by comparing the NDVI with the moving standard deviation index (MSDI), which they describe as a measurement of landscape heterogeneity, a key determinant of degradation status. With the exception of the most arid site within a single ecosystem, the NDVI and MSDI resulted in similar conclusions in terms of degradation. Tested across five different ecosystems, the MSDI performed consistently while NDVI produced erroneous results in the arid and semi-arid ecosystems. Their conclusion was that the MSDI is a powerful adjunct to the NDVI. Lambin and Strahler's (1994) study in west Africa using a similar measurement termed the 'spatial structure indicator' found that the NDVI and spatial structure indicator were slightly redundant as indicators of land cover change, but that the indicator measured over a long term, may be able to detect anthropogenic processes of change. Liu and Kogan (1996) used the NDVI and the vegetation condition index (VCI) derived from NOAA AVHRR data, to map a time series of potential drought areas on a continental and regional scale for South America. Threshold values for the NDVI and VCI were set, as determined in previous studies, and pixels with values below the thresholds were defined as drought areas. Milich and Weiss (2000) tested the interannual coefficient of variation of the mean growing season maximum monthly NDVI composites for 1980-1994, calculated from the AVHRR satellite.

Several authors have conducted studies using the concept of rain-use efficiency (RUE) of vegetation. RUE is defined as the ratio of net primary production (NPP) to rainfall, and a decrease in this efficiency occurs in association with land degradation (Diouf and Lambin 2001). Diouf and Lambin (2001) assessed dryland land cover modification in Senegal by using a combination of remote sensing and field-based measurements. They compared field-based measures of biomass to NDVI (as a proxy variable for biomass), in terms of both rain use efficiency (RUE) and resilience of the vegetation post-drought. They found that in years of normal rainfall and on sites with no degradation, as established through field studies, the use of NDVI did not reveal trends in degradation. Further, the indicator that would most likely reveal

trends in land cover modification was RUE, based on field measured biomass rather than remotely sensed vegetation index data. Other research (Prince et al., 1998; Nicholson et al. 1998; Herrmann et al., 2005) conducted in the Sahel, has used NDVI as a proxy variable for NPP in the computation of RUE, and all studies agree that there has been no reduction in productivity of the area. Herrmann et al. (2005) show that there has in fact been a recent greening over a large area of the Sahel, largely due a recovery in rainfall from the great Sahelian drought.

A further trend in desertification research, is the use of localized scaling or local variance analysis of both NDVI, and the relationship between NDVI as a proxy for productivity, and rainfall. This is aimed at removing the potential effects of terrain type on productivity and thus its effects on NDVI values. Several studies (for example Li et al., 2004; Wessels et al., 2004; Scholes and Biggs, 2004) have used NDVI data to investigate the relationship for different ecozones or land-cover types, while Budde et al., (2004) used a moving window of 9x9 or 15x15 pixels to identify anomalies in relation to a pixel surroundings in Senegal. In some of these studies, identification of anomalies outside of a certain threshold is the technique used to identify degraded areas.

Prince's (2002) research in Zimbabwe, Mozambique and the surrounds, proposes the use of RUE as a useful indicator of degradation using a carbon cycle model which utilises satellite imagery to estimate net primary productivity (NPP).

A shortcoming of using RUE in the measurement of desertification is that RUE is applicable only when rainfall is the major limiting factor in productivity (Prince 2002). He therefore proposes the use of a biogeochemical model to estimate potential NPP, and uses this to compare with the actual NPP. The indicator proposed is therefore the difference between the potential and actual NPP. A further indicator proposed is the Locally Scaled NPP, which for each pixel in a specific terrain type, is the proportion of the maximum observed NPP within that terrain type.

Due to Prince's (2002) proposal of the importance of scale in the definition of desertification, he believes that assessment using remote sensing is the only practical method to objectively assess desertification. He states that despite the mapping initiatives that have

been carried out to date, progress has been inhibited because of the lack of any ready measured, objective indicators, applicable over a large area. He refers to both the Global Assessment of Soil Degradation (GLASOD) and the World Atlas of Desertification (UNEP 1997), which he states relied on qualitative measurement and incorporated significant subjectivity into the analyses. This echoes the most recent and comprehensive assessment of degradation in South Africa, a perception-based survey undertaken by Hoffman et al. (1999) to identify the main forms and locations of degradation in South Africa. They found that there were large differences in the forms and severity of degradation between the commercial and communal agricultural systems, and emphasised that in past research, the communal areas were omitted. This is supported by other research including Kiguli et al. (1999), who compared traditional rangeland condition assessment techniques with vegetation indices in the Peddie district in the Eastern Cape. Makhanya (1993) found that there was a significant contrast between the state of vegetation in the densely populated former homelands of Kangwane, and the adjacent Kruger National Park areas. The Hoffman et al. (1999) study has pointed to the communal areas where a combined degradation index of vegetation and soil was the highest. The main forms of degradation were, overwhelmingly, believed to be loss of vegetation cover and change in species composition. The limitations of their survey are twofold: firstly, the survey could identify the areas most severely affected only in a relative sense as it was not based on quantitative measurements but rather on perception; secondly the survey was undertaken at the magisterial district level and the precise location of degradation is not known.

Most of the studies discussed above have examined the use indicators related to a specific component of desertification, mostly vegetation degradation or a variation thereof, especially those derived from satellite imagery. The FAO/UNEP Provisional Methodology for Assessment and Mapping of Desertification (FAO/UNEP 1984) however, recommends the use of a suite of indicators, as modelled by Grunblatt *et al.* (1992), including the physical, biological and anthropogenic environments, not all of which are easily estimated from remote sensing. The analysis therefore is more holistic and with the increased number of independent factors which define desertification considered, the analysis is likely to yield a more accurate

result (Lambin and Strahler 1994). The present research is not attempting to advocate the use of NDVI solely as an indicator of degradation, but rather as a first step in exploring the likely affected areas. It is emphasised that, as has been mentioned in the literature, ground truthing is an essential component of the use of satellite imagery.

As the Hoffman et al. (1999) study identified the communal rangelands as the principle location of degradation, and adopting the definition of degradation from the NAP, as

'Degradation is a persistent decrease in the supply of ecosystem services as a result of loss or changes in the composition of soil or vegetation',

then a satellite-based measure of productivity should be able to reveal degraded areas. They should have a productivity below what is expected from their climatic, edaphic and vegetation environment.

Despite the wide use of satellite imagery in monitoring vegetation, land use and land cover, the limitations of satellite measures and specifically the NDVI as a measure of vegetation density or biomass (it is sensitive to soil colour, atmospheric effects, illumination and observation geometry (Herrmann et al. 2005)), in areas with sparse vegetation is well documented (Milich and Weiss 2000). Further, as noted by Herrmann et al. (2005) and others, satellite data can hide changes in vegetation cover not associated with biomass or greenness. An undesirable change in species composition (for example bush encroachment, alien plant invasion and herbaceous change from perennial to annual species (Beck et al. 1990)) is not easily detectable as degradation. Bush encroachment and alien plant invasion will potentially be seen on satellite images as an increase in greenness and therefore an improvement in the condition of the vegetation.

We have for the purposes of this study restricted the definition to two processes, erosion and the loss of vegetation productivity.

Indeed, parts of the study area are sparsely vegetated, and so the use of the NDVI could be questioned. Other vegetation indices have been developed which attempt to circumvent the problems with the NDVI - the Soil Adjusted Vegetation Index (SAVI), which was developed for use in sparsely vegetated areas (Huete, 1988), the Modified Soil Adjusted Vegetation Index (MSAVI)(Qi et al., 1994), and the Enhanced Vegetation Index (EVI) (Huete et al., 2002). The

limitation with these however is that they are more complex in that they require the use of user defined constants and scaling factors, which would vary over and be difficult to determine for a large study area. There is therefore no long-term time series of data. There is evidence that the NDVI performs suitably in sparsely vegetated areas. Jacobberger-Jellison (1994) for example showed that the SAVI and the Leaf Vegetation Index did not perform more reliably than the NDVI in a sparsely vegetated area, in the Tombouctou region in Mali. It is seemingly the most widely used index for large-scale studies of vegetation productivity. NDVI is therefore the most appropriate measure in this case.

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