Landuse Characterisation and Change Detection Analysis for Hydrological Model Parameterisation of Large Scale Afforested Areas Using Remote Sensing

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Abstract: The impact of large scale landuse changes such as afforestation on the hydrological system behaviour of river basins is of major interest to water resources managers. Particularly in semiarid areas, where water is scarce and limited, the continuous assessment and monitoring of landuse system components are necessary. Their analysis and prognostic hydrological modelling requires both the determination of updated landuse patterns and an estimation of their spatial dynamics over time. In this study optical remote sensing data were used in order to provide such hydrological model input parameters at different scales. Landsat TM data from 1995 and 1999 have been utilized to produce various scale dependent landuse maps within the semiarid Umzimvubu catchment, South Africa. The classification results were compared in terms of temporal landuse changes resulting from progressive afforestation. Based on a complex accuracy estimation procedure comprising all processing steps, significant changes of the landuse patterns could be quantified. In addition, the distribution of Leaf Area Index (LAI) has been simulated for the Mooi river subcatchment by transforming of the Normalized Difference Vegetation Index (NDVI) derived from Landsat TM data to corresponding LAI values by means of an empiric model.

Keywords: Remote sensing; Hydrological modelling; Parameterisation; Landuse; Change detection; LAI

1. INTRODUCTION

Water is one of the most important natural resources in South Africa, due to its limited availability. Because of the variable nature of a large proportion of South Africa's water resources continuous assessment and monitoring of hydrological system components and their interactions is very important. Therefore, detailed information on geology, topography, landuse, etc. are needed for physically based modelling of hydrological processes and dynamics. Particularly in semi-arid areas, which are characterised by a strong limitation of water facing a remarkable increase of domestic, agricultural and industrial water demands, the impact of landuse changes on the basinwide runoff is of major interest to water resources planners, managers and local authorities.

The objective of the study presented herein was to investigate the impacts of large scale afforestation on the hydrological dynamics of semi-arid upland catchments in the North East Cape Province (NECP).

Many studies have demonstrated that remotely sensed data provide both actual and spatial distributed information for hydrological catchment modelling, especially in large scale areas which are difficult to monitor when using conventional techniques [Mauser et al., 1998; Schultz and Engman, 2000]. The integration of such information into Geographical Information Systems (GIS) and their analysis is of importance for the parameterisation of distributed hydrological models [Meijerink et al., 1994].

The study is also providing essential data for the subsequent delineation of Hydrological Response Units (HRU) as introduced by Flügel (1995).

2. STUDY AREA

The Umzimvubu catchment is located in the southeastern part of South Africa and covers an area of 19845 km^2 (Figure 1). The study area is mainly underlain by triassic sedimentary strata of the Karoo Sequence, often intruded in place by sills and dykes of Jurassic dolerite. The manifold geological

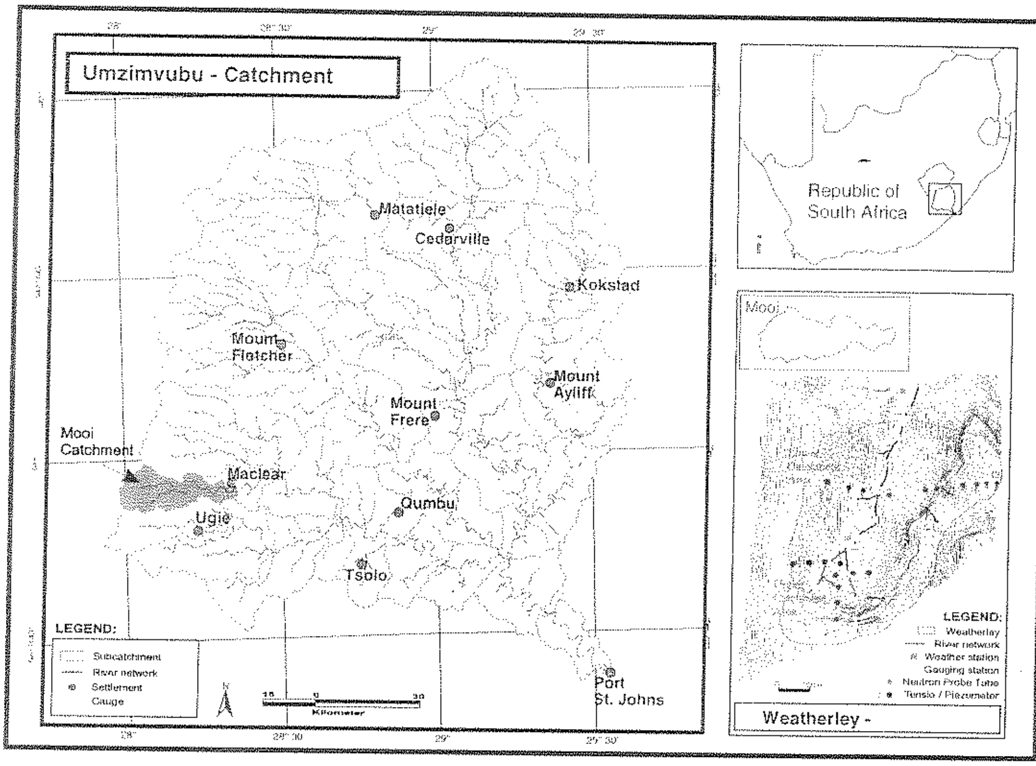

Figure1. Location of the Umzimvubu catchment and basin characteristics.

strata are the prerequisite for the forming of an impressive scarpland with wide valleys, numerous canyons and series of sloping plateaus. The soils in turn are a result of the interaction of weathering processes, the parent geological material and the hydro-meteorological conditions. The catchment receives summer rainfall between 750 and 1500 mm/year falling from September till April. However, temperature and precipitation show a high seasonal variation.

The vegetation is characterised by a grassveld type namely Highland Sourveld in the upper parts and Dohne Sourveld in the warmer and drier lower elevations. The grassveld becomes scrubby on steeper slopes as a savanna of Protea multibracteata. Relics of indigenous forest dominated by Podocarpus latifolius occur in the sheltered kloofs along the escarpment. In the Umzimvubu mouth area the vegetation is dominated by dense coastal forest [Acocks, 1988].

The landuse is mainly characterised by rangeland, dryland agriculture and some small scale irrigation patches. Extensive stock farming and annual burning has led to the degradation of the natural grassveld and to areal soil losses caused by erosion. Since the establishment of forest industries in 1989, large scale afforestation has resulted in significant changes in landuse especially in the headwater catchments of the Umzimvubu catchment.

During the last ten years North East Cape Forests bought some 120000 ha of land and afforested almost half of it with Pinus patula, Pinus radiata, Pinus elliottii and eucalypt. The hydrological and ecological impacts of these activities are not yet fully understood in this area so far [Forsyth et al., 1997].

3. DATA SETS

3.1 Remote Sensing Data

Two full Landsat-5 TM images were used for a basinwide multitemporal landuse classification. They were taken at the beginning of the dry season in May 1995 and in April 1999 to reduce seasonal variations. Both scenes have been system corrected to Level 8, that means the data were radiometrically and geometric corrected. The 1999 data contain a minimum of smoke caused by effects from veld burning. In general, the quality of the data was excellent, but there were remarkable reference inaccuracies, which had to be corrected. Two sets of digital aerial photographs (1989, 1998) were available and could be used for validation purposes.

3.2 Reference Data

Landuse information for larger parts of the Umzimvubu catchment exists from several field campaigns, encompassing 29 mapped landuse classes for more than 800 specific areas. These data were complemented by farmer interviews and information derived from the forest data base. The majority of the mapped areas has been used to train the classifier. The residuals have been used for validation and verification of the classification results. A 200m Digital Elevation Model of the whole area was complemented by a 25m DEM of the Mooi subcatchment, derived from stereoscopic SPOT Pan data. Additionally, different plant physiological parameters such as Leaf Area Index, cover density, mean heights, etc. for pine and eucalyptus forest stands and different grassland canopies and other physiological data were available from previous studies and have been added to the GIS data base used in the project.

4. DATA PROCESSING AND IMAGE ANALYSES

4.1 Landuse Classification

Based on two Landsat TM-scenes from 1995 and 1999, landuse was classified by means of a simplified hierarchic 2-level approach as shown in Table 1. It was developed considering the needs for the subsequent HRU-delineation [Flügel, 1995] by combining the Standard South African Landuse Classification Scheme [Thompson, 1996] with field mapping in the tributary catchment of the Mooi river.

Table 1. Level-based Classification Scheme.

Level 1		Level 2		Level 3	
#	Name	#	Name	#	
1	Forest Plantations	11	Pine	111	(1990)
				112	(1993)
				113	(1996)
		12	Eucalyptus		
2	Ind. Woodlands				
3	Grassland	31	Degradation (< 20%)		
		32	Degradation (20-60%)		
		33	Degradation (> 60%)		
4	Agriculture	41	Maize		
		42	Crops		
5	Bare rock				
6	Bare soil				
7	Wetlands				
8	Water				
9	No data				

Data preprocessing was necessary to improve the quality of the data, and entailed the application of a destriping algorithm on the TM data to reduce the regular striping together with appropriate edge enhancements filter techniques for image sharpening. According to Richter [1996], an atmospheric correction has to be carried out, if optical data are used for multi-temporal classification approaches. Therefore the TM data were atmospherically corrected using ATCOR 2.1, which resulted in an improvement of the data quality. The necessary rectification to a unique geodetic system (UTM, Zone 35, Spheroid: WGS 84) was carried out by 98 GPS-measured ground control points using a polynomial second order transformation with nearest neighbour resampling. Mean RMS errors less than one pixel resolution were achieved. Since topography affects the spectral signature, an attempt was made to correct the image data for slope and aspect. However, this failed due to the poor quality of the digital elevation data.

A hybrid classification approach was chosen for the landuse classification. The approach considered an unsupervised ISODATA clustering to get an overview of the spectral contents of the images. This information was used to create class signature files. Based on a complex signature analysis this catalogue and the information derived from the landuse mapping was utilized to define training areas with unimodal spectral characteristics. Capability approval was carried out at all stages of the signature evaluation using covariance matrices and mean vector analyses. The classification procedure was performed by using a Maximum-Likelihood-Classifier. The verification of the classification results has been done by statistical comparison with a class weighted amount of reference areas for each object class. Finally a postprocessing of the classification result was done by reclassifying inaccurately classified or „mixed" pixels utilizing several filter algorithms to improve the classification accuracy.

The classification accuracies were evaluated at two levels, i.e. after the Maximum Likelihood Classification and at different stages during the postprocessing. This was done by comparing the percentage of pixels correctly labelled with those incorrectly classified for each class using confusion matrices [Congalton et al., 1983].

4.2 Determination of Leaf Area Index (LAI)

LAI was calculated for the Mooi river catchment based on the pixelwise transformation of the Normalized Difference Vegetation Index (NDVI) derived from the preprocessed Landsat-5 TM using the empirical model given by Maas and Doraiswamy [1996] for semi arid conditions:

$$LAI = 4.147 * NDVI - 0.276$$

The LAIs for grassland and afforested areas were subsequently validated by literature values and data provided by the models ACRU [Schulze, 1995] and 3-PG [Dye, 2001]. In comparison to a variety of empiric functions, the adopted regression equation showed the best results and LAIs were analysed due to their dynamics over this four year period.

5. RESULTS AND DISCUSSION

5.1 Landuse Classification and Change Detection

As a result of the classification process, various scale-dependent landuse maps were produced representing both the spatial distribution of the landuse units and their area-wide quantification.

For the Umzimvubu catchment the landuse map consisting of 11 landuse classes is shown in Table 2. About 50 % of the Umzimvubu catchment is dominated by different types of grassland. Altogether three different levels of land degradation were distinguished, each differing in grass cover densities (< 20 % = no degradation, 20-50 % = medium degradation and > 50 % = heavily degraded rangeland). The bare soil class (12 %) was characterized by completely eroded grassland or areas prepared for afforestation. The major part of the cultivated areas (8 %) is dominated by maize, greenfeeding or meadow. Actually only about 5 % of the basin is covered by forest plantations. Deciduous woodland and indigenous forests (11 %) are mainly concentrated in the mouth area and the middle part of the catchment.

Table 2. May 1995 Landsat TM landuse classification for the Umzimvubu catchment.

Landuse	Area [km²]	Area [%]
No data (shadow, clouds)	1530.216	7.72
Bare rock	687.099	3.46
Bare soil	2435.641	12.27
Cultivated land	1635.317	8.24
Grassland (< 20% degr.)	4154.788	20.94
Grassland (20-50% degr.)	3953.386	19.92
Grassland (> 50% degr.)	1978.992	9.97
Forest plantation	940.739	4.74
Deciduous woodland	2087.577	10.52
Wetlands	422.792	2.13
Water bodies	18.303	0.09
	19844.85	**100**

The overall accuracy of the classification was about 86 % ranging from a minimum of 76.3 % for high degraded grassland (> 50 %) to a maximum of 94.4 % for deciduous woodlands. Basically the landuse classes that could be classified with consistently high accuracies (> 90 %) were water bodies, barren lands, dense vegetated and agricultural areas. According to the significant spectral responses it was possible to separate natural woodlands and forest plantations with adequate accuracy. Some problems occurred in wetland areas (80%) and eroded grasslands, due to the spectral heterogeneity of these classes. A variety of different species of bushes, grass, reeds and additional soil information led to a problematic spectral response within the wetlands, while the spectral information of the grassland was influenced by varying soil moisture distribution, different soil types, aspect effects and disturbed vegetation patterns.

In the Mooi river catchment pine and eucalyptus stands of different ages could be separated from the other landuse classes. This procedure has been complemented by both field data and information from the forestry data base. The classification results for both years are shown in Table 3. Classification accuracies were summarized using errors of omission and commission derived from the confusion matrices. An overall accuracy of 89.4 % after postprocessing was achieved for 1995, ranging between 81.6 % for degraded rangeland and up to 99.4 % for Eucalyptus plantations. Although eroded rangeland showed the slightest class accuracy (87.1 %), the lower errors of commission led to a better overall accuracy of 91.4 % for the classification of the 1999 scene if compared with the other scene from 1995. Here the highest class accuracy was in the eucalyptus class (98,8 %).

Table 3. Landuse distribution within the Mooi subcatchment, based on Landsat TM images from 1995 and 1999.

Landuse	1995 Mooi [km²]	1999 Mooi [km²]
Shadow	34.956	35.870
Bare rock	21.117	12.597
Bare soil	4.936	28.322
Agriculture 1	0.084	2.134
Agriculture 2	0.164	3.821
Grassland (< 20% degr.)	63.434	53.972
Grassland (20-50% degr.)	51.558	44.712
Grassland (> 50% degr.)	36.957	27.586
Pine 1990	16.869	18.733
Pine 1993	11.882	1.544
Pine 1996	0	19.830
Eucalyptus	2.015	1.869
Deciduous woodland	26.441	25.640
Wetland	34.631	26.761
Water bodies	0.016	1.669
	305.06	**305.06**

The class-related accuracy assessment for each image proved that the highest classification uncertainty was caused by overlapping within the grassland categories and the border between bare soil and bare rock (1995), and bare soil and cultivated lands (1999), respectively. A similar spectral response of wetlands and grasslands without degradation indicates that both were characterized by comparable vegetation societies.

Finally, a GIS-supported change detection analysis was carried out considering all classes with accuracies better then 96%. Additional information from the forestry data base, landuse maps and field surveys have been integrated in the change detection analysis procedure for validation purposes. The following results can be summarized:

- A remarkable increase of pine stands (+3%) associated with a simultaneous decrease of grassland (8.5 %) could be recognised. The constancy of eucalyptus stands can be explained by the cessation of eucalyptus planting since 1992 due to economic reasons. Because of their spatial distribution, these changes have been validated by masking afforested areas and overlaying than with digitised forest maps.
- An accurate quantification of the spatial dynamics of the individual pine stands and grassland classes by TM data only, is pretty much limited because of the classification uncertainties, but a reasonable enhancement could be achieved by adding related data.
- The significant increase of the soil class (+8 %) can be explained by the preparation of former rangeland for afforestation by contour ripping, burning etc.
- The decrease of the wetland areas (-2.6 %) could be explained by planting around wetlands, with the possible effect of drying out of wetland patches. Lower rainfalls in 1995 provide a further indication for this assumption. Field survey on selected areas indicated that there is an areal loss of wetlands as a consequence of large scale afforestation.

5.2 Leaf Area Index

LAI values have been calculated for the area of the Mooi subcatchment by processing Landsat-5 TM data from 1995 and 1999. The afforested areas can be clearly identified due to their areal dimensions in both LAI maps. The spatial and areal distribution of the afforestation has been validated by applying structural analysis and comparison with available forest maps. Basically, older stands with higher cover densities are characterized by LAIs greater than 3. Although having a similar LAI of about 1-2.5 a significant differentiation between younger stands, which are characterised by dense grass cover and grassveld could be established. This can be explained because of the specific combination of site preparation techniques and phenologic characteristics of the grass vegetation. While the rangeland is burned annually during the rainy season, the grass of the young pine stands develops undisturbed and shows a more intensive reflection in the near infrared channels. Finally the age specific comparison of the LAIs derived from the TM data with LAI measurements collected in the field by allometric methods ($r = 0.86$) as well as simulated LAI data ($r = 0.96$) confirmed the high quality of the generated data and the general applicability of the evaluation approach.

6. CONCLUSION

Physically-based, distributed hydrological models require an areal analysis of the water cycle components for parameterisation. Besides topographical, geological and pedological factors, landuse and vegetation characteristics as well as their temporal dynamic changes are important input parameters for the modelling of the watershed hydrology.

In this study optical remote sensing data were successfully used for the delineation of such parameters for distributed hydrological modelling of the Umzimvubu river catchment in the Northern East Cape Province, South Africa. Multispectral and multitemporal Landsat TM data from 1995 and 1999 were processed for landuse classification and their dynamics within the catchment. After the data preprocessing, a hybrid approach combining unsupervised ISODATA clustering and supervised Maximum Likelihood Classification was applied. After several postprocessing techniques which improved the classification result noticeably, a variety of landuse maps were provided on different scales and class hierarchies. It was shown, that major landuse classes could be identified clearly with high accuracies.

The Leaf Area Index (LAI) distribution was calculated on the subcatchment scale of the Mooi river and provided additional information due to the vegetation patterns and their temporal and spatial dynamics. The LAI data have been utilized to separate the afforested areas from the rangeland, and were validated by ground truth data and digital forest maps utilizing structural analysis successfully. All these data were integrated into the GIS data base to be used together with other existing information to delineate Hydrological Response Units (HRU).

The classification approach used in this study was a standard method, but other advanced procedures exist [Huete and Escadafal, 1991; Palubinskas et al. 1995; Skidmore et al., 1997; Ton et al., 1991] for further testing. Future research in this project therefore will focus on the application of more flexible classification techniques like neural networks, segment based approaches or texture analyses and the integration of alternative sensors with higher spectral and spatial resolution in terms of data. First attempts to apply these methods have started by processing new TM data acquired 2001.

A further objective of future studies will be the more detailed assessment of wetland changes in the headwater catchments. Knowledge-based subpixel classifier presented by Huguenin et al. [1997] and modified change detection analysis based on image to image differentiation [Macleod and Congalton, 1998] are encouraging approaches to quantify such landuse changes successfully.

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