
Remote sensing and GIS based determination of groundwater dependent ecosystems in the Western Cape, South Africa

Zahn Münch · Julian Conrad

Abstract Finding the location of groundwater dependent ecosystems (GDEs) is important in determining the extent of restrictions that need to be placed upon the abstraction of groundwater. Remote sensing was combined with geographical information system (GIS) modelling to produce a GDE probability rating map for the Sandveld region, South Africa. Landsat TM imagery identified the areas indicating the probable presence of GDEs and GIS assisted in their delineation. Three GIS models were generated: a GIS model predicting landscape wetness potential (LWP model) based on terrain morphological features; the LWP model was modified to highlight groundwater generated landscape wetness potential (the resulting GglWP model); and a groundwater elevation model was interpolated, combining groundwater level measurements in boreholes in the region with digital elevation model data. Biomass indicators generated from Landsat were classified and combined with the GIS models, followed by field verification of riverine and wetland GDEs. The LWP model provided the most accurate results of the three models tested for GDEs in this region.

Résumé Dans le cadre de la délimitation géographique des restrictions sur les prélèvements en eau souterraine, la localisation des écosystèmes dépendant des eaux souterraines (EDES, ou GDE) a son importance. La télédétection a été combinée à une modélisation sous SIG (Système d'Information Géographique) afin de produire une carte de probabilité de présence des EDES sur la région de Sandveld, en Afrique du Sud. Les images Landsat TM ont identifié les secteurs indicateurs de

présence de EDES, et les SIG ont contribué à leur délimitation. Trois modèles SIG ont été créés: un premier modèle prédisant le potentiel d'humidité des terrains d'après la morphologie locale (modèle LWP); ce modèle a été modifié dans le but de souligner le potentiel d'humidité généré par les eaux souterraines (modèle résultant GglWP); enfin, un modèle piézométrique a été interpolé par combinaison des levés piézométriques dans les forages du secteur et des données du modèle numérique de terrain. Les indicateurs de biomasse issus des données Landsat ont été classés et combinés aux modèles SIG, puis les EDES de zones humides et de cours d'eau ont été vérifiés sur le terrain. Sur les trois modèles testés pour ce secteur, le modèle LWP a donné les résultats les plus probants.

Resumen Definir la localización de los ecosistemas dependientes de las aguas subterráneas (GDEs) es importante para determinar la extensión de las restricciones que hay que tomar en la extracción de aguas subterráneas. La teledetección se ha combinado con la modelación utilizando Sistemas de Información Geográfica (GIS), para producir un mapa de valoración de probabilidades para la región Sandveld, en Sudáfrica. Las imágenes Landsat TM identificaron las áreas con presencia de GDEs y el GIS ayudó en su delimitación. Se generaron tres modelos GIS: un Modelo GIS para predecir los paisajes húmedos potenciales (LWP model) basado en las características morfológicas del terreno; el modelo LWP fue modificado para destacar los paisajes húmedos potenciales producidos por las aguas subterráneas (dando lugar al modelo GglWP); y se interpoló un modelo de niveles de aguas subterráneas, combinando medidas de niveles de agua subterránea en sondeos en la región con datos de un modelo digital de niveles. Los indicadores de biomasa generados mediante Landsat fueron clasificados y combinados con los modelos GIS, seguidos por verificaciones de campo en GDEs de rivera y humedales. El modelo LWP proporciona los resultados más precisos de los tres modelos probados por GDEs en esta región.

Keywords Remote sensing ·
Geographical information systems ·
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Introduction

In South Africa, as in other arid and semi-arid areas, groundwater allocation has become an important issue. The revised National Water Act (NWA) of South Africa (DWA 1998) makes provision for water resources to be allocated for use once a reserve has been set aside for essential human needs and the sustainable ecological needs of aquatic systems. Environmental water maintains ecosystem services such as soil formation, prevention of soil erosion, regulation of water flow (recharge) and water purification (Eamus et al. 2006), which are often overlooked. The process of determining the allocation of additional groundwater in South Africa after quantifying a reserve has been investigated and documented (Xu et al. 2003). Identifying the location of groundwater dependent ecosystems (GDEs) is important in defining what restriction should be placed on the available groundwater allocation. GDEs rely on groundwater for some, or all, of their water requirements, mostly to maintain the structure, composition and functioning of such ecosystems (Colvin et al. 2002; Murray et al. 2003). The varying degrees of groundwater dependency are likely to increase with increased aridity of the associated environment (Hatton and Evans 1998). Understanding the nature and location-dependency of GDEs is crucial where ecosystem survival might be critically affected by even a small change in groundwater levels (Eamus et al. 2006), yet the resilience of some GDEs to altered groundwater availability needs to be acknowledged (Eamus and Froend 2006).

According to Hatton and Evans (1998), GDEs can be found in aquatic, riparian, in-stream, wetland, terrestrial, cave and aquifer environments. Eamus et al. (2006) suggest three primary classes of GDEs, being: aquifer and cave ecosystems (class I); ecosystems dependent on surface expression of groundwater (class II) and ecosystems not requiring surface expression of groundwater (class III). This paper deals predominantly with class II GDEs and, therefore, includes base-flow driven rivers and streams, wetlands and springs.

As part of a South African national assessment of terrestrial groundwater dependent ecosystems (TGDEs), a national scale map of potential GDEs, based upon groundwater levels and soil moisture availability has been produced (Colvin et al. 2002). During a recent detailed study in the northern Sandveld—situated on the west coast of South Africa (Fig. 1a)—in an area comprising three longitudinal wetland systems characterised as predominantly groundwater fed, remote sensing combined with geographical information systems (GIS) modelling was used to detect the probable location of GDEs (Conrad et al. 2005). The Sandveld has come under the spotlight, as there is increased pressure on groundwater resources due to agricultural expansion and groundwater exploitation coupled with a decrease in rainfall due to global climate change. A method, combining aerial photography, remote sensing, GIS modelling and field validation, developed by Thompson et al. (2002) for large-scale, cost effective, wetland identification was tested for GDE location. The

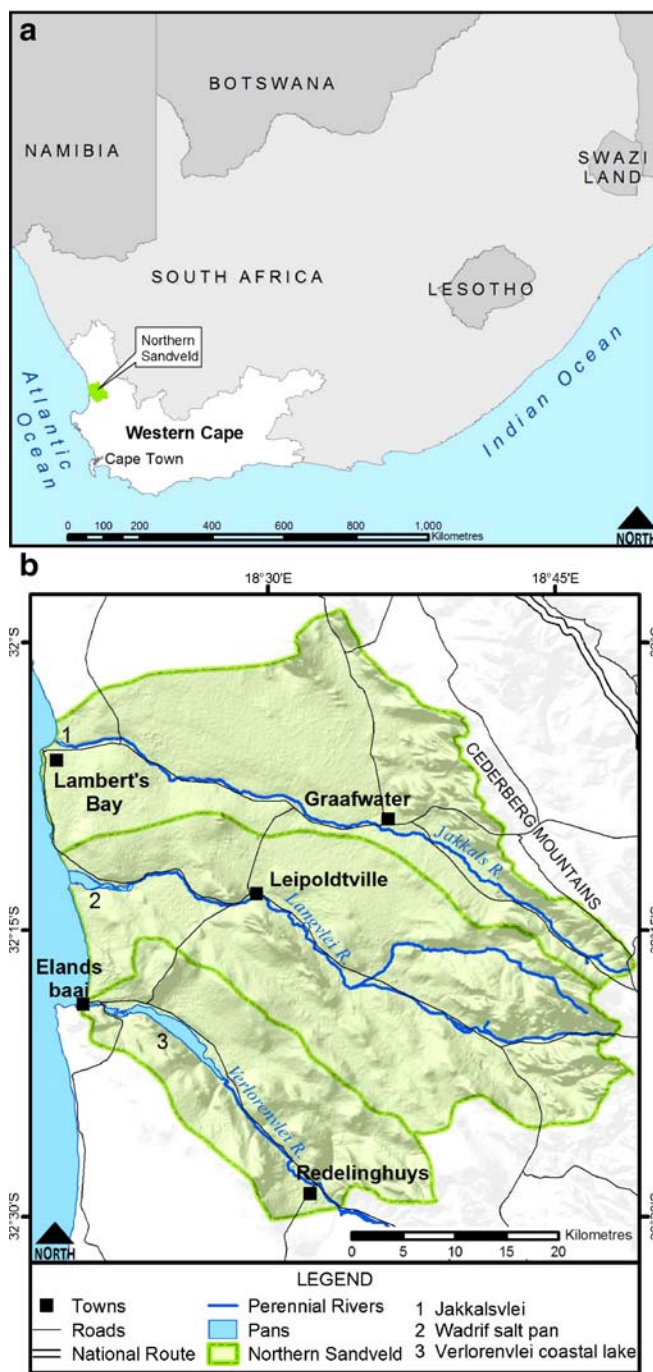


Fig. 1 a Location of study area in South Africa. b northern Sandveld region containing the three studied catchment areas¹

use of remote sensing for wetland mapping worldwide is well documented (Harvey and Hill 2001; Jensen et al. 1986, 1995; Lunetta and Balogh 1999; Munyati 2000), especially in the use of aerial photography where inferior satellite spectral resolution would result in the inability to distinguish between different vegetation types. The combination of remote sensing and GIS modelling has been

¹ Map projection: Transverse Mercator, central meridian: 19°E. spheroid: WGS84.

used with success to enhance the results obtained from image analysis (Chuanyan et al. 2006; Elumnoh and Shrestha 2000; Gritzner et al. 2001) in many different environmental applications. Elmore et al. (2003) documents vegetation response due to changes in water, using remote sensing.

This paper reviews the image analysis and GIS processing undertaken to delineate the probable location of GDEs. The objectives of this study were: (1) to undertake image analyses using aerial photography, satellite imagery and remote sensing techniques to identify areas indicating the presence of GDEs; (2) to use GIS to assist in the delineation of GDEs by implementing spatial modelling independent of present land-cover; (3) to combine the spectrally predicted GDEs with the GIS modelled data sets so that the extent of GDE boundaries could be refined; and (4) to identify enhancements to improve the methodology, thereby reducing the cost of field verification.

Materials and methods

Study area

In the northern Sandveld, three surface-water catchment areas were selected for analysis (Fig. 1b). Each of the three parallel river systems exists as a series of longitudinal wetlands, connected by surface channels in places, but largely groundwater driven. The northern Sandveld encompasses the Verlorenvlei River which terminates in the Verlorenvlei coastal lake², the non-perennial Langvlei River, which passes through the erstwhile Wadrif “wetland”, ending in the Wadrif salt pan, and the Jakkalsvlei River to the north which terminates in the Jakkalsvlei pan, formerly a seasonal pan with an intermittent connection to the sea. The Wadrif salt pan and Jakkalsvlei seasonal pan areas are deemed complementary to the avifaunal habitat provided by Verlorenvlei, and sustaining the environmental integrity of the aggregate area is of international importance. Ecological significance and sensitivity have been determined by the Department of Water Affairs and Forestry, South Africa (DWAF 2003). The area, an arid and highly seasonal environment, is characterised by low rainfall at the coast (100–400 mm/a) with higher rainfall (500–1000 mm/a) in the mountainous areas at catchment boundaries in the Cederberg Mountains, falling mainly in the winter (Cowan 1995). Summers are characterised by hot temperatures (>35°C) and warm winds. Agriculture (potatoes, citrus and vineyards), supported by extensive irrigation (mostly from groundwater), places increased pressure on groundwater resources within the study area.

Study design

The methodology used was based on a framework developed by Thompson et al. (2002) as part of the

National Wetland Inventory project in South Africa using Landsat imagery as a generic “presence or absence” mapping of “core” wetland areas, combined with GIS terrain modelling. This methodology, used to delineate wetlands, was tested to determine if it could be used to identify GDEs in the Sandveld by determining “wetness potential”. GIS processing was carried out to create a groundwater level data set (depth to water table (DWT)) which was classified to indicate wetness potential. The *landscape wetness potential* (LWP) model of Thompson et al. (2002), was modified in this study to show *groundwater generated landscape wetness potential* (GglWP) by including factors considered to influence groundwater dependence of ecosystems, i.e. depth to water table (Eamus et al. 2006; Murray et al. 2003) and selected geological features as indicators of fractured aquifer potential (Colvin et al. 2002). Wetness potential results from the three spatial models (LWP, GglWP and DWT) were compared with each other. GDE probabilities from the three spatial models combined with the spectral data set were compared to each other and to the spectral classified data set itself. Extensive botanical field verification, based on identifying indicator species, enhanced the quality of the generated output.

Geology

The geology of the study area (Fig. 2) is complex. The Sandveld area along the west coast of southern Africa is underlain by the Neoproterozoic Malmesbury Group and the Gariiep Supergroup, and a cover comprised of the Palaeozoic Cape Supergroup. The basement rocks are primarily soft, easy weathering argillaceous rocks, whilst the Cape Supergroup comprises the Cederberg Mountain Ranges on the eastern fringe of the Sandveld. Thick quartzose sandstones of the Table Mountain Group (TMG) dominate the Cape Supergroup. Cenozoic deposits extensively cover the coastal plain. Deformation during the Pan-African Event left a NW–SE structural grain on the basement rocks, which, together with deep crustal weaknesses of the same trend, controlled the deposition of the sedimentary cover and its deformation during the Permo-Triassic Cape Orogeny. The study areas are situated within the western branch of the Cape Fold Belt, where fold axes trend NW–SE. Faults formed during the Mesozoic break-up of Gondwanaland have roughly the same orientation, but a subsidiary WNW–ESE trend of fractures, some of which were utilised for intrusion of regional dolerite dykes, also occur. Rifting of the Atlantic margin and subsequent drifting were followed by continuous erosion of the rock superstructure from about 120 Ma (10⁶ years) ago to the present. Several changes of sea level during middle and late Cenozoic times produced the lowermost of the Cenozoic deposits in the Sandveld, which are in turn covered by extensive Quaternary sand deposits. From airborne geophysics data, it appears as if major, undiscovered faults may occur beneath the sand cover in several places. Structurally the area has undergone many phases of deformation and tectonism (De Beer 2003).

² The term “pans” is used in all maps to describe the Verlorenvlei coastal lake, the Wadrif salt pan and the Jakkalsvlei seasonal pan.

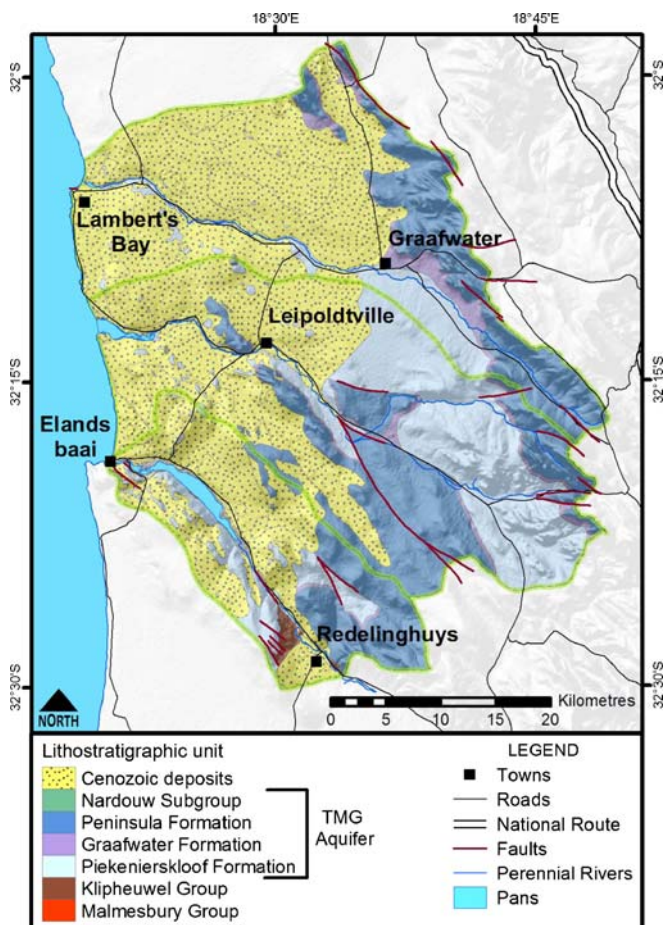


Fig. 2 Simplified geology of the study area

Hydrogeology

A major lithological difference exists between the Palaeozoic sedimentary cover rocks and its Neoproterozoic basement. This difference practically divides the geological sequence into two essentially different flow domains. The upper domain in the TMG is dominated by water moving along bedding planes and fractures, being collected in regional faults and flowing down-gradient to the sea. In the lower domain of the Malmesbury Group, water flows along foliation planes, bedding (where preserved), fractures and faults, but the higher component of clay minerals and micas in the succession significantly impede groundwater flow, compared to a proliferation of open fractures in the competent TMG. A consequence of this is that water collected in the TMG outcrop area preferentially remains within this succession, rather than infiltrating into the basement rocks over most of the area. However, the situation can be quite different along significant faults.

In the case where large masses of TMG rocks abut regional faults, the difference in character between the TMG and its basement inhibits flow across the faults into the Malmesbury Group to a large extent, and promotes down-gradient flow along these fault zones. Bedding planes in such TMG rock commonly dip towards the fault and are cut by numerous secondary fractures that

intersect the large regional fault at high angles, greatly enhancing the flow of groundwater towards such large faults. Such situations of flow “abutting” relatively less permeable basement rocks, can lead to enormous amounts of groundwater being present in these major faults (De Beer 2003).

The TMG Aquifer is a regional scale fractured aquifer. Groundwater movement takes place in various scales of fractures, and the aquifer comprises three major fractured sandstone horizons, separated by shale rich aquitards. The Piekenierskloof Formation forms the basal aquifer unit, overlain by the Graafwater Formation (considered by some as an aquitard). The Peninsula and Pakhuis Formation forms the middle aquifer unit, confined by the overlying Cedarberg Shale. The uppermost aquifer in the TMG Aquifer is the Nardouw Formation.

The sandy Cenozoic cover is the layer in the Sandveld region that is utilised most for agriculture. Its high porosity and extreme horizontal permeability, which is only restricted by palaeotopographical highs, greatly enhance flow characteristics over that of the hard rocks. The presence of clay horizons in places does, however, restrict vertical water movement. These sediments were deposited in palaeo-valleys of old river courses and on marine planed surfaces (De Beer 2003).

Geological structures and lithology control the groundwater flow and impose aquifer boundary conditions, within which groundwater circulates. Fold axes, fault structures and intrusive dykes may form preferred flow paths or barriers to groundwater movement.

Spectral analysis

The analysis of the satellite imagery consisted of image selection and acquisition, image preparation (atmospheric and radiometric correction, geo-registration and orthorectification, and topographic normalisation), extraction of biomass indicators—Normalised Difference Vegetation Index (NDVI) and Tasseled Cap (TC) wetness and greenness—and image classification. Landsat 5 Thematic Mapper (TM) image data sets (175–082/3) were used. Landsat imagery offered the best combination of spatial and spectral resolutions, competitive costing structures in comparison to other medium resolution image formats (e.g. SPOT), and an extensive local archive supported by ongoing data reception, providing the choice of multiple image acquisition dates. Landsat 7 Enhanced Thematic Mapper (ETM+) was not considered due to the duplication or data loss in images since the failure of the satellite’s scan line corrector (SLC).

The optimal image acquisition date would be at the point when GDE areas exhibit significantly different characteristics to the surrounding land-cover, usually coinciding with a period of seasonal climatic change and associated vegetative response (Jensen et al. 1986; Lunetta and Balogh 1999). For the Sandveld, with a winter rainfall season, images were selected from July 1998 (shortly after the onset of winter rain in a dry year), August 2002 (after a wet year) and February 2004 (towards the end of dry

season), when GDEs should be wetter and therefore greener. The February 2004 image was selected to coincide with the field visit to maximise verification efforts. All the image datasets were geometrically corrected to a standard geo-projection format (Transverse Mercator projection, WGS 1984 spheroid, central meridian 19°E). All image data were re-sampled to 25-m spatial resolution, using the nearest neighbour algorithm to maintain spectral integrity.

For image classification, a two-step approach was used, starting with (step 1) an initial broad-level land cover classification to identify, mask and subsequently exclude from further data processing, any land cover categories that would not contain any GDEs such as cultivated land, thereby identifying a subset of the data set representing sections of the landscape which could potentially contain GDEs. Basic land cover classification was done on multi-seasonal images to maximise land cover variety (Harvey and Hill 2001). Image classification was completed within the Earth Resources Data Analysis System (ERDAS). The process of unsupervised classification was done using ERDAS. Unsupervised classification is the process whereby ERDAS uses the ISODATA algorithm (ie. Iterative Self-Organizing Data Analysis Technique), which uses the minimum spectral distance formula to form clusters, repeating the clustering until the maximum number of iterations is reached or a maximum percentage of unchanged pixel assignments have been reached between iterations. All unsupervised classifications were completed using 99 iterations, with a threshold setting of 0.950. Post-classification editing using 'area-of-interest' masks were used for final class recoding of specific cover types which were impossible to separate on a spectral basis alone.

Further processing (step 2) was done on a multi-layered data set created from various indices with known biomass and wetness indicator characteristics. The new image was constructed from the NDVI, TC Greenness index and TC Wetness index of the February 2004 image to highlight the elevated greenness and soil moisture content associated with GDEs in the summer. Higher NDVI values, based on the differences in reflectance by healthy vegetation of the visible red and near infrared wavelengths, generally indicate vegetated areas and in the dry season image would highlight GDEs. The Thematic Mapper (TM)-TC transformation (Crist and Cicone 1984) is an orthogonal index that describes image brightness, greenness and wetness, and offers an alternative method for data viewing in vegetation studies. The TM-TC transformation is an adaptation of the original TC index devised for Landsat Multispectral Scanner (MSS) imagery (ERDAS 2002). The first axis, a weighted sum of all bands, expresses brightness in the direction of the principal variation in soil reflectance. The second axis describes image greenness, and is based on the contrast between the near-infrared and visible bands, and has been shown to be strongly related to the amount of green vegetation in a scene (ERDAS 2002). The third axis describes image wetness, and relates to canopy and soil moisture, based on the TM water absorption bands 5 and 7

(Lillesand and Kiefer 1987). GDEs are more likely to be found in areas with higher soil moisture content (Colvin et al. 2002; Murray et al. 2003). The multi-layered data set was used in unsupervised classification routines (20 classes) in ERDAS to derive a series of spectral classes representing the likelihood of location of GDEs based on their spectral vegetation rating, greenness and wetness as indicator of soil moisture. These 20 classes were grouped into three probability classes, i.e. low, medium and high. All image analysis was accomplished using ERDAS Imagine 8.6.

GIS modelling

Terrain-based spatial modelling was accomplished using ArcView GIS Spatial Analyst. The objective of the spatial modelling was to determine areas where groundwater may be likely to accumulate for use by GDEs, largely based on surface hydrological accumulation and terrain features. In addition, a groundwater level surface (DWT) was interpolated from groundwater levels collected from boreholes in the study area. The LWP model, as well as the GglWP model, used a weighted overlay technique combining several physical parameters with influence factors for each parameter based on the importance of the parameter in providing groundwater feed to GDEs. The weighted overlay technique was used to apply a common scale of values to diverse parameters in order to create an integrated analysis. ArcView 3.2 ModelBuilder was used to integrate the input parameters.

One of the major input parameters to the models was a topologically correct digital elevation model (DEM). A 20×20 m DEM was provided to perform the GIS modelling, which was re-sampled to 25×25 m to correlate with geo-corrected satellite images.

Interpolating groundwater levels (DWT model)

Groundwater elevation was calculated by subtracting measured groundwater levels (metres below ground level; m bgl) from land surface elevations (either from the DEM, or surveyed). Groundwater level data for 159 boreholes, collected in the Sandveld during the summer of 2004, were used in this analysis. Upon examination, it was found that in this study area, groundwater elevation and topography are highly correlated ($r=0.9974$; $p<0.0001$; $R^2=0.9948$), which meant that Bayesian Kriging (interpolation) could be used to generate the groundwater elevation using surface elevation from a DEM as an additional external variable. Bayesian interpolation is an approach that uses the knowledge from external variables as a qualified guess to reduce uncertainty during data interpolation (Van Sandwyk et al. 1992). Bayesian interpolation is especially useful in groundwater studies due to the ability to use correlated data to estimate unknown variables, in this case topography from the DEM. The interpolated groundwater elevation surface was subtracted from the DEM to produce the depth to water table (DWT) surface (m bgl). Five classes were applied to

the DWT model to describe the “wetness potential” based on depth below ground level as seen in Table 1.

The LWP model

The LWP model, suggested by Thompson et al. (2002) for wetland delineation, was tested for use in identifying GDEs. The LWP model combined the following four parameters into one integrated model through the use of a weighted overlay function: occurrence of sinks or depressions, slope steepness, flow accumulation, and relative slope position or topographic index (TPI). See Table 2 for parameter ratings and weights.

Flow accumulation represents the movement or flow of water across a surface. For each cell on the surface, the direction of flow was determined and then the number of cells flowing into any given cell, i.e. accumulated flow per cell, was calculated. This modelling technique is generally used to delineate stream networks through the extraction of cells with a high flow accumulation (i.e. areas of concentrated flow), but for the purposes of the LWP model, the cells *not* comprising stream channels were of particular interest. All cells in the flow accumulation surface represent the amount of run-off per cell. Those cells with a high flow accumulation, but not constituting a stream or river, could be interpreted as areas of wetness and, therefore, potential areas for GDEs. A DEM was used as input to the analysis. For slope steepness, the percent slope was calculated from the DEM. The relative slope position was generated from the DEM identifying topographic characteristics such as ridge tops, valleys, mid-slopes, foot-slopes, upper-slopes, and flat surfaces using a procedure documented by Biasi (2001). Sinks can be errors in the DEM or they may be valid depressions in the landscape and for the LWP model were assumed to be valid internal drainage areas.

The GglWP model

The GglWP model was designed in order to suggest additional parameters applicable to groundwater which could affect the location of GDEs and provide a cost-effective methodology. The input data sets for the GglWP model were: groundwater levels; lineaments and faults obtained for the study area from the Council for Geoscience, South Africa (1:250,000 scale); and a 20-m DEM obtained from DWAF. Six parameters were combined: depth to water table; lineament density; groundwa-

Table 2 LWP model weighted overlay function parameters

Parameter	Parameter values	Rating (1–5)	Weight factor (%)
Flow accumulation (no. of cells)	1–20	1	40
	21–100	5	
	101–10,000	4	
	10,001–600,000	3	
Relative slope position	Ridge	1	35
	Valley	5	
	Flat	5	
	Footslope	4	
	Midslope	3	
	Upperslope	1	
Slope steepness (%)	0–3	5	20
	>3–12	3	
	>12–20	2	
	>20	1	
Depressions	1	5	5

ter convergence zones; groundwater flow accumulation; slope steepness; and relative slope position or topographic index (TPI). The previously created depth to water table (DWT model) was used. A method used for analysing fractured aquifer potential is to analyse the structural geology of an area looking primarily for lineaments and fracture zones (Colvin et al. 2002). GDEs are likely to be associated with lineaments and fractures in the study area. Lineament density grids were generated using a search radius of 250 m and a 25-m cell size. The density was reported in hectares. Similar to flow accumulation in the LWP model, the groundwater flow accumulation parameter represents, in this case, the movement of groundwater across the groundwater elevation surface created during Bayesian interpolation. Groundwater convergence zones represent internal drainage areas derived from the groundwater elevation model. The final weights and ratings for GglWP can be found in Table 3.

The output surfaces generated from both the GglWP and LWP models were smoothed to create more homogeneous zones by applying mean and maximum statistical focal functions using a 3×3 grid cell size neighbourhood. The maximum statistic enhanced the higher potential zones. Modelling of GglWP and LWP was completely independent from image analysis and was not influenced by any spectrally defined parameters.

Spectral plus spatial modelling

Spatial modelling was used to combine the output from the spectral image analysis using the wetness potential classes resulting from GIS modelling with (1) the result from the GIS modelling (LWP and GglWP) and (2) the rated groundwater level layer (DWT), to produce a GDE probability layer. A probability table (Table 4) was constructed which combined spectral GDE classes with the GIS delineated wetness potential classes, in order to determine the best combinations representing probable locations of GDEs in the landscape.

Table 1 Depth to water table translated to wetness potential classes

Wetness potential class	Groundwater levels (m bgl)
1	>50
2	>30–50
3	>15–30
4	>5–15
5	0–5

Table 3 GglWP model weighted overlay function parameters

Parameter	Parameter values	Rating (1–5)	Weight factor (%)
Depth to water table (m bgl)	0–5	5	25
	>5–15	4	
	>15–30	3	
	>30–50	2	
	>50–104	1	
Lineament density (lineaments/ha)	0	0	15
	0–1.0	2	
	>1.0–2.0	3	
	>2.0–3.2	5	
Relative slope position	Ridge	1	25
	Valley	5	
	Flat	5	
	Foot-slope	4	
	Mid-slope	3	
Slope steepness (%)	Upper-slope	1	20
	0–3	5	
	>3–12	3	
	>12–20	2	
	>20	1	
GW flow accumulation (no. of cells)	1–9	1	10
	10–45	5	
	46–4,500	4	
	4,501–751,970	3	
GW convergence zones	1	5	5

Botanical field mapping and validation

Extensive field verification of riverine and wetland systems which showed indications of being groundwater dependent (Conrad et al. 2005) was done with associated cost implications. The extent of the wetland-riverine botanical footprint was digitised from 1:10,000 aerial photographs based on the presence of open water and riparian vegetation, vegetation clumps or patterns indicative of soil moisture and ground-truthing of groundwater dependent indicator communities/species (Conrad et al. 2005). The three different GDE probability data sets created through combining image-analysis output with the three spatial models (LWP, GglWP and DWT), as well as the image-analysis output only, were compared to these botanically mapped GDEs.

Results

The three-stage classification approach, involving (1) pre-classification of basic land cover to eliminate areas where

Table 4 Probability table used to combine image-classified spectral GDE probability with spatially defined wetness potential classes to produce GDE probability classes

Image-classified GDE probability classes	Spatially modelled wetness potential classes				
	1	2	3	4	5
Low	Low	Low	Low	Medium	Medium
Medium	Low	Low	Medium	High	High
High	Medium	Medium	Medium	High	High

GDEs are unlikely to occur such as cultivated land and urban areas, (2) classification of spectrally delineated GDEs within selected areas, and (3) modification of the spectrally defined GDE boundaries using terrain-derived topographical models, was applied.

A basic land cover classification data set was created from multi-temporal satellite images (dates: 18 July 1998, 06 August 2002, 09 February 2004). This was done to maximise the variety of classes that can be identified using unsupervised classification and exclude areas particularly unlikely to sustain GDEs such as cultivated land, urban areas and sand. These are shown in the masked areas in Fig. 3.

A single image date (09 February 2004) was used for biomass indicator extraction. NDVI, TC wetness and greenness indices were generated for the selected image and combined into a single image which was classified using unsupervised classification with 20 output classes. Table 5 shows the ranges for the three indices used. GDE probability classes (low, medium and high) were derived from values for identifiable features, such as open water, known wetlands.

Three spatial models were considered: (1) the LWP model proposed by Thompson et al. (2002); (2) the GglWP model based on the LWP; and (3) the DWT model, interpolated from groundwater levels. The LWP model, based primarily on slope morphology with respect to hydrological flow accumulation, was built using Arc-View. Since slope steepness and relative slope position comprise such a great proportion of the weight in this model (55%), the likelihood of very discrete predictions in areas of low relief, like the northern Sandveld, are small, and in such cases Thompson et al. (2002) suggested that additional information such as specific geological structures could be used to enhance the “wetness potential” identified.

LWP and GglWP are a combination of rated and weighted GIS layers, combined into 5 classes describing “wetness potential” representing spatial GDE occurrence probability. By applying neighbourhood statistics in a 3×3 cell sampling area, a maximum class value was selected to ensure that in any given grid unit, the highest probability was automatically selected. The GglWP model shows more variation than the LWP model for low relief areas. A similar 5-class wetland potential was devised for the DWT model based on groundwater levels. A groundwater level surface was generated from groundwater level measurements from 159 boreholes within the study area. Interpolated groundwater levels ranged from 0 to 104 m bgl. The quality of this type of data set is related to the availability of suitable borehole data. It is important to note that the distribution of boreholes within the study area is biased towards the location of anthropogenic development and may not accurately reflect the groundwater levels, especially in unsampled areas. An interpolated surface depicting the water table may not necessarily give an accurate reflection of groundwater flow.

Using the ERDAS matrix function, spectrally defined GDE probability classes were combined with the three

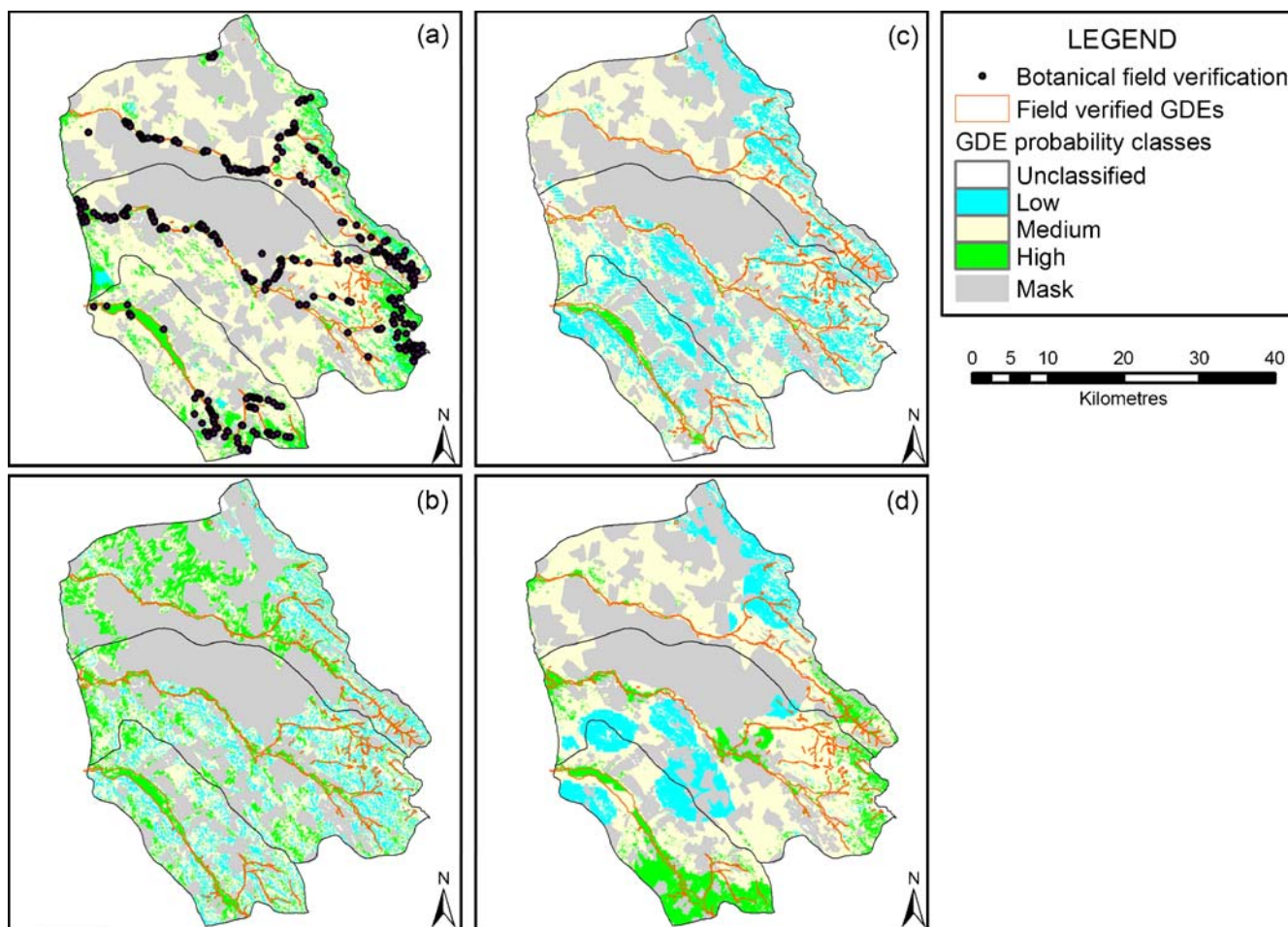


Fig. 3 a Locations of botanical field verification sites for riverine and wetland systems displayed against the backdrop of GDE probability classes derived from spectral classification. GDE

probability classes for the b LWP model, c GglWP model, and d DWT model derived from GIS analysis combined with spectral classification

spatial models (LWP, GglWP and DWT) representing wetness potential according to Table 4, resulting in four GDE probability data sets with classes low, medium and high: spectral only, LWP, GglWP and DWT.

Locations of field verification sites for riverine and wetland systems can be found in Fig. 3. These are displayed against the backdrop of the GDE probability classes derived from spectral classification only. Table 6 shows a comparison of the wetland potential of the GIS models at the field verification sites, expressed as a percentage. GDE probabilities of the spectral model only, then combined with each of the GIS models are displayed in Table 7.

Discussion

Using remote sensing techniques, a land-cover data set could be generated to use as a masking layer to show extensive anthropogenic development in the study area as seen in Fig. 3. The quality of the land-cover classification determines the accuracy with which the final GDE potential layer has been masked to show the probable location of GDEs. Identifying areas with elevated vegetation, “wetness” and “greenness” could be done successfully using a single-date image. There was, however, not a marked difference in these indicators for the field-mapped riverine and wetland GDEs, with only

Table 5 Biomass indicator statistics

Biomass indicator	Stretched values			
	Range	Mean	Median	SD
NDVI	104–255	190.092	190	7.133
TC greenness	8–240	120.523	122	13.346
TC wetness	17–250	104.433	105	25.546

SD standard deviation

Table 6 Comparison of wetness potential from spatial models with field verified GDE locations expressed as percentage

Wetness potential class	Unclassified	1	2	3	4	5
GglWP	3.6	0.9	12.0	52.6	30.9	0.0
LWP	0.0	1.2	8.1	17.7	35.1	37.8
DWT	0.3	1.5	5.4	15.6	48.9	28.2

Table 7 Comparison of GDE probability classes from spectral classification and three combined models with field verified GDE locations expressed as percentage

GDE probability class	Unclassified	Low	Medium	High
Spectral only	4.2	2.4	59.8	33.6
GglWP	7.5	6.6	78.4	7.5
LWP	4.2	5.1	40.5	50.2
DWT	3.9	5.4	45.6	45.0

33.6% of the verified points occurring within the spectrally classified “high” probability class. This was observed during the field verification where it was found that GDEs indicator species clumps were too fragmented, with spectral characteristics similar to the adjacent land-cover, covering a small area, and could not be detected uniquely using Landsat images due to the resolution of 30 m. It would require 10–15 pixels to uniquely and reliably identify a particular feature (Wilkie and Finn 1996). The occurrence of dense populations of sonkwariet (*Willdenowia incurvata*), a non-groundwater dependent species, as well as tall shrubs such as non-indigenous Port Jackson willow (*Acacia saligna*) and rooikrans (*Acacia cyclops*), produced high spectral classification values. Using the biomass indicators (NDVI and TC), all classes of vegetation were identified, not only groundwater dependent vegetation.

During field verification, riverine and wetland GDEs boundaries were considerably extended in the lowlands, where aerial photography and remote sensing failed to detect GDE systems in the absence of obvious wetland or riverine plant communities (caused by drought, water abstraction and reduced flow). In the uplands, however, the extent of GDEs was severely reduced locally as a result of gradients that were too steep to retain sufficient soil moisture because of runoff. Floristic analysis established these systems as groundwater dependent, with a high proportion of obligate riverine and wetland species. These provided a botanical signature which indicated the presence of groundwater dependent plant species (Conrad et al. 2005).

Using GIS and spatial modelling, a spatial model could be developed, based on the physical landscape characteristics, to predict the probability of the occurrence of GDEs. From Table 6, it appears as if the LWP model and the DWT model provide slightly better predictors for landscape wetness potential as indicators of groundwater dependency, compared to the field-verified data with 73% of verification points in classes 4 and 5 for the LWP and 77.2% for the DWT model. The GglWP model suggests a high wetness potential for only 30.9% of the points verified. From Table 7, it can be seen that the LWP and DWT models combined with biomass indicator classification still provided superior results with respectively 50.2 and 45% of field-verified points falling within the “high” GDE probability classes. Using the GglWP model, 78.4% of verification points were classified as having a “medium” probability of supporting GDEs.

The LWP model used in the northern Sandveld combined with the spectrally classified data, produced adequate results at regional scale and was modified and validated against the botanically mapped GDE boundaries from which riverine and wetland GDEs were identified. Botanical field mapping altered many of the GDE boundaries to include the extent of unmodified areas, which could not be determined from satellite imagery. The limitations of the resolution of Landsat images were highlighted during this exercise where many of the botanically identified indicator communities were smaller than the identifiable resolution of Landsat. An important consideration here is the objectives in trying to find GDEs. Was the objective to find the original, unmodified footprint of a particular ecosystem before modification, or was the objective to determine the current status of ecosystems that exist within the particular study area? Given enough time and resources, the particular GDE would be able to recover to its previous status, if unaffected by alien vegetation.

A shortcoming of the GglWP spatial model, as well as the groundwater level model, was that the input data for the groundwater elevation grid is dependent on the borehole distribution within the area, which may not be representative of the whole area. By expanding the GglWP model to contain reference to soils and geology, it can be enhanced.

Since the focus of the field verification was on distinguishing communities of riverine and wetland GDEs, other areas potentially housing terrestrial GDE communities, were not identified. From visual comparison of the combined LWP model with the other models and the spectral classification (Fig. 3), it appears as if there are large areas of “high” GDE probability not identified using any of the other models, especially in areas where there is a high degree of modification due to agriculture with a low relief. The only conclusive way of proving the accuracy of any one of the models, would be to investigate the chemical composition of particular plants in the selected sites.

Conclusion

Remote sensing based classification combined with spatial GIS based modelling is a cost effective solution which can provide useful results, in this case only at a regional scale. Some GDEs located within areas masked by the effects of land-use activities (i.e. land clearing and cultivation) or with a spectral resolution less than 30 m could not be identified, even if they existed. This infers that satellite imagery such as Landsat, is inappropriate, in terms of scale and resolution, for detailed mapping of GDE features which have been modified to some extent by alternate land-use activities. As suggested by Thompson et al. (2002), there are also various other biomass indicator combinations, which beg investigation, that may be used to more accurately or efficiently interpret the data spectrally.

Prior knowledge of the study area (in terms of expected landscape structure and associated land-cover/land-use characteristics) is a key factor in the speed of data processing, especially in the allocating of spectral classes to land-cover and GDE classes, since spectral classification remains a subjective process. In conjunction with vegetation mapping and field verification, which may be expensive and time consuming, remote sensing combined with spatial modelling can become a powerful tool for managing areas that are increasingly under ecological stress due to cultivation and urbanisation.

As a predictive tool, this methodology has produced adequate results for riverine and wetland GDEs, but needs to be field tested for terrestrial GDEs and chemically verified. Once this has been done, the model can be enhanced to include additional predictive parameters such as geology and soils, to identify the hydrogeological typesetting determining the location of the groundwater dependent ecosystems. The cost-effective nature of a predictive model of this type cannot be overstated.

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