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Physio-climatic classification of South Africa's woodland biome

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Abstract

In an effort to develop more holistic ecosystem approaches to resource assessment and management, landscapes need to be stratified into homogeneous geographic regions. These regions can then be used in a monitoring framework to develop reliable estimates of ecosystem productivity. A regional characterization of the woodland biome has been developed for South Africa, delineated by satellite imagery and using environmental data and a rigorous statistical methodology. Distribution maps of key environmental variables are analyzed by factor analysis, an iterative clustering technique and maximum likelihood classification to quantify and identify homogeneous physio-climatic units.

A spatial clustering technique was used to identify regions, which are statistically different with regard to five physiographic, climatic and edaphic variables deemed important within southern African savanna woodlands. The woodland biome of South Africa at 1km resolution was successively divided. Thirty year mean monthly temperature, total plant-available water balance of soil, elevation, landscape topographic position, and landscape soil fertility were used as input classification variables.

The map data were submitted to a factor analysis and varimax axis rotation. The factor analysis removes correlations from the input variables, reduces the dimensionality, and normalizes the axis measurements. A cluster analysis was performed on the three principal factor scores using a modified iterative optimization clustering procedure to determine the finest level of classes statistically permitable. Twenty-seven identified unimodal cluster signatures were then submitted to a maximum likelihood classification where the statistical probability of the GIS cell assignment is carried out to determine class membership. The final map of custom physio-climatic regions is described, and these custom regions are compared with a vegetation potential map of the woodland types identified in the South African summer rainfall zone.

Introduction

Large-scale vegetation maps are a mainstay of natural resource planning, management and conservation, where they are used to estimate trends in habitat extent, to formulate policy regarding sustainable harvest, and to site new nature reserves (Zonneveld 1988). Large-scale (i.e., finer than 1:50 000 scale) maps have been used by vegetation ecologists to locate field samples, to generate hypotheses about controls over plant distributions (Westman 1991), and most recently as input to spatially explicit ecological models of disturbance propagation and species persistence in heterogeneous landscapes (Turner 1987). Although remote sensing has reduced the cost of stand mapping, the expense of producing and maintaining accurate, large-scale maps limits their availability for most land surfaces, where information is only available at medium- or small-scale maps of generalized vegetation types.

Until recently, medium- and small-scale vegetation maps (e.g., 1:250 000–1:5 000 000) have had much less application in natural resource planning, management, and conservation or scientific research, aside from initial exploration, reconnaissance, or phytogeographic research (Kuchler 1988). Such maps are being used increasingly for rapid resource production estimates and conservation assessments, and to model the impacts of global climate change. At the medium and small scale, vegetation pattern must be greatly simplified both spatially and taxonomically, and the resulting depiction of vegetation both masks and distorts the true complexity of vegetation structure and composition, as well as the associated functional aspects. The crudeness of existing information at regional scales has obstructed both policy formulation and research addressing issues, such as sustainable resource management and impacts of global climate change.

Recent interest in the analysis and management of landscapes has required the development of spatial frameworks that stratify landscapes into relatively homogeneous regions. At the same time, geographic information systems (GIS) for spatial data management and analysis make possible new ways to characterize functionality associated with vegetation patterns, by allowing statistical analysis of important abiotic factors mapped for a given ecosystem type (see Goodchild 1994; Franklin 1995). This does not obviate the need to conduct field work. Instead, a rigorous analysis can lead to optimal definitions of functional regions within an ecosystem, which can then be used to develop an appropriate monitoring framework for measuring ecosystem productivity in the field. Mapping and identifying vegetation communities and their floristic components is an important task for conservation (Scott et al. 1993), but current and future focus will be on identifying and understanding the functionality of biomes and ecosystems for sustainable resource management (Lubchenco et al. 1991). GIS, remote sensing, and statistical analysis makes it possible to study the inter-relationship of scale, pattern, and process, and how they relate to the grain and extent of landscape measurement and observation within hierarchically nested systems.

Development of ecoregions

The goals and objectives of environmental management frequently require classification of distinct categories or regions based on measurable environmental characteristics. The delineation of ecological landscapes is useful in a variety of contexts, for example, for assessing or allocating the regional representation of conservation (Franklin 1993), defining zones for sustainable ecological management (Omi et al. 1979; Forman 1995), and as a framework for assessing the diversity of species within whole landscape ecosystems and their processes (Lapin & Barnes 1995). Sound environmental management is not only based on the understanding of spatial patterns, processes, and characteristics of ecosystems, but also an estimate of the environmental sustainability realistically attainable within a specific region.

Towards this end, the utility of multi-purpose ecoregional frameworks, such as have been developed for the United States (Omernik 1987; Bailey 1995) and Canada (Wiken 1986), has been successfully demonstrated in a variety of projects (e.g., U.S. Environmental Protection Agency: Environmental Monitoring and Assessment Program). Other ecoregional classifications, based on other criteria and for other purposes, have been specified by Thornwaite (1933), Raunkaier (1934), Holdridge (1947), and Walter & Box (1976). Recently, attention has been directed towards building a consensus in ecoregion development and distinguishing between the roles of watersheds and ecoregions (Omernik & Bailey 1997). They note that ecoregions can provide the spatial framework within which the quality and quantity of environmental resources, and ecosystems in general, can be expected to exhibit a particular pattern. Where watersheds are relevant and can be defined, they are necessary for studying the relationships of natural and anthropogenic phenomena with water quality, as well as for providing the spatial unit for reference areas within ecoregions at all scales.

Franklin (1995) reviewed the progress in predictive vegetation mapping from a geographic modelling perspective and noted that, to date, few studies have employed models that explicitly account for or exploit the spatial heterogeneity and dependence inherent in biotic patterns on the physical landscape. To further these aims, the objective of this study was to develop an objective and repeatable technique to delineate geographic physio-climatic regions within the woodland biome of South Africa based on environmental variables that drive growth of woody vegetation, to quantify the environmental factors associated with regional gradients in the woodland system, and to map and describe the geographic patterns. The physioclimatic units are divided based on multivariate geographic clustering of five variables important to tree growth in the savanna woodlands: mean monthly temperature, total plant-available water balance of soil, elevation, landscape topographic position, and landscape soil fertility (Huntley 1982; Scholes & Walker 1993; Scholes 1997). The woodland environment of South Africa serves as an opportunistic test of the methods as it represents a large geographic, varied topographic, and extremely varied climate zones (e.g., Indian Ocean coastal belt to the Kalahari plains). This situation has derived an unique set of woody vegetation patterns and dynamics that includes representative examples of many of the world's savanna ecosystems (Scholes 1997).

Factors associated with regional variation in savanna woodland communities

It is hypothesized that macroclimate, an expression of broad-scale temperature and moisture environment, is the primary associate of regional-scale patterns of community differences, and that substrate (geologic parent material and soils) and local factors (topography and site disturbance) are secondary. Macroclimate indirectly influences communities by modifying or regulating the importance of fine-scale factors and by favoring certain species and growth forms in interspecific competition. It is almost axiomatic that, at a regional scale, patterns of vegetation physiognomy and community composition are associated primarily with coarse-scale climate (Woodward 1987). Empirical studies that quantified environmental associations of patterns of savanna and grassland vegetation in southern Africa (Huntley 1982; Ellery et al. 1992) have consistently demonstrated the importance of temperature, moisture and parent geology.

The main functional distinction within southern African savannas is between the broad- and fine-leaved savannas (Huntley 1982). The underlying ecological difference is nutrient-rich, arid environments (fine-leaved) and savannas in nutrient-poor, moister environments (broad-leaved) (Scholes 1997). Studies have shown that soil chemistry differences are strongly associated with savanna vegetation patterns, as the savanna biome's main spatial organizing process is geomorphological (Scholes 1997). As a result, the ridges support broad-leaved savannas, while the valley bottoms support fine-leaved savannas. Landscape position has been found in other studies to significantly influence ecosystem patterns, especially controlling water movement (Kratz et al. 1991; Forman 1995).

Interactions among disturbance and successional processes with other environmental factors in determining regional savanna patterns are well understood. Although fire is a key disturbance in savannas, it is so frequent that it has become an 'included' disturbance, i.e. one which is so intimately part of the system that all organisms must be adapted to it. A significant part of the landscape structure and diversity in the 'undisturbed' savannas is a consequence of human disturbance over the ages (Blackmore et al. 1990), and 'Megaherbivores' such as elephants (Owen-Smith & Danckwerts 1997).

Abiotic controls of South African woodlands

The principal control in savanna woodland production is the soil water balance. The productivity of grasses, shrubs, and trees is strongly correlated with the quantity of water they transpire relative to the quantity that they could potentially transpire if the soil moisture supply was unlimited (Scholes & Walker 1993). This could be because the processes by which key nutrients such as nitrogen are made available to the plant are strongly controlled by the presence of moisture in the soil (Scholes 1993; Scholes & Walker 1993).

The nutrient-supplying capacity of the soil has a powerful effect on the production of woodlands per unit of rainfall transpired (Scholes 1993). The ecology and distribution of savanna in South Africa is largely determined by soil fertility (Scholes & Walker 1993), which effects the species composition pattern, production, and stability. Geological material from which the soil was formed is typically used as an indicator of the soil landscape fertility (Bell 1982). This works well in southern Africa because there is generally a good match between geology, soil, and vegetation, since the soils typically form from the geology immediately beneath them. These landscapes have not generally been subject to massive recent disturbances such as glaciation (i.e., 350 million years; Partridge 1997), which disrupts the soil-geology match in the Northern Hemisphere.

Methods

Study area

The study area is located between 22° and 32° S latitude and between 26° and 31° E longitude (Figure 1). Range of climate, physiography, geology, and soils are varied and complex (Table 1). In this study the woodland biome comprises the savanna biome and the unformally recognized 'thicket biome' (Low & Rebelo 1996).

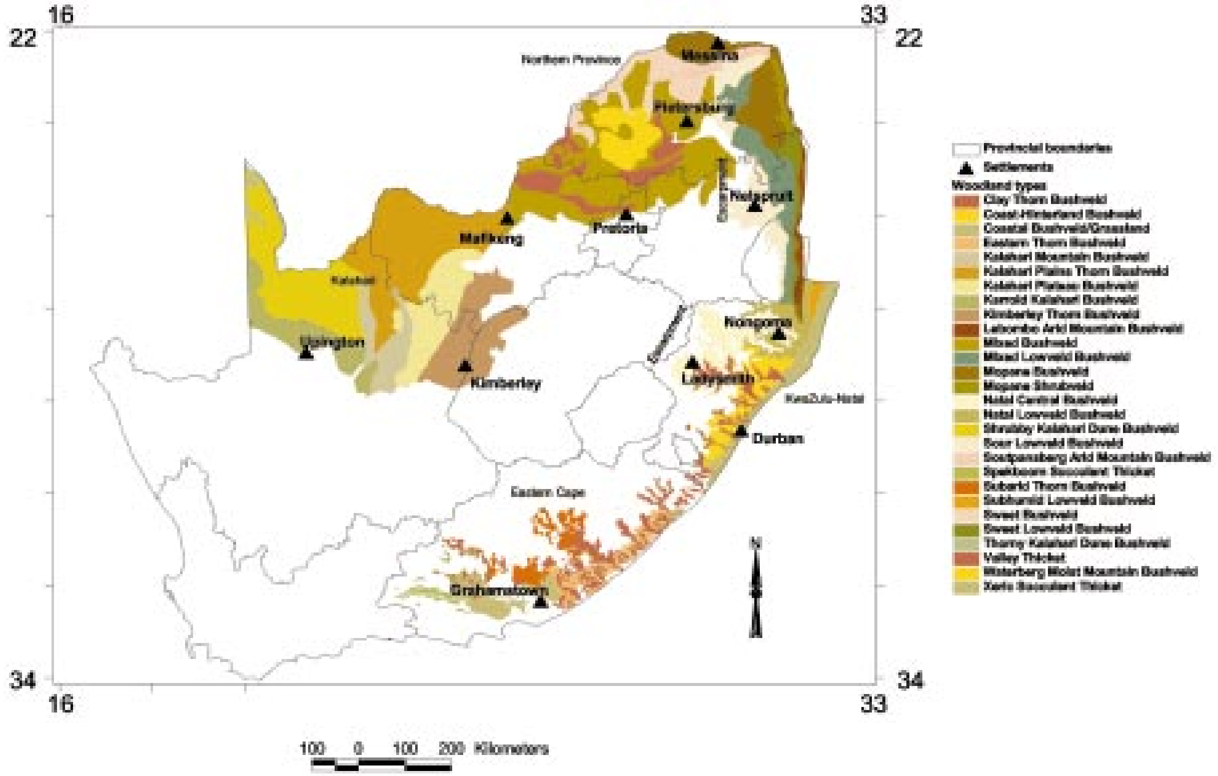

Figure 1. South African study area showing the woodland biome and its component vegetation types (Low & Rebelo 1996) that are the subject of this study, neighboring settlements, and major physiographic features.

Table 1. Minimum, maximum, mean and standard deviation (stdv) of continuous explanatory variables for the mapped woodland biome of South Africa. See Table 2 for explanation of codes for variables.

Variable	Minimum	Maximum	Mean	Stdev
DEM Land_slp	0	2857	929	398.8
Grow_dln	0	1	0.9	0.24
Grow_temp	4	303	83	40.6
Geol_fert	0	1.12	0.77	0.416

The important feature common to tropical savannas world-wide is a climate with a hot wet season of four- to eight-month duration and a warm dry season for the rest of the year (Nix 1983). In southern African savannas the wet season is unimodal, and falls in summer, between October and April.

Subtropical thicket is a transitional type between indigenous forest and savanna. It does not generally have a conspicuous grassy ground layer. The rainfall is too low and the lack of multiple strata in the canopy does not warrant its inclusion with the forest type (Everard 1987). Subtropical thicket is a closed shrubland to low forest dominated by evergreen, sclerophyllous or succulent trees, and shrubs. Because the vegetation types within the ‘thicket biome’ share floristic components with many other phytochoria which lie within almost all the formal biomes, thicket types have been referred to as ‘transitional’ (Everard 1987).

In South Africa the importance of these two woody biome types combined lies in their large contribution to the formal and subsistence economies. First, they supply fertile grazing lands, fuelwood, timber, medicines, and other resources (Brigham et al. 1996). Second, they contribute to the formal economy as the main location of the ecotourism industries (Grossman & Gandar 1989). Third, their global impact through the emissions of trace gases from fires, soils, vegetation, and animals (Justice et al. 1994) is significant. Fourth, they provide significant regional sequestration of carbon in their soils and biomass (Scholes & Hall 1996). Fifth, they provide important habitats for, and are made up of, large amounts of biological diversity (Cowling et al. 1997).

Distribution of woodland biome

The current distribution of the woodland biome was obtained from a satellite derived land-cover classification of South Africa, Swaziland, and Lesotho (Fairbanks & Thompson 1996; Fairbanks et al. 2000). The digital data from the South African National Land-Cover (NLC) Database project was used to delineate the current (Figure 2) rather than potential (Figure 1) distribution of the woodland biome. Before the NLC there were two potential vegetation maps available for South Africa: Acocks (1953) vegetation types of South Africa, which is largely based on the agricultural potential of the vegetation; and Low & Rebelo's (1996) vegetation of South Africa, Swaziland and Lesotho, which is based on a structural and floristic re-working of Acocks (1953). These works, while having been well received in the ecological and botanical communities, are somewhat lacking in portraying the realities of the land-cover in South Africa.

Explanatory variables

Data were compiled on the physical environment from interpolated field-records of weather stations, topographic contours and geology (Table 2). The mapped data was set in a geographic information system (GIS) (Arc/Info Grid, a raster based GIS; Environmental Systems Research Institute [ESRI] 1998) at a 1 km × 1 km grid cell resolution. The analysis cell size was partly determined by the largest cell size of the already rasterised data sets and a logical cell size for future integrative work. All data sets were converted to Albers Equal-Area projection for analysis.

Topography

A national digital elevation model (DEM; South African Surveyor General 1993) having an original cell resolution of 400 m and derived from 20 m contour intervals was used to derive the elevation and the topographic steepness of the land, which is calculated using standard routines in the GIS. A percent slope surface was transformed to a surface representing flat/undulating ($< 4\%$) and ridge landscapes ($> 35\%$) and then a linear function (-0.0322*slope% $+1.1234$), based on a mid-slope of 19%, scaled the slope data between the two extremes.

Water availability and temperature

The mean number of days per annum on which sufficient water is available to permit plant growth was considered a biologically meaningful index of water availability. Ellery et al. (1992) developed such a water balance index, which calculates the water budget from available climatology data. The index, called 'growth days' (GD), is defined as the sum of the monthly ratios of precipitation to potential evaporation, where the ratio is not permitted to exceed 1 in any given month (i.e., if rainfall is larger than evaporation, it is not carried over into subsequent months, but is assumed to have been lost as runoff). It is expressed as days just to be intuitively understandable. This is achieved by multiplying the monthly ratios by the number of days in the month and summing over the year.

$$GD = \Sigma_{12}(P/E^{*}d);\ P/E = 1,$$

where P is the long-term mean monthly rainfall, E is the monthly open water potential evaporation ('lake evaporation', using Lineacres' equation (Lineacre 1989) which uses maximum and minimum temperature, altitude, and latitude), and d is the number of days in the month. Intuitively it can be thought of as the number of days per year when soil moisture does not limit plant growth, though it is less than the actual growing period, since plant growth continues, at a reduced rate, even when soil moisture is not optimal. Daily maximum evaporation in South African woodlands is close to 3 mm d^{-1}, whereas lake evaporation is typically around 6 mm d^{-1}. Therefore, the actual growing season is close to twice the growth day index, but it is nevertheless highly correlated with plant production (Scholes & Hall 1996).

The GD index was calculated from the 1 km × 1 km monthly mean rainfall (1960–1990) grid covering the entire country and the monthly means of maximum and minimum daily temperatures (Dent et al. 1989). The index was log-transformed, because vegetation does not respond linearly to the amount of precipitation. A one day difference in available water is more important at a low number than at high numbers of days.

The annual mean of the monthly mean temperature weighted by the monthly growth days was recorded as 'growth temperature' (GT), giving an indication of energy supply during the growing season (Ellery et al. 1992). GT was calculated on the available mean monthly temperature surfaces (Schulze 1998). The estimated standard error is about 10% for the precip-

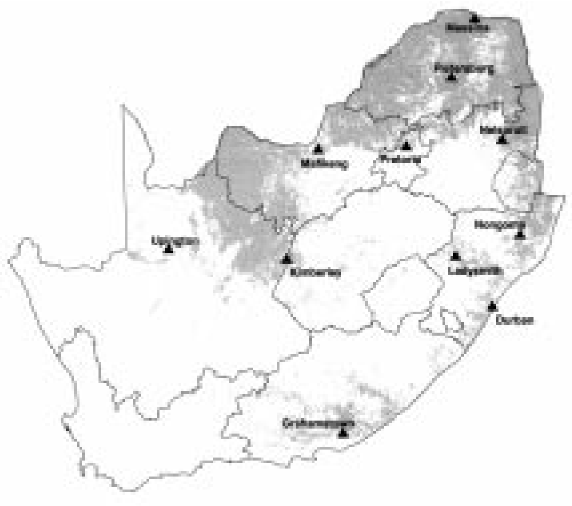

Figure 2. Extent of woodland biome derived from satellite imagery (1995) used in the analysis.

Table 2. Codes and definitions of explanatory variables used in factor analysis, by variable subset.

Code	Definition
Topography	
LAND_SLP	Slope (%) and transformed to identify flat, sloping, and ridges
Climate	
DEM	Elevation (m)
GROW_DLN	Positive soil water balance (natural logarithm, days per year)
GROW_TEMP	Mean temperature during positve soil water balance
Geology	
GEOL_FERT	Landscape fertility based on primary lithology

itation surface, 0.3–0.5 °C for minimum temperature, and 0.2–0.4 °C for maximum temperature.

Soil fertility

A comprehensive definition of the mineral nutrient regime requires detailed soil/substrate data. While these data were not available for the region, the parent material rock type had been recorded. An alternative is to use these geological data as surrogates for soil attributes. For a given region, classes of lithology can be ranked according to their potential mineral nutrient supply. The nutrient levels of soils can then be assumed to be related to these rankings.

The 1:1 000 000 geological map of South Africa (Visser 1989) was reclassified into three ranked classes (high, medium, low) on the basis of the primary lithology (Table 3). The information used for classification was the clay-forming potential of the material, its weathering rate and nutrient content. The author was aided in this task by a geologist (T. McCarthy) and guided by the work cited earlier.

Cluster modeling methodology

A principal component analysis (PCA) was used for data simplification and reduction of the effective dimensionality of the environmental variables (PRINCOMP, ESRI 1998). The goal of PCA is not to predict one variable with others, but rather to reveal how different variables change in relation to each other, or how they are associated. This is done by transforming correlated original variables into a new set of uncorrelated underlying variables using the standardized form of the correlation matrix. Each new variable accounts for as much of the remaining total variance of the original data as possible. The expectation from conducting a PCA is that correlations among original

Table 3. Classification of primary lithologies in the legend of the 1:1 M geological map of South Africa in terms of the capacity of the landscapes which they form to supply nutrients to plants. Classification performed by T. S. McCarthy.

Low fertility landscapes	Medium fertility landscapes	High fertility landscapes
Arenite	Limestone	Pyroclastic breccia
Lutaceous arenite	Dolomite	Siltstone
Silcrete	Tuff	Mudstone
Sand	Marble	Dolerite
Conglomerate	Andesite	Basalt
Rhyolite	diamictite	Shale
Granophyre		Peridotite
Serpentenite		Pyroxenite
Schist		Gabbro
Greenstone		Norite
Quartzite		Phyllite
Syenite		Sedimentary
Tonalite		Epidiorite
Granite		Lava
Gneiss		Charnocktite
Granitoid		Metamorphic
Granodiorite		Volcanic rocks
Harzburgite		Pyroclastic
Iron formation		Diorite
Quartz porphyry		Clinopyroxinite
Hornfels		Amphibolite
Siliciclastic		Dunite
Quartz monzanite		Anthothosite
Migmatite		
Ultramafic rocks		
Granite-gneiss, gneiss/granite		
Calc-silicate rock		
Chert		

variables are large enough so that the first few new variables or principal components account for most of the variance. If this holds, no essential insight is lost by applying the first few principal components for further analysis or decision making, and parsimony and clarity in the structure of the relationships is achieved. The correlation matrix, rather than the covariance matrix, is adopted for the PCA, which implies that all the five indicators included in the analysis are assigned equal weights in forming the principal components (Legendre & Legendre 1998).

The five raster maps of variables at 1 km × 1 km resolution are submitted to a PCA analysis with a varimax rotation. Usually the initial factor extraction does not give interpretable factors. One of the purposes of rotation is to obtain factors that can be named and interpreted. The varimax method minimizes the number of variables that have high loadings on each factor, thus simplifying the interpretation of the factors. The PCA performed on the raw data associated with each pixel, removes correlations among the input variables, standardizes the mean and variance, and reduces the dimensionality of the data set.

Unsupervised image classification methods within the remote sensing community are a form of user defined (i.e., custom) iterative clustering algorithms, based on landsurface reflectance characteristics, which results in the delineation of similar spectral areas within an image. These methods have rarely been applied to primary (i.e., non-spectral) environmental parameters (e.g., climate, topography, etc.) outside traditional image classification (but see Omi et al.

1979). These partitioning type of clustering methods are commonly used in the remote sensing community because of their ability to handle large, heterogeneous data amounts, but are not known to have been used among ecologists for environmental analysis. Clustering methods in ecology commonly use measures of similarity between sites (Q mode) or variables (R mode). Techniques commonly available to ecologists include hierarchical agglomerative, hierarchical divisive, and K-means partitioning, all of which while used extensively are problematic when working with very large data sets (see Legendre & Legendre 1998 for extensive discussion). The PCA results were inputs to a modified iterative optimization (migrating means) clustering algorithm (Richards 1986). This method assigns a cluster for each cell based on minimum parameter distance then iteratively recalculates the means of each cluster until the means no longer shift (Tou & Gonzalez 1974). The algorithm separates all cells into a user specified number of distinct unimodal signature groups in the multidimensional space of variables, then iteratively goes through the data matrix, modifying cluster characteristics until results converge on a stable result (ISOCLUSTER, ESRI 1998). The final classified surface created with this approach is based on a maximum likelihood decision rule with prior probabilities proportional to the number of cells in each class in the signature, and since the final clusters are required to be unimodal variable non-normality is not violated. This clustering method has several advantages over the others mentioned:

(1) it is designed to work with very large data sets;

(2) it is not scale dependent;

(3) it does not impose a 'spherical' or 'similar shape' structure on the clusters found, rather it retains the 'natural' clusters in the data when of other shapes; (4) it uses a common clustering criterion in the sum of squared error measure by which the 'quality' of clustering can be measured.

This measure insures that the final cluster assignment of the data is the optimal one over all others (Richards 1986).

The method requires the optimal number of classes be specified beforehand, but subjectively assigning what one would think is the number of physio-climatic units in the woodland biome would defeat the purpose of objective data-driven and empirical clustering. However, the clustering method used here can be used in a multistage strategy that exploits the data matrix variance. By initially specifying a conservatively high number of classes, which over-divides the samples into many small clusters, one can test for the stability of the clusters over many iterations. When the specified number of classes is set too high relative to the available data variance, it will result in singular covariance matrices for classes (the restriction that each cluster contains at least $p + 1$ individuals is necessary to avoid singular within group dispersion matrices, the determinants of which would be zero). Clusters merge with neighboring clusters when the statistical values are very similar after the clusters become stable. Some clusters may be so close to each other and have such similar statistics that keeping them apart would be an unnecessary division of the data. The unsupervised classification then fails. Exploiting this feature allows for a multistage approach to clustering, first by specifying an unrealizable high number of classes that will fail, and second stepping down from the high number in an iterative fashion until a stable optimal result with statistical significance in cluster differences is met. The optimal solution is then run through a maximum-likelihood classifier that considers both the variances and covariance's of the cluster signatures when assigning each cell to one of the classes represented in the signature file to produce the final map. The major steps in the analytical procedure used by this study are described as a flow chart in Figure 3.

Finally, as with most environmental data collected in the field or developed through extrapolation, spatial autocorrelation plays a role affecting the independence of the data. This in turn may affect one's understanding of the environment understudy. In this case the use of PCA or the clustering methodology does not require data independence and may instead with respect to the clustering method, benefit from environmental autocorrelation in defining the clusters.

Mapping of dominant gradients and classification results

PCA factor scores were kriged (Burrough 1986) in the Arc/Info GIS (ESRI 1998) to help visualize the factor analysis results through interpolation. Kriging is a linear, weighted-average interpolation method that considers spatial autocorrelation in the data and does not require that the data be normally distributed or uncorrelated. The linear model and exponential models were selected as having the best fit between actual and predicted semivariograms for principal component (PC) axes 1 and 2, and 3 respectfully at the biome scale. The factor scores were interpolated to a lattice with 5 km spacing and then contoured (LATTICECONTOUR,

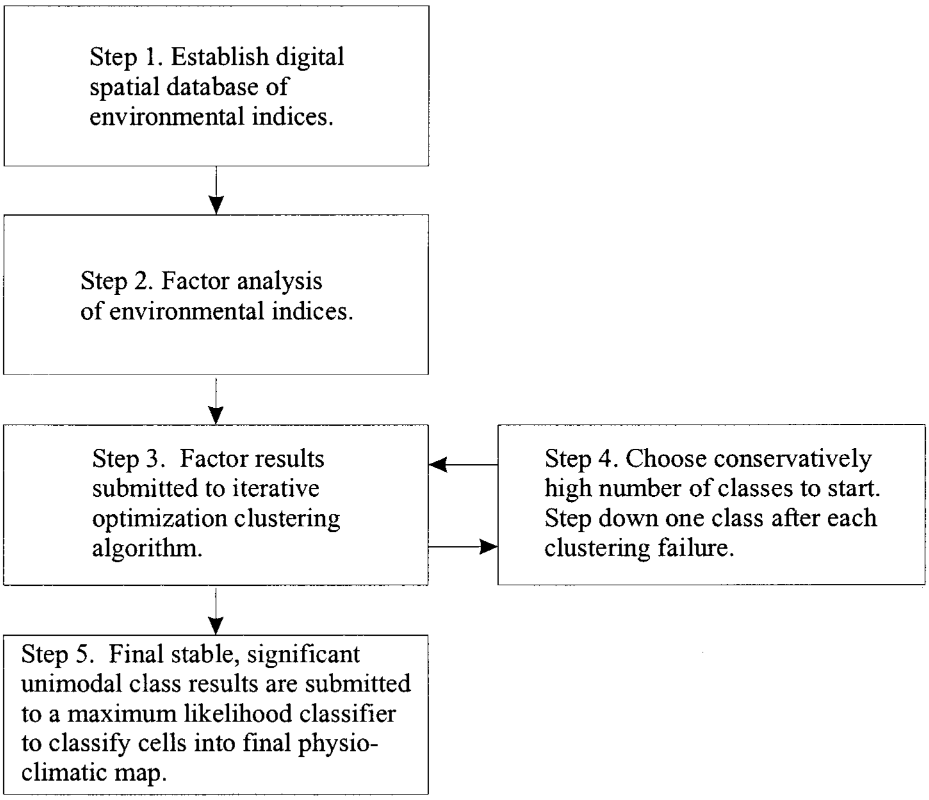

Figure 3. Flow chart of the major steps in the analytical procedure used in this study.

Table 4. Pearson correlation coefficients of the randomly sampled environmental variables.

Variables	DEM	Land_slp	Grow_dln	Grow_temp	Geol_fert
DEM	1.00				
Land_slp	−0.006	1.00			
Grow_dln	−0.193	−0.368	1.00		
Grow_temp	−0.435	0.377	−0.228	1.00	
Geol_fert	0.029	0.095	−0.173	0.253	1.00

Table 5. PCA eigenvalues with a varimax rotation of the randomly sampled environmental variables.

Variable	Axis 1	Axis 2	Axis 3
DEM	0.1834	− **0.9011**	0.0835
Land_slp	**0.8264**	0.1992	−0.0596
Grow_dln	−**0.7957**	0.1833	−0.1879
Grow_temp	0.4223	**0.7468**	0.2625
Geol_fert	0.0658	0.0468	**0.9784**
Variance explained	1.53	1.44	1.07
% Explained	30.65	28.91	21.45

ESRI 1998). Sizes of the sampling windows and contour intervals were subjectively selected to achieve comparable appearances among contour maps.

Results

Principal component analysis

Table 4 provides the correlation matrix of the variables. The eigenvalues and eigenvectors of the correlation matrix are given in Table 5.

The first three principal components (eigenvalue $>$ 1.0), which account for 81% of the total variation (Table 5), can be approximately classified according to three major environmental categories. The first axis represents water balance-topographic roughness, the second axis represents available energy budget, and the third axis represents landscape fertility. PC axis results show that the environmental parameters are generally colinear and independently significant on

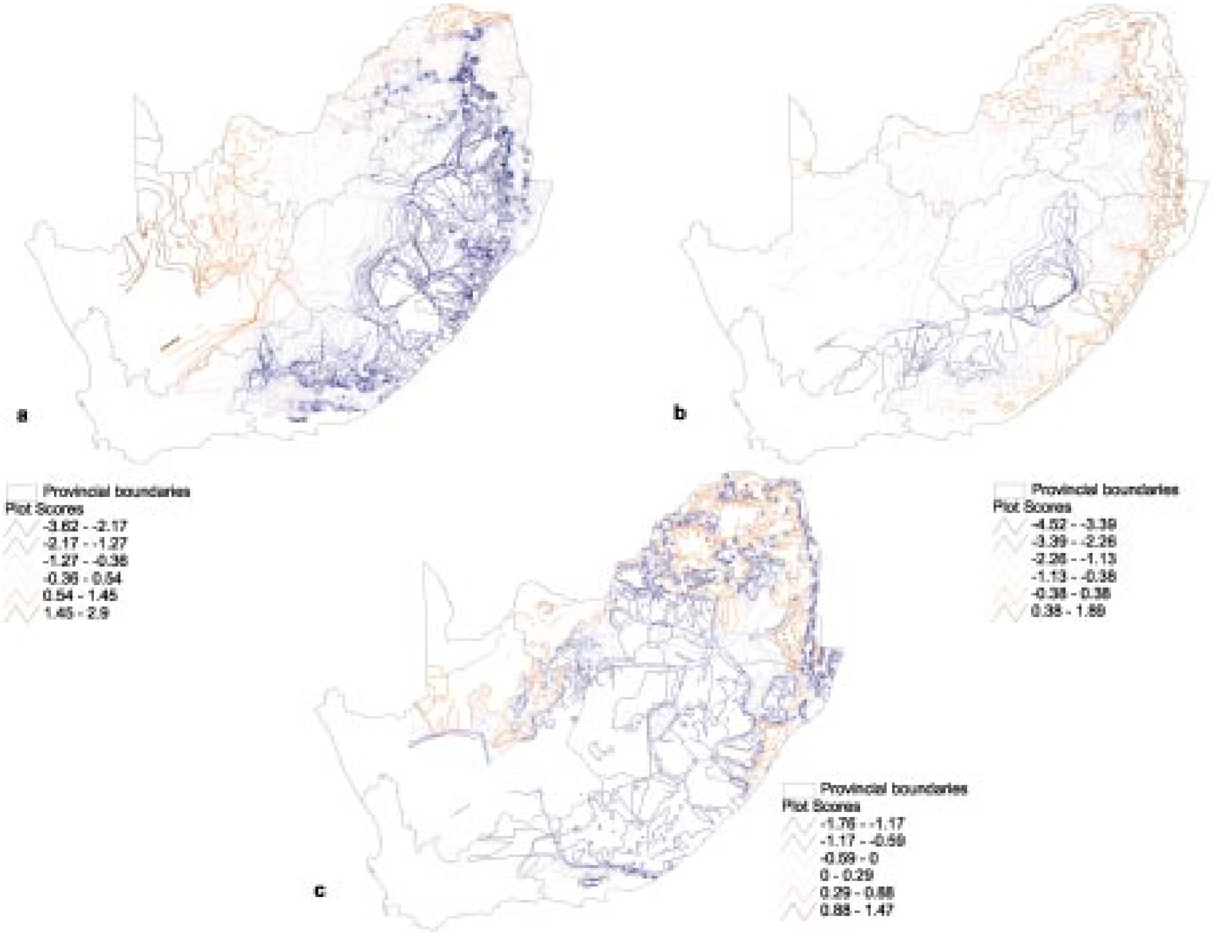

Figure 4. Plot scores (linear combinations) from principal components analysis of environmental parameters, woodland biome: (a) axis 1 (contour interval 0.181); (b) axis 2 (contour interval 0.377); (c) axis 3 (contour interval 0.293).

each axis in their contribution to the defining of the woodland biome.

Table 5 shows that the first PC has high positive coefficients (loadings) with: Land_slp, landscape topographic position (0.826) and Grow_dln, positive soil water balance (−0.795). Axis 1 reflected a gradient from the moister mountainous areas to the more continental climate of interior western- northwestern South Africa (Figure 4a). Samples with the lowest scores on axis 1 were landscapes of heterogeneous topographic roughness and experienced longer positive soil water balance durations. These areas were concentrated with the Waterberg Mtns., Drakensberg escarpment, and KwaZulu-Natal midlands (Figure 4a) which comprises the various vegetation types of sour lowveld bushveld, Natal central bushveld, coast-hinterland bushveld and eastern thorn bushveld zones (Low & Rebelo 1996). Samples with high scores on axis 1 were on flatter landscape areas and were characterized by a lower amount of positive soil water balance durations. The highest sample scores were concentrated in the areas below the Drakensberg escarpment, along the Limpopo river valley and in the far western end of the range representing the start of the Kalahari desert (Figure 4a). High-scoring samples fell largely within the Soutpansberg arid mountain bushveld, mopane bushveld, Kalahari plains thorn bushveld, shrubby Kalahari dune bushveld, and karroid Kalahari bushveld (Low & Rebelo 1996).

The second PC axis has high loadings with DEM, the elevation (−0.901) and Grow_temp, the mean temperature during positive soil water balance (0.747). Axis 2 reflected a gradient from the hotter lower elevation interior and coastal areas to the cooler regions on the high South African interior plateau (Figure 4b). The second axis was a gradient in growing season energy supply, from areas of hot growing seasons at lower elevations to areas of warm- cool growing seasons at higher elevations (Figure 4b). Lowest sample scores representing lower available energy during times of positive soil water balance were concentrated in areas above the Drakensberg escarpment, on the high interior plateau and in the higher elevation mountainous regions (Figure 4b), within the subarid thorn bushveld, Waterberg moist mountain bushveld, and sourish mixed bushveld (Acocks 1953; Low & Rebelo 1996). Highest sample scores on axis 2 were in the lower lying coastal and interior plains of Maputaland, eastern Swaziland, Kruger National Park, and along the Limpopo river valley (Figure 4b).

The third PC axis has high loadings with Geol_fert, landscape fertility based on primary lithology (0.978). Axis 3 was most strongly correlated with the transformed geologic variable. Low-scoring samples were on geologic landscapes of high fertility (Figure 4c) within the subarid thorn bushveld, eastern thorn bushveld, Natal lowveld bushveld, sweet lowveld bushveld, mopane shrubveld, and Kimberley thorn bushveld (Low & Rebelo 1996). High scoring samples were on geologic landscapes of lower fertility (Figure 4c) within the coast-hinterland bushveld, sour lowveld bushveld, mopane bushveld, mixed bushveld, Waterberg moist mountain bushveld, and Kalahari plains thorn bushveld (Low & Rebelo 1996).

Cluster analysis

The three PC axes were clustered with the multistage approach starting with 200 clusters using 200 iterations and complete data sampling in a batch step-down model. As expected a stable result is not met, with the algorithm failing with a singularity covariance matrix until reaching 27 cluster classes, which are accepted as stable and statistically significant by the algorithm. This represents the finest level of classification or optimal ‘natural’ number of clusters that can be obtained from the environmental data space. The 27 unimodal cluster classes were processed through a maximum likelihood classifier to yield a final classification map (Figure 5), and then a descriptive table was derived of the environmental variable limits for each class (Table 6).

The following provides descriptions of each identified unit, and representative species identified for each unit to be used for productivity measurements are provided in Appendix 1. Unit one represents areas along the southern Eastern Cape coast extending inland up hot, dry valley basins on fertile soils. Two is along a humid coastal strip covering the Tongoland and Pondoland areas with flat to undulating terrain and medium fertility soils. Three is found in the relatively low-lying, dry-warm valleys of the White and Black Kei rivers in the Eastern Cape on fertile soils. Four occurs in moist tropical lower eastern slopes of the Drakensberg and lower Tugela river valley on infertile soils. Five occurs in lower Zululand and Maputaland plain, being flat low-lying subtropical with moderately fertile soils. Six represents the hot semi-moist tropical bottom eastern slopes of the Drakensberg, lowveld Swaziland and interior Zululand on infertile soils. Seven occurs in the hot-dry flat lower northern slopes of the Soutpansberg Mtns. to the Limpopo river valley on infertile soils. Eight represents the reasonably flat hot sub-tropical plains of the Kruger National Park with reasonably infertile soils. Nine describes the moist tropical steep, deeply dissected river valleys of southern KwaZulu-Natal on moderate fertility soils. Ten occurs in the dry and hot Limpopo river valley and associated tributary valleys from the eastern end of the Soutpansberg Mtns. on infertile soils. Eleven represents mid-lying hot-dry flat plains of moderate soil fertility in the Northern province. Twelve is along the warm-dry midslopes of the eastern Eastern Cape mountains on fertile soils. Thirteen represents the flat, arid-hot plains surrounding the Orange river drainage basin on highly infertile soils. Fourteen occurs in the mid-lying, flat arid-hot Kalahari plains on highly infertile soils. Fifteen occurs in the mid-lying flat, dry-hot areas of the Kimberley and Pietersburg Plateaus of moderate fertility soils. Sixteen occurs in the mid-lying, flat dry-hot Kalahari plains on highly infertile soils. Seventeen represents the high-lying, dry-hot Kuruman Hills are with soils of moderate fertility. Eighteen occurs in the mid-lying, flat dry-hot sandy Kalahari plains on highly infertile soils. Nineteen represents the flat, dry-hot plains surrounding the upper Limpopo river drainage basin on moderately fertile soils. Twenty represents mid-lying, hot sub-tropical plains in the Northern province on moderate fertility soils. Twenty-one describes the mid-lying KwaZulu-Natal hilly midlands and river valleys with a warm moist tropical clime and soils of moderate fertility. Twenty-two represents the dry-hot, flat high-lying Kalahari Plateau on moderately fertile soils. Twenty-three occurs in the dry-warm, flat high-lying Kuruman Hills and southern Pietersburg Plateau on moderately fertile soils. Twenty-four rep-

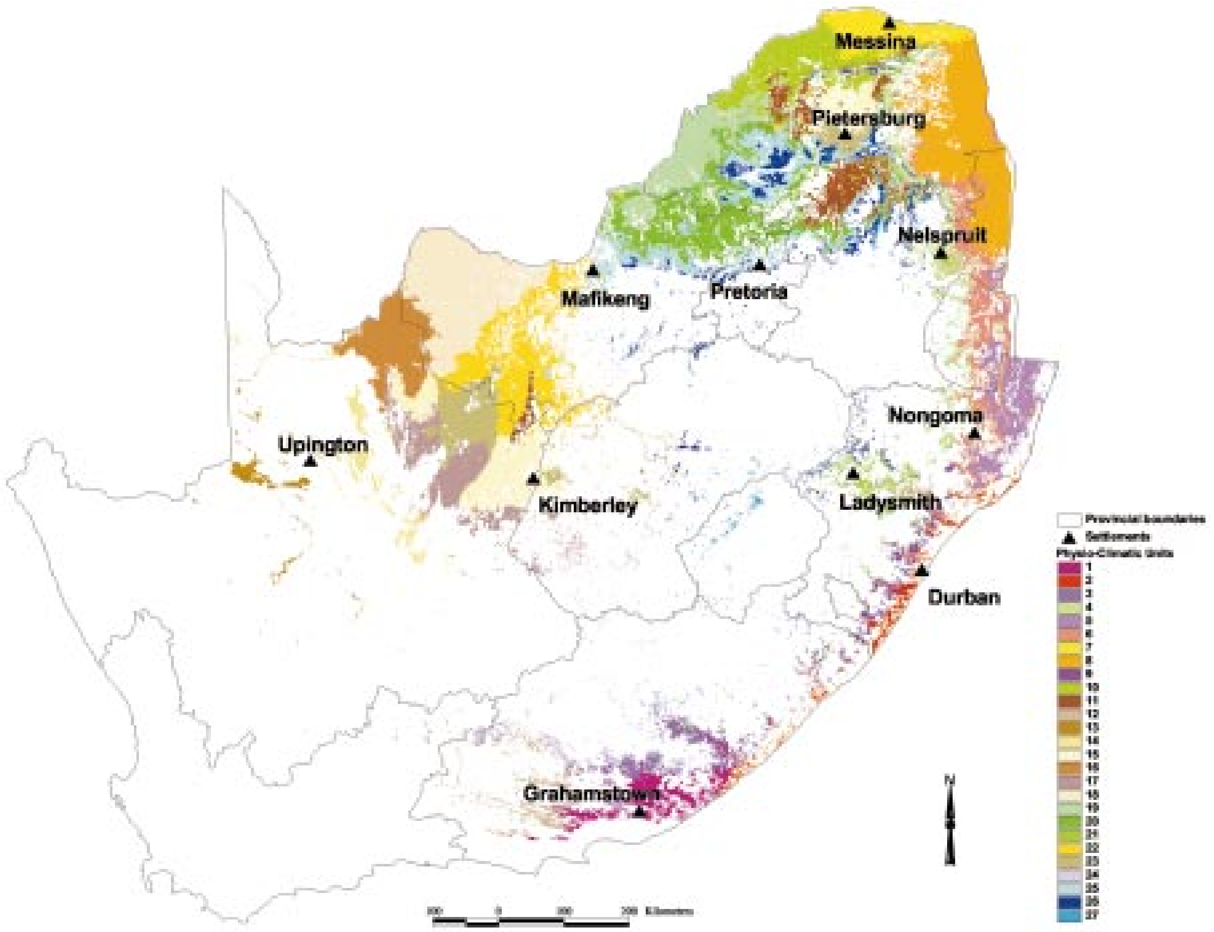

Figure 5. South African woodland biome clustered into 27 physio-climatic regions.

resents the cool-dry, high-lying undulating and hilly interior of the Eastern Cape with very highly fertile soils. Twenty-five represents high-lying undulating to flat plains of the lower inland plateau of hot subtropical clime and low fertility soils. Twenty-six represents the moist temperate higher-lying ridges along the inland plateau and the Waterberg Mtns. on moderately fertile soils. Twenty-seven represents the highest-lying areas of woody plant growth with a cool moist temperate clime occurring in ridges and steep slopes on moderate fertility soils.

Discussion

The integrated index of growth days and landscape topographic position contributed to total variation explained on the first PCA axis. Elevation and growth temperature ‘productive energy supply’ contributed to the total variation explained on the second PCA axis. Landscape fertility contributed to the total variation explained on the third PCA axis. The order of emergence of each variable on the axes is related to the amount of variation in the data set in respect to other variables. This can be shown in Table 1 by dividing the standard deviation by the mean (i.e., normalizing) for each variable. Grow_dln has the highest normalized variance followed by Land_slp, Grow_temp, DEM, and Geol_fert. The fact that each axis explains almost exactly the same fraction of the total variation means they are all essential, and equally important to the classification outcome.

The analytical model used proved efficient in objectively deriving a fine level of woodland physio-climatic detail within a statistically rigorous procedure. As such, the technique developed here is a very useful way of understanding the patterns of abiotic determinants in any ecosystem. This is an important

Table 6. Climatic and topographic limits of the 27 derived physio-climatic units.

Unit	DEM			Grow_day			Grow_temp			Land_slp	Geol_fert
	Min	Max	Mean	Min	Max	Mean	Min	Max	Mean	Mean	Mean
1	4	663.2	343.2	42.6	184.6	91.7	16.4	20.5	18.6	0.81	0.42
2	0.5	412.5	190.3	106	303.3	201.1	18.4	23	20.8	0.71	0.66
3	547.2	1196.8	836.9	50.7	221.2	99.2	15.4	20	17.7	0.66	0.29
4	444	1003.6	735.4	72.9	225.8	148.4	19.7	26.3	22	0.60	0.85
5	0.5	333.9	148.9	64.2	183.1	114.8	21.6	24.7	23.4	0.95	0.64
6	82.6	699.3	425	72.3	200.8	128	21.3	25.2	23.1	0.84	0.89
7	195.5	834.9	569.9	24.8	64.5	41.9	23.3	26.5	24.8	0.99	0.85
8	134.3	709.4	383	47.9	122.9	81.6	23	26.1	24.5	0.99	0.87
9	291	885.6	576.8	86.2	237.8	160.2	17.2	21.7	19.8	0.55	0.56
10	588.3	1013.6	830.8	39	85.7	58.1	22.2	26.5	23.7	0.99	0.88
11	692.6	1166.1	957.6	52.8	128.9	83.5	20.6	23.5	22.2	0.92	0.71
12	65.3	1329.3	671.2	13.3	90	40.6	14.2	20.1	17.8	0.73	0.47
13	423.8	1147.8	764.1	3.6	16.2	9.2	15.9	25.5	21.6	0.98	0.90
14	793.3	1349.5	1025.2	10	33.3	20.8	17.9	28.3	21.6	0.98	0.95
15	923.2	1305	1132.4	33.7	94.8	53	19.8	23	21.4	0.99	0.64
16	875	1185.1	1025.2	19.3	51.1	33.8	21.7	24.9	23	0.99	1.11
17	1004.3	1537.4	1301.8	29.1	64.5	44.6	18.3	22.3	20.5	0.98	0.73
18	941.6	1268	1107.3	25.3	63.1	45.3	21.9	27.6	23.6	0.99	1.10
19	739.7	1131.3	956.5	55.5	112	80.6	22.6	25.8	23.5	0.98	0.64
20	886.5	1268.4	1089.6	66.7	157.7	102.8	20.7	23.9	22.2	0.91	0.62
21	821.4	1358.8	1090.3	72	233.7	152.1	16.2	22.6	19.8	0.54	0.56
22	1107.7	1458.4	1290.5	47.4	92.4	66.3	20.7	23.3	21.9	0.99	0.77
23	1178	1781	1429.1	46.2	107.6	67.4	18.2	21.5	20.4	0.98	0.78
24	856.3	2248.6	1418	28.2	241.6	78.8	6.7	29	16.2	0.53	0.26
25	1096.3	1537.8	1304.3	72.3	172.3	109.4	19.5	22.9	21	0.83	0.79
26	1271.2	1831.3	1483.6	81.9	216.7	130.8	17.2	21.6	19.3	0.67	0.73
27	1291.6	2857	1814.4	85.2	260	162.6	6.1	19.4	16.3	0.42	0.54

finding as other classification methods may be data driven, but they tend to be over generous in defining clusters, which then allows any 'expert' the ability to subjectively ask the system for any number of classes (i.e., K-means). The value of a classification system breaks down for monitoring and management purposes when it is overly burdened with superfluous classes, thus a more parsimonious approach is required.

To be sure, we can recognize all natural ecosystems by differences in climatic regime. Climate, as a source of energy and moisture, and its component timing acts as the primary control for ecosystems (Stephenson 1990). More importantly from a management point of view, as this component changes, the other components change in response. Landforms (i.e., geologic substrate, surface shape, and relief) are an important criterion for recognizing smaller divisions within macroecosystems. Landform modifies climatic regimes at all scales within macroclimatic zones. It causes the modification of macroclimate to local climate. At the mesoscale, the landform and landform pattern form a natural ecological unit. The primary elements of defining functional ecosystem units, or what I have termed physio-climatic units, are in contrast to using present or potential vegetation type which are useful to describe the status of ecosystem in terms of age and disturbance, but only part of the picture when delineating the boundary of an ecosystem.

In this study the physio-climatic units were also conceived as ecosystems of hierarchical spatial sizes (O'Neill et al. 1986). It is recognized that management objectives and proposed uses determine which sizes are judged important, but that these sizes should be logically collapseable within the given hierarchy so that researchers can use data from several levels of a hierarchy. One could take the results here and subject them to an hierarchical classification analysis to identify the relationship among the clusters and to aggregate hierarchically similar clusters. An hierarchical system becomes advantageous because the finer spatial units can be lumped to a relatively few units to which all ecological land managers can relate. The number of levels required all depends on the kind of question being asked and the scale of the study.

The results of this study pose some interesting questions and issues. Many of the woodland vegetation types in the vegetation potential map (Figure 1) have several physio-climatic units as their functional base (Table 7). Most of the vegetation types are dominated by 2–3 physio-climatic types (> 10% coverage), but the total variety of types (i.e., < 10% coverage) collectively defining their distribution could be as much as 18 physio-climatic units (i.e., sour lowveld bushveld, which is considered to be a poorly defined unit anyway; R.J. Scholes pers. comm.). Some of the physio-climatic units covered such small portions of vegetation types that it is probably error represented in the database by spurious units surrounded by a dominant homogenous unit, or GIS overlay error. Not surprisingly, the vegetation types with the most variability either occur over large geographic gradients (O'Brien 1993; O'Brien et al. 1998) and are generally noted as being diverse (i.e., mixed bushveld and coast-hinterland bushveld; Low & Rebelo 1996), or are topographically complex (i.e., Waterberg moist mountain bushveld and valley thicket). This is not an issue as the vegetation map is based on physiognomic and floristic characteristics, whereas the classification is environmentally based. The issue for management rests in the need to recognize and validate the woody productivity of the potential vegetation types in conjunction with the physio-climatic classification. Though not a concern, having fewer physio-climatic zones being elucidated than the number of vegetation types can be explained four ways: first, the distribution data used to define the woodland biome was based on actual satellite interpretation, not the vegetation potential map; second, potential error in vegetation potential boundaries drawn by 'experts'; third, the environmental data used had a moderate coarse resolution versus the broad thematic definition of vegetation potential classes, thus the detailed physio-climatic heterogeneity found within these 'homogeneous' class boundaries can be identified; and fourth the role of another important abiotic factor could have been overlooked. Therefore, by nature of the potential vegetation mapping it is possible that one floristic unit can span more than one physio-climatic unit. The other important question to raise is, what other biologically meaningful environmental variables could be used to further split the homogeneous physio-climatic units into zones that define some of the more complex vegetation units (i.e., mopane bushveld, mixed bushveld, sour lowveld bushveld). This analysis suffers from the lack of a good soil database, which defines soil attributes (i.e., clay content, nitrogen availability, etc.). Information on the intrinsic fertility of the soil is an important consideration in plant functioning and also for assessing the rate at which nitrogen is mineralised in the soil. The availability of a good soil database could also have led to a refinement of the soil water availability map, here defined strictly climatically by growth days, into a map of plant available water of a soil profile. The role of existing species in community structure and dynamics, especially tree-grass (Scholes & Walker 1993) and tree-tree interactions (Smith & Goodman 1986), could have been addressed, which are the result of disturbances (i.e., fire). The co-occurrence of different vegetation types under the same macroclimate, and often on similar soils, has long been noted as the importance of disturbance in determining vegetation patterns (e.g., Phillips 1930) in southern Africa.

As a first approximation of the physio-climatic heterogeneity of the woodland biome the variables used in this analysis provide a well defined baseline, but refinements with better databases will lead to improvements. Nevertheless, the information provided in Table 7 shows the danger in only using vegetation potential classes for resource management planning, the landscape variability is under sampled and thus weakly characterized.

Ecologically defined maps represent hypotheses about factors that control ecosystem structure and function (Rowe & Sheard 1981). The testing or validation of this physio-climatic map is thus an important prerequisite to its application. The units express a sense of what is theorized to be important in the landscape. If actual data on productivity are assembled for the regions, this hypothesis can be tested statistically and the validity of the regional structure (map) can be evaluated objectively. In this case the testing of this map was confounded by the difficulty of obtaining independent data and sufficient numbers of samples to characterize the regional areas. In this respect this map will first be used to delineate a woodland productivity monitoring network with full regional coverage.

Table 7. Crosstabulation of the proportions of the 27 physio-climatic units identified within the Low & Rebelo (1996) potential vegetation map types.

Vegetation type (Low & Rebelo 1996)	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	Variety
Clay thorn bushveld	0.00	0.00	0.00	0.04	0.00	0.00	0.00	0.00	0.00	0.03	8.24	0.00	0.00	0.00	0.00	0.00	0.00	0.00	**32.13**	**52.17**	0.03	0.11	0.00	0.00	6.21	1.05	0.00	9
Coast-hinterland bushveld	0.00	**17.33**	0.12	6.71	**17.10**	**12.27**	0.00	0.00	**40.71**	0.00	0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	5.73	0.00	0.00	0.00	0.00	0.00	0.00	8
Coastal bushveld/grassland	0.00	**54.35**	0.00	0.00	**40.29**	0.03	0.00	0.00	5.33	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	4
Eastern thorn bushveld	**53.79**	8.56	**12.48**	0.00	0.00	0.00	0.00	0.00	**24.87**	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.22	0.00	0.00	0.05	0.00	0.00	0.05	7
Kalahari mountain bushveld	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.56	**10.70**	4.15	**50.44**	0.49	0.00	0.00	0.00	1.57	**30.78**	0.29	0.00	0.03	0.00	9
Kalahari plains thorn bushveld	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	5.69	**20.16**	2.79	**53.82**	1.06	0.41	0.00	**14.62**	1.00	0.05	0.40	0.00	0.00	14
Kalahari plateau bushveld	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.19	0.00	0.00	0.00	4.52	0.00	**20.59**	0.00	0.00	0.00	0.00	**44.30**	**30.38**	0.00	0.02	0.00	0.00	6
Karroid kalahari bushveld	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	**10.28**	**89.01**	0.00	0.00	0.71	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	3
Kimberley thorn bushveld	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	5.86	0.00	0.00	0.00	**58.67**	0.00	1.44	0.00	0.00	0.00	0.00	**28.70**	4.36	0.00	0.97	0.00	0.00	6
Lebombo arid mountain bushveld	0.00	0.03	0.00	5.80	**22.57**	**34.11**	0.00	**37.49**	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	5
Mixed bushveld	0.00	0.00	0.00	0.76	0.00	0.03	0.00	0.00	0.00	5.86	**14.52**	0.00	0.00	0.00	4.98	0.00	0.08	0.00	**13.41**	**30.93**	1.04	0.69	4.28	0.00	**18.74**	4.21	0.47	14
Mixed lowveld bushveld	0.00	0.00	0.00	5.17	6.81	**31.26**	0.02	**56.46**	0.00	0.01	0.06	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.06	0.12	0.00	0.00	0.00	0.03	0.00	0.00	10
Mopane bushveld	0.00	0.00	0.00	0.03	0.00	0.31	**36.41**	**57.56**	0.00	5.70	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	5
Mopane shrubveld	0.00	0.00	0.00	0.00	0.00	3.53	0.08	**96.40**	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	3
Natal central bushveld	0.00	0.00	0.00	**19.96**	5.08	**15.95**	0.00	0.00	1.57	0.00	0.09	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	**47.27**	0.00	0.00	0.03	0.06	9.18	0.80	10
Natal lowveld bushveld	0.00	0.05	0.00	9.51	**59.34**	**29.44**	0.00	0.05	0.48	0.00	0.05	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.03	1.05	0.00	0.00	0.00	0.00	0.00	0.00	9
Shrubby kalahari dune bushveld	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.53	**31.61**	0.00	**67.31**	0.51	0.04	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	5
Sour lowveld bushveld	0.00	0.01	0.00	**40.19**	1.00	**31.52**	0.60	7.74	0.11	0.52	3.20	0.00	0.00	0.00	0.16	0.00	0.00	0.00	0.28	2.92	7.64	0.10	0.02	0.00	2.05	1.68	0.27	18
Soutpansberg arid mountain bushveld	0.00	0.00	0.00	1.64	0.00	0.16	**43.72**	5.12	0.00	**21.81**	7.90	0.00	0.00	0.00	0.91	0.11	0.00	0.21	2.76	4.69	0.11	1.23	0.66	0.00	4.99	3.99	0.00	16
Spekboom succulent thicket	0.24	0.00	3.61	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	**87.47**	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	8.68	0.00	0.00	0.00	4
Subarid thorn bushveld	**17.32**	0.04	**64.29**	0.00	0.00	0.00	0.00	0.00	1.05	0.00	0.00	4.15	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.84	0.00	0.00	**10.68**	0.00	0.14	0.51	9
Subhumid lowveld bushveld	0.00	0.00	0.00	0.00	**100.00**	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1
Sweet bushveld	0.00	0.00	0.00	0.11	0.01	0.00	1.86	0.00	0.00	**58.49**	3.74	0.00	0.00	0.00	**12.12**	0.00	0.00	0.00	**20.42**	2.60	0.00	0.14	0.12	0.00	0.37	0.04	0.00	12
Sweet lowveld bushveld	0.00	0.06	0.00	0.92	**14.98**	**13.93**	0.00	**70.10**	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	5
Thorny Kalahari dune bushveld	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	**29.03**	0.00	**64.52**	0.00	6.45	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	3
Valley thicket	**14.41**	**14.87**	**11.19**	6.99	2.74	3.49	0.00	0.00	**25.88**	0.00	0.10	4.54	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	**11.68**	0.00	0.00	3.88	0.00	0.15	0.09	13
Waterberg moist mountain bushveld	0.00	0.00	0.00	0.06	0.00	0.00	0.00	0.00	0.00	0.86	2.05	0.00	0.00	0.00	0.00	0.00	0.00	0.00	**10.77**	**22.01**	0.16	1.69	0.00	0.00	**41.22**	**21.13**	0.06	10
Xeric succulent thicket	**71.28**	0.00	5.50	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	**23.22**	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	3
Total area of the physio-climatic unit (100 000’s ha)	7.44	4.67	4.65	9.62	10.13	14.20	9.29	27.50	5.60	13.78	10.72	3.51	2.52	5.12	17.86	12.87	11.72	24.68	14.86	24.63	6.93	21.86	12.71	3.45	17.61	9.74	2.44	
% of unit found outside defined NBI woodland biome	21.10	12.50	28.91	18.80	0.95	8.92	0.02	0.26	18.01	0.13	2.49	47.97	90.95	32.92	4.55	0.03	21.20	0.04	0.15	1.28	38.57	6.33	9.26	79.08	13.11	46.71	86.86	

A final issue that must be addressed is the robustness of the derived physio-climatic classification system over time and space. The physio-climatic classification system developed was based on both structural and climatic components. The structural data layers are expected to be robust over time and space due to their slow geological evolution, but climate may present resiliency problems for the current classification. Under a predicted climate change scenario for precipitation and temperature in southern Africa (Joubert & Hewitson 1997) the growth days index and growth temperature can both be expected to change over space and in magnitude. The relevance of the physio-climatic classification system can therefore be retained by re-defining the classification when newer climatic data sets become available. This is not in conflict with the objective of providing a classification system for a *functional region*, which is also expected to undergo evolutionary change over time. However, there is a trade-off between too much data resolution versus the expected resilience of the classification system, which can be tested through sensitivity analysis.

Conclusions

The multivariate geographic clustering methodology used for this study has several advantages: (1) it is an empirical technique that defines relatively homogeneous areas with respect to the input variables; (2) it is repeatable, not subjective ‘expert’ opinion; (3) the methods are statistically significant and ‘naturally’ recognizable results can be revealed without defining the number of classes. Clustering is data-driven and empirical. This is in contrast to expert consensus to derive ecoregions or potential vegetation maps. Users control what data are included for consideration in the multistage clustering process based on what is appropriate for their purposes. Users are also able to select how many classes to start with in the iteration process based on knowledge of their data’s variance space and to reach a stable and statistically significant solution.

While chosen data layers and analytical methods are relatively objective, there are a number of decisions that require some understanding of the region under study. It is unrealistic to expect that the process of ecoregional classification can be accomplished entirely by spatial and numeric analysis; human understanding is also an important component (Host et al. 1996).

Regional ecosystem classification is important for understanding the spatial pattern and productivity of the landscape. Land management deals with productivity systems (i.e., ecosystems) from which it attempts to efficiently, and continuously, extract renewable products, such as wood or water. Adaptive environmental management of land ensures that all land uses consistently sustain resource productivity and maintain ecosystem processes and function (Holling 1976). The development of regional ecosystem functional maps for continuously utilised disequilibrium systems, like the woodland biome in South Africa, allows for the adjustment of strategic resource policy, tactical landscape management, and operational site monitoring within an ecologically meaningful partioning of the ecosystem.

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Appendix. List of representative trees and shrubs associated with each physio-climatic zone to be used for productivity measurements in the field. Nomenclature follows Palgrave (1988).

Physio-climatic zones	Representative species
1	*Grewia robusta, Brachylaena ilicifolia*
2	*Drypetes gerrardii, Millettia grandis, Acacia karroo, Rhus lancea, Ehretia rigida, Dalbergia obovata*
3	*Acacia karroo*
4	*Dombeya cymosa, Euphorbia tirucalli, Acacia robusta*
5	*Albizia adianthifolia, Acacia nigrescens*
6	*Acacia tortilis, Terminalia sericea*
7	*Colophospermum mopane, Androstachys johnsonii, Adansonia digitata*
8	*Combretum collinum, Combretum imberbe, Sclerocarya birrea, Acacia nigrescens, Acacia nilotica, Albizia harveyi, Combretum apiculatum*
9	*Cassine aethiopica, Diospyros dichrophylla*
10	*Croton gratissimus, Burkea africana, Terminalia sericea, Grewia flava, Commiphora pyracanthoides*
11	*Terminalia sericea, Ochna pulchra, Peltophorum africanum*
12	*Lycium austrinum, Crassula aborescens, Crassula ovata, Portulacaria afra*
13	*Acacia mellifera, Rhigozum obovatum, Boscia foetida*
14	*Salsola tuberculata, Rhigozum trichotomum, Acacia erioloba, Acacia luederritzii*
15	*Acacia tortilis, Acacia erioloba, Acacia Rehmanniana* (Pietersburg plateau region)
16	*Acacia haematoxylon, Grewia retineruis*
17	*Tarchonanthus camphoratus, Rhus undulata, Rhus dregeana*
18	*Acacia erioloba, Acacia mellifera, Acacia hebeclada*
19	*Acacia nilotica, Acacia gerrardii, Acacia Robusta, Grewia flava*
20	*Acacia tortilis, Acacia nilotica, Acacia karroo, Acacia tenuispina, Acacia caffra, Combretum apiculatum*
21	*Acacia sieberianna*
22	*Tarchonanthus camphoratus, Ehretia rigida, Rhigozum trichotomum, Acacia tortilis*
23	*Tarchonanthus camphoratus, Rhus undulata, Rhus dregeana, Acacia permixta* (Pietersburg plateau region)
24	*Portulacaria afra, Pappea capensis, Euclea undulata, Acacia karroo, Pentzia incana, Eriocephalus ericoides*
25	*Faurea saligna, Burkea africana, Terminalia sericea, Combretum apiculatum, Dichrostachys cinerea, Lannea discolor*
26	*Kirkia wilmsii, Bequaertio dendron, Magalis montanum, Protea caffra*
27	*Leucosidea sericea, Grewia occidentalis, Protea caffra*

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