MANAGING THE PASTORAL LANDSCAPE: ADDING A SPATIAL DIMENSION?

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Summary. Integrating remotely sensed data and environmental databases within a geographic information system (GIS) provides information for managing pastoral environments ranging from the paddock to the catchment, regional and continental scale. Four approaches ranging from development of a single data layer to integration of many diverse data layers are described in the context of monitoring and managing temperate grassland landscapes. The question of reality or illusion in regard to the *spatial* nature of these approaches is discussed.

INTRODUCTION

In order to improve the sustainability of Australian agriculture, new technologies are needed to monitor and assist the management decisions associated with the use of grazing systems. Point source models applicable to land management decision making have been developed to a high level of complexity. These models (3) are needed to simulate the effects of changes in management of grazing lands. Model application is constrained by poor spatial distribution and frequency of input data for initial conditions and critical threshold parameters. Satellite imagery may be processed to provide quantitative or categorical data layers which describe these initial conditions and critical parameters, as well as end product maps describing vegetation and landscape features. Integration of modelling with spatial information, and map products from processed satellite imagery, should provide decision aids for government and graziers from continental to paddock scales. This paper describes some examples of land use management information developed from satellite remote sensing, and the integration of spatial information with mathematical models.

REMOTE SENSING AND SPATIAL MODELLING

A. Potential of Synthetic Aperture Radar for Grassland Monitoring

Airborne synthetic aperture radar (SAR) from a CSIRO/Jet Propulsion Laboratory joint mission provided detailed imagery for the CSIRO Division of Animal Production properties located at Armidale. SAR is sensitive to moisture and architecture of the target and could enhance the utility of satellite imagery for vegetation monitoring. The SAR images comprised polarimetric data for C, L and P bands with wavelengths of 6, 23 and 68 cm respectively. Soil moisture, herbage biomass and herbage moisture data were collected at the time of overpass. Subsequently, detailed botanical surveys were conducted for all paddocks on the property *Chiswick*. Six channels, the two with the best dynamic range from each band, were subjected to polythetic divisive clustering (5) to produce a 20 class map based on backscatter (Fig. 1a). The classification 9 classes of grassland cover, wet areas and other landscape features. Backscatter coefficients for L band varied from -9 to -20 dB between the thickest and barest grassland. Multiple linear regressions produced strong relationships between SAR and grassland biomass (r^2 =0.82).

B. Potential of Landsat TM for Identifying Risk of Dryland Salinity

A Salt Action community project with Landcare groups around Uralla Shire sought to devise a method for processing Landsat Thematic Mapper (TM) imagery to identify areas of potential dryland salinity. High digital numbers from the near infrared and thermal channels of a Landsat TM image respectively, were postulated to be associated with a flush of growth from a high water table and signs of salt stress. It was further postulated that the probability of high salinity/water table was greatest for flat, treeless areas with a high water flow, and treeless areas within 750 m of a geological contact. Using a digital geological database, a 750 m buffer was created around each geological contact in the test area. A slope map was generated from a 250 m resolution digital elevation model (DEM) and water flow was determined using a hydrological algorithm. The map of treeless areas with high flow or near a geological contact (Fig. 1b) was intersected with a classified image identifying green vegetation with a high thermal signature. Assessment of the effectiveness of this approach awaits ground-based validation measurements of electrical conductivity.

C. Pasture Suitability for a Large Grazing Enterprise from Landsat TM and Climate Maps

Landsat TM imagery, a DEM, the Australian Climate Surfaces, a growth index model and published pasture trials were used to develop a pasture suitability profile for a cattle breeding property east of Nowendoc, NSW. The property is approximately 21,000 ha with elevation ranging from 200 to 1000 m asl. A 25 m resolution DEM from NSW Conservation and Land Management provided the basis for the work. Monthly climate maps for the property were interpolated from the Australian Climate Surfaces using ESOCLIM (2) with latitude, longitude and elevation as independent variables and distance from the coast as a covariate. Rainfall, maximum and minimum temperature, radiation and evaporation layers provided input for a growth index model (4) coded to operate on cells in the GIS. Maximum potential growth rates for several pasture types were estimated from published experimental data. Growth index layers were used to scale potential monthly pasture production for a number of pasture types over the property. Digitised property and paddock boundaries enabled tabulation of potential pasture production for individual paddocks. A Landsat TM image was processed to identify tree cover and current pasture growth status (5). Monthly pasture growth maps were combined and classes were aggregated to define annual production profiles where temperate, sub-tropical or tropical pasture types provided the highest average biomass production (Fig. 1c).

D. Pasture Plant Adaptation Zones from Logical Modelling with Climate Maps.

The National Pasture Improvement Coordinating Committee was interested in utilising modelling and survey techniques to more accurately target research activities for pasture plant improvement. As part of this process, monthly climate maps for continental Australia were used with simple logical models to identify potential adaptation zones for some major pasture species (1). Monthly maximum and minimum temperature, rainfall, evaporation and radiation surfaces were generated for Australia using the methods described in C above. Simple logical models were constructed using critical thresholds for persistence and growth for each species. As an example, the following rules were used to define a main white clover zone: (summer $P/E \geq 0.50$ and annual rainfall ≥ 1000 mm) or (summer $P\text{-}E \geq -30.0$ mm and annual rainfall ≥ 1000) or (January maximum temperature < 26.5 and annual rainfall ≥ 1000 mm) and winter $P/E \geq 0.5$ (P - precipitation; E - evaporation). These logical models operate on the climate layers in a GIS and produce potential adaptation maps (Fig. 1d). These maps can be combined with land tenure data and soil pH maps to give a highly plausible estimate of the area of suitability for pasture species.

DISCUSSION

The examples described here form a *multi-dimensional* continuum; from the development of a single data layer describing one characteristic; though integration of information from many, diverse data layers to describe edaphic, biotic and climatic characteristics of the farm landscape; to a continent-wide simplification of many variables into a binary zone of adaptation for plants. The *dimensions* involved include scale (farm to continent), resolution (6-2000 m pixels), number of data sets, complexity of algorithms and precision of output. They beg the questions of *How can we explicitly describe error and precision?* and *How can we balance the complexity of information needed to describe changes in landscape processes, with error propagation through many data layers, to produce management outputs with useful precision?*. Answers to these questions are essential for efficient and effective management of spatially and temporally complex systems.

Apart from the strategic research on SAR described in A above, each of the projects described was carried out under a short-term consulting or contractual agreement. In each case, there was little scope for the development of innovative methodologies by pursuit of several approaches in parallel; the projects required more resources than was envisaged in planning; and the course of the research followed a different path to that defined in the proposals. Development of effective spatial information for land management will require a balance between strategic development of approaches and application of mature methodologies to practical problems.

Despite the importance of spatial dependence and interrelationships, only in the salinity mapping, and only at a rudimentary level, is the spatial association of features or factors utilised in our analysis. Our modelling at a property and continental scale assumes each pixel to be an independent unit such that the value of adjoining pixels had no influence on the value of the target pixel. Fortunately, climate data has inherent spatial dependence originating from the influence of topography and the scale of continental weather patterns. Geostatistical techniques such as kriging explicitly address issues of spatial association with point data. However, many of these methods are complex, and it is not yet clear to the biologist how or when such methods should be incorporated into modelling and analysis of spatial data. There is a need to step back from the hyperbole associated with GIS and address the pressing need to develop robust, accessible analytical methods which are truly spatial, i.e. take into account the proximity of features in multiple layers. The analysis of SAR and multi-spectral imagery requires an understanding of the spatial association and orientation of target objects. The relationships between backscatter or spectral signatures or reflectance components and target architecture can be mechanistically modelled. The mathematical relationships and manipulations involved are complex, but in future, quantitative calibrated data layers, rather than site-specific categorical classifications, will be available from remote sensing.

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