USE OF THESES

This copy is supplied for purposes of private study and research only. Passages from the thesis may not be copied or closely paraphrased without the written consent of the author.
This thesis is dedicated to Evangeline and Juliet
~ the future is yours

le avenir est a toi
Declaration:

All biophysical, GPS and field data were collected by the author. All statistical analysis, GIS interrogation and modelling were completed solely by the author as were all the figures and map productions (using ARCINFO). All published papers were analysed and written by the author with helpful advice and editorial comments from Dr Mike Hutchinson and Professor Jetse Kalma. The three articles published from this thesis involve the spatially distribution of vegetation by incorporating i) aircraft data only, ii) aircraft and satellite data, and iii) the topographic impact on biomass distribution.

Their titles are:


To the author’s best knowledge this thesis contains no material previously written or published by any other, except where stated in the text.

G A Cusack
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My part time Ph.D. journey has been eventful in two extremes, from the unfortunate death of my supervisor Professor Ian Moore to the wondrous births of my two daughters Evangeline and Juliet. Many people have supported me along this journey and I am very grateful for all the different types of support I received. Sometimes the support was in the form of a cup of coffee and often it was through fruitful thesis discussions with Dr Mike Hutchinson.

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Abstract

Environmental problems include erosion, salinisation, eutrophication, carbon allocation and rising CO₂ in the atmosphere. Environmental modelling, mapping, research and management are part of the solution to biophysical degradation. However, field data are usually limited and alternative data sources such as modelled or remotely sensed data must be calibrated. The resolutions between the different data sets must also be matched. Therefore there is a need to develop spatio-temporal models at an appropriate resolution to enhance limited field data. Such models need to be linked to the terrain surface (the spatial data) and incorporate climate (time varying) data. Preferably these models would maintain the integrity of source data (physical catchment attributes), have a predictive capacity and reflect catchment processes.

In southern and eastern Australia catchments are mostly cleared, particularly those in low relief landscapes. These catchments have limited spatio-temporal vegetation data and therefore monitoring, research and management are constrained. Digital Elevation Models (DEM) can supply accurate spatial information about the terrain shape if appropriate source data, resolution and accurate interpolation methods are used. Hutchinson (1988) developed a locally adaptive algorithm which automatically calculates ridge and stream lines from points of locally maximum curvature on contour lines (chapter 2). Further developments by Hutchinson (1996) have provided a smoothing method, which has yielded useful error estimates for grid DEMs and a criterion for matching grid resolution to the information content of the source data. DEMs are essential input data for modelling terrain effects, which directly influence the surface conditions for plant growth. Climate is another dominant control over vegetative growth and climate data can also be limited. Climatic data can be modelled using interpolation methods developed by Hutchinson (1997).

In this thesis, three approaches are developed to model the spatio-temporal distribution of biomass. These models are referred to as the Sub-catchment model, the Satellite model and the Topo-climate models. The Sub-catchment model calibrates the GROWEST model to biomass averaged over three separate sub-catchments (chapter 4). Combining catchment averaged climate data with disaggregated temperature and biomass GROWEST produced growth indices at each sub-catchment for 13 and 26 week growth accumulation periods. The 26 week growth accumulation period matched observed biomass data with greater accuracy than the 13 week period.
The Satellite model simply calibrates biomass data with observed satellite data (chapter 3). Satellite data although spatially extensive requires atmospheric corrections and normalisation over time if direct comparisons are required. These models have limited predictive capacity, although they can be good for monitoring instantaneous catchment condition and structural features in the landscape.

The third approach develops full spatio-temporal models, which simultaneously include effects of terrain (the spatial component) and climate (the temporal component) on biomass distribution (chapters 4, 5). The Topo-climate models are fitted using thin plate smoothing splines (Hutchinson 1999) (chapter 7). The Topo-climate models form a process based approach to spatio-temporal biomass modelling. They were successful in achieving spatio-temporal modelling of biomass in this catchment. They also have excellent predictive capacity, requiring only standard climate data.

Model validation and statistical model comparisons were examined to determine the degree of parameterisation and accuracy of the different models. Model veracity is discussed and different applications for the various model types are suggested. Further research includes land management and research areas of vegetation modelling and carbon allocation.

Predictive modelling of landscape processes such as the topo-climate models developed in this thesis, help to address environmental problems by providing spatio-temporal biomass data under varying climatic conditions for management and research purposes.
SPATIO-TEMPORAL MODELLING OF BIOMASS

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Introduction

Cone of Knowledge

- Starting points
- Exploratory plots & results
- Models with minimal error
CHAPTER 1. INTRODUCTION

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1.1.1 Environmental problem: limited spatio-temporal data
1.1.2 Applications for spatio-temporal biomass data
1.1.3 Principle hypothesis and broad objectives

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1.3.2 Study site, methodologies and tools
1.3.3 Model development and statistical validation
1.3.4 Geographical Information Systems (GIS) Capabilities
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Chapter 1. Introduction
Spatio-temporal Modelling of Biomass

Australia is a geologically 'old' landscape that predominantly consists of a low-relief landscape. Since European settlement approximately 200 years ago many of the low-relief river catchments have been largely cleared. Such activity has inevitably had a major impact on water and land resources. These altered landscapes need spatio-temporally varying environmental data for management purposes, including restoration and prevention of further damage to the landscape and preservation of uncleared areas. At the global scale, permanent grassland (including pastures) covered approximately 26% (34 x 10^6 km^2) of the Earth's land surface in 1994 (FAO 1996). In Australia, as of 1990, a total of 103 x 10^4 km^2 forests and woodlands had been cleared or thinned over the preceding 200 years. This represents 52% of the landuse and 20% of the entire continent (Graetz 1995). Grasslands provide forage for many grazing animals, but these animals can destroy land cover if biomass monitoring and management are not a priority. Given increasing pressures on these landscapes from rising populations it is now essential to able to monitor grassland production more wisely, supported by explicit, spatially detailed information.

Since climatic variability is a major environmental concern as well, it is necessary to determine the spatio-temporal dimensions of grassland production under different climatic conditions. In Australia, with its large landmass, even relatively minor broadscale fluxes in vegetation-stored carbon can represent a large portion of the national carbon budget (Fensham et al 2000). Such changes can be rapid with broadscale clearing and regrowth (Burrows 1995). Predictive spatio-temporal biomass models can provide the necessary information on biomass levels under a range of climatic conditions, for both catchment management purposes and for greenhouse gas inventories.

It is known that topography has spatially varying effects on hydrologic and biophysical processes (Dozier et al 1980, Davis et al 1992, Dubayah and Loechel 1997, Hutchinson and Gallant 2000). Terrain shape has a dominant control over the climatic and moisture regimes available for vegetative growth, especially grasses and pastures that utilise the upper layers of the soil surface and lower layers of the atmospheric processes. Water quality is inextricably linked to land surface characteristics, land use and its surface cover (Prowse 1995), and is also of extreme importance as all humans, flora and fauna depend on it. Salinity is another major environmental problem in Australia that could benefit from spatio-temporal biomass data. Primary terrain attributes are investigated in this thesis to determine their link with biological processes, in order to address environmental problems of land and water deterioration. The principal aim of this thesis is to determine spatially temporally varying estimates of biomass in a small, low relief, yet typical catchment (figure 1.4).
Figure 1.1 The spatial extension of point based data sets.

Generic environmental problem: Limited spatio-temporal biomass data.
1.1.1 Environmental problem: limited spatio-temporal data

A generic environmental problem that is addressed in this thesis is, what is the most suitable extrapolation process for extending data from point source biomass data to spatio-temporal dimensions. Figure 1.1 shows a simplified flow diagram of one process to derive spatio-temporal biomass from point source data. Spline interpolation analysis allows the combination of point data, spatial terrain features and temporal climatic data to model catchment processes such as biomass distribution in both time and space.

1.1.2 Applications of spatio-temporal biomass data

Spatio-temporal biomass data is important for many reasons. Figure 1.2 lists the applications of spatio-temporal biomass for the modelling of catchment processes.

Figure 1.2 Table of potential uses for spatio-temporal biomass data

| Applications of Spatio-temporal Biomass Data on Catchment Processes |
|--------------------|--------------------|
| **Catchment process** | **Applications** |
| Evaporation potential | Vegetated surfaces reduce evaporation from soil, bare surfaces have high evaporation from the soil |
| Erosion | Vegetated surfaces reduce erosion |
| Fire | Understanding the fuel load provides vital information for potential fire risk management |
| Impacts of climate change | Impact of increases in CO₂ on biomass |
| | Impact of increases in temperature on biomass patterns |
| Farm animal production | Food and shelter provided by spatio-temporal biomass data |
| Feral animal movement | Habitats, affected by spatio-temporal biomass patterns |
| Water quality | Catchment land cover and upstream activities affect the water quality. (For example, high total phosphorus occurs during summer in many streams in Australia and this is partially due to fertilizer application.) |
Chapter 1. Introduction
Spatio-temporal Modelling of Biomass

<table>
<thead>
<tr>
<th>Water quantity</th>
<th>Low water levels in summer with low rainfall and high evaporation rates and non-vegetated surfaces carry high sediment and soil load to streams</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wildlife Refuge</td>
<td>Food, shelter and water for native animals depend on vegetation type and quantity</td>
</tr>
<tr>
<td>Plant disease</td>
<td>Effect of plant diseases on biomass distribution</td>
</tr>
<tr>
<td>Biodiversity</td>
<td>Spatial vegetation data supplies information on the rate of change of the landcover which affects the diversity and size of habits and therefore plant and animal diversity</td>
</tr>
<tr>
<td>Salt accumulation</td>
<td>Exposed bare surfaces can accumulate salt</td>
</tr>
<tr>
<td>Interface between the earth’s crust and the atmosphere</td>
<td>Biomass influences the exchange of energy and matter in biogeochemical cycles</td>
</tr>
<tr>
<td>Nutrients available for vegetation</td>
<td>Biomass influences on the spatial movement of nutrients through plants, soil and water</td>
</tr>
<tr>
<td>Plant species and hybrid differences</td>
<td>Species and hybrid associations and their inter and intra spatial biomass patterns</td>
</tr>
</tbody>
</table>

1.1.3 Principle hypothesis and broad objectives

Principle
Hypothesis: Topographic and climatic attributes combined with modelled growth outputs can be used to model the spatio-temporal distribution of biomass in a low relief catchment

Broad
Objectives: 1. Develop a Sub-catchment model of biomass distribution  
2. Develop a Satellite model of biomass distribution  
3. Develop a spatio-temporal Topo-climate model of biomass distribution  
4. Statistical comparisons of three models  
5. Use Geographical Information System (GIS) for model extension and further development

Each chapter also has specific aims, which are included at the beginning of each chapter.
1.2 Scale and Resolution

The development of spatio-temporal biomass models requires an understanding of space-time dimensions of the input/source data. Scale and the modelling process are innately linked. The resolution of terrain models, and dependent terrain parameters, must be matched to the information content of source topographic data (pers. com. M Hutchinson 2000).

1.2.1 Scale: spatial density and the temporal frequency of parameters

Landscape properties and ecological processes are inherently linked to the analysis of spatial and temporal scale (Meentemeyer and Box 1987, Milne 1992, Moody and Woodcock 1995). In this study, landscape properties are determined by terrain shape as modelled by ANUDEM (Hutchinson 1989) and the ecological process being examined is the spatio-temporal distribution of biomass.

Moody and Woodcock (1994) found that large errors can arise as the landscape is represented at increasingly coarse spatial scales. In 1995, Moody and Woodcock investigated the proportion of error between landscape pattern and observation scale. They found significant relationships between spatial characteristics of cover types and scale-dependent proportion errors. Their cover classes were grass/baron, brush, hardwood, meadow, conifer and water. Turner (1990) concluded that the spatial scale at which landscape patterns are quantified can influence the result, and that measurements (land cover type) made at different scales may not be comparable. She suggests the definition and methods of changing scale must always be explicitly stated. Hutchinson and Gallant (1998) indicated that DEMs have the potential to address issues of scale and structure in landscape analysis. In this study, one cover class (grass/pasture) is isolated to determine the role terrain shape has on the spatial distribution of this biomass. It is also known that terrain controls other earth surface properties and near surface atmospheric processes at various scales (Hutchinson and Gallant 1998).

The issue of scale is especially relevant when using remote sensing to examine surface processes. Satellite imagery must incorporate an understanding between scale of observation, spatial organisation of land-cover classes and classification error (Moody and Woodcock 1995). Theoretical investigations between scale issues and the modelling of land-surface physical processes using remotely sensed data has been performed by several researchers including Jupp et al (1988) and Raffy (1992).
The spatial scale of processes can be categorised in different ways. Discrete categories can be made between microscale, fine toposcale, coarse toposcale, mesoscale and macroscale. Microscale < 50 m is where a discrete localised object occurs. Fine toposcale is important for hydrologic modelling, vegetation analysis, soil assessment, determining terrain shape and for calibrating remotely sensed data. Coarse toposcale (50-200km) is where attributes such as aspect, slope, cold air drainage are important. Mesoscale is where elevation is the most important attribute and aspect is of secondary importance. Macroscale is where DEMs can be used for downscaling for GCM outputs (adapted from Hutchinson and Gallant 2000). Other ways to categorize scale issues are spatial resolution groupings (Figure 1.3).

Figure 1.3 Table showing dominant processes at different spatial resolutions (adapted from Hutchinson and Gallant 2000)

<table>
<thead>
<tr>
<th>Spatial Resolution</th>
<th>Dominant Process at this Scale</th>
</tr>
</thead>
<tbody>
<tr>
<td>Microscale 0 – 50 m</td>
<td>Point source features (tree, rock outcrop, dam, salt pan, building)</td>
</tr>
<tr>
<td>Fine Toposcale 5 – 50 m</td>
<td>Hydrologic modelling (surface *, sub-surface and ground water)</td>
</tr>
<tr>
<td></td>
<td>Biomass (spatio-temporal distribution * and growth*)</td>
</tr>
<tr>
<td></td>
<td>Soil (types, textures, hydraulic conductivity, wetness index *)</td>
</tr>
<tr>
<td></td>
<td>Topography (terrain shape) *</td>
</tr>
<tr>
<td></td>
<td>Remote sensing (calibration) *</td>
</tr>
<tr>
<td>Coarse Mesoscale 50 – 200 m</td>
<td>Micro-climate (surface temperature, soil temperature, inversion etc)</td>
</tr>
<tr>
<td></td>
<td>Terrain shape*</td>
</tr>
<tr>
<td></td>
<td>Radiation data*</td>
</tr>
<tr>
<td></td>
<td>Cold air drainage</td>
</tr>
<tr>
<td>Mesoscale 200 m – 5 km</td>
<td>Elevation *</td>
</tr>
<tr>
<td>Macroscale 5 km – 500 km</td>
<td>Global Climate Modelling (GCMs) outputs for downscaling to regional scale landscapes</td>
</tr>
</tbody>
</table>

* investigated in this thesis
1.2.2 Biomass Mapping

Appropriate scaling procedures are essential for all ecological modelling, including biomass modelling. Traditional techniques used for biomass mapping are limited in spatio-temporal dimensions despite the fact that such data are essential for ecosystem/catchment management of contemporary environmental problems. As vegetation interacts with the climatic cycle, accurate biomass mapping and the development of spatio-temporal biomass models are essential to assess the impact of climate change. Evapotranspiration varies with different vegetation types and under different climatic conditions. Tattari and Granlund (1991) showed vegetation cover had a strong effect on the spatial variability of soil water. Their conclusion was that a dense grass field was able to evapotranspirate more than twice as much water as cultivated barley. This study investigates relationships between biomass and both climatic and terrain parameters.

1.2.3 Topography

One of the key questions addressed in this thesis is what type of relationship exists between biomass and topography in this low relief catchment. To answer this question an understanding of the relationship between data, scale, resolution and topography is required. Closed depressions and flat areas in a DEM are often the artifacts from input data errors, interpolation procedures and limited horizontal and vertical resolution of the DEM (Zhang and Montgomery 1994). However, in a low relief catchment some areas may be flat and DEM accuracy is essential for the examination of fine scale processes.

The size and shape of the catchment surface is important in determining the most appropriate resolution and the resolution strongly influences the nature of the terrain parameters calculated (Hutchinson and Gallant 2000). Input data accuracy and availability as well as the spatial distribution of the data are crucial determining factors in spatio-temporal analysis. Remotely sensed data can be correlated to DEM and ground collected data, however rectification and calibration are just as important as the information contained in the scene. Digital Elevation Models (DEMs) calculate the surface topography. The ANUDEM program (Hutchinson 1986, 1989) uses locally adaptive thin plate spline interpolation to determine surface shape. Some of the features of ANUDEM are that the interpolation method uses a finite difference technique, a modified roughness penalty (this is especially important for sharp corners), drainage enforcement and is compatible with standard GIS systems.

Drainage patterns and changes in slope and aspect can all be reproduced in an accurate DEM. The effect of surface shape can then be transferred to biomass distribution. Topographic
Chapter 1. Introduction
Spatio-temporal Modelling of Biomass

shapes can reveal biomass potentials or growth patterns, depending on the climate and soil. There are a range of terrain parameters that can be calculated from an accurate DEM. Wetness index (a terrain parameter) depends on the shape of the topographic surface and the upslope conditions. However, Crave and Gascuel-Odoux (1997) suggest that the downslope topographic conditions may control the spatial distribution of the surface wetness of a catchment. Therefore they conclude that surface water content is a function of topography and the spatial distribution of soils. The wetness index can be derived as a static terrain attribute or a dynamic wetness index (Moore et al 1992). Other terrain variables indicate whether the surface water will flow onto or away from a specific geographic location of cell of a DEM. Fine-scale terrain parameters, such as water flow patterns, are important in low relief catchments.

1.2.4 Hydrology

Catchment runoff includes infiltration excess runoff, which can be simulated using an extended version of the Green and Ampt (1911) equation (Coles et al 1997). To simulate infiltration excess runoff it can be assumed that topography and hydrogeology influence the spatial distribution of soil moisture. The topographic or wetness index is defined as $\ln (\alpha / \tan \beta)$ (Bevan and Kirby, 1979), where $\alpha$ is the specific catchment area and $\beta$ is the slope angle degree. The hydrogeology index $\ln (K_0 / f)$ (Sivapalan et al 1987). Within the experimental catchment in this study there is minimal relief and the land cover is predominately grass and pasture, therefore the lateral distribution of soil moisture and subsurface flow are not explicitly considered. The instantaneous runoff infiltration excess and saturation excess mechanisms are incorporated only through runoff scenarios as calculated by GROWEST (Nix 1981), collected by stream gauges (Daniel et al 1994), and surface routing of water using DEMON algorithm in TAPES-G (Moore et al 1991).

1.2.5 Remote Sensing

Satellite and airborne data provide a powerful view of the earth’s surface (Graetz et al 1995), providing information on the spatial heterogeneity of surface properties (Kustas and Humes 1997). This view is spatially extensive and can be calculated at a range of surface resolutions, waveband combinations and lengths. Remotely sensed data can observe the ground regularly (via satellites), irregularly (via aircraft data) to obtain dynamic information of ground properties and the water cycles (Chen et al 1997). Temporally, however, satellite data are limited to the orbital dates and cloud-free skies. Remotely sensed data in image form provide an engaging method of communication (Graetz et al 1995). However, calibration of remotely sensed data to
the land surface (georeferencing), land cover (biomass) and atmosphere and are essential (Cusack et al 1997).

Surface resolution of satellite data varies from the AVHRR with a 1 km surface resolution to SPOT with a 10 m resolution, while AIRSAR radar data have variable resolution as fine as 5 m. AVHRR radar data have been used to predict forest biomass (Ranson et al 1997, Hame et al 1997) and laser data to predict a range of forest attributes (Nelson et al 1997). Biomass has been monitored using red and near infrared bands of Landsat multispectral scanner system (MSS) and Thematic Mapper (TMSAT) predominantly for agricultural crops (Boissard et al 1993), but also in rangelands (Prince and Astle 1986, Prince and Tucker 1986).

1.3 Modelling Environmental Data

1.3.1 Introduction to Modelling Environmental Data

The term 'model' means to describe an object in a simple and meaningful way. It has been used in a wide range of contexts from mental models to mathematical models. This thesis refers to physically based statistical models. Mathematical and statistical models are central to understanding natural phenomena (Chambers and Hastie 1992, Moore et al 1993). There are a range of statistical models which incorporate both parametric and non-parametric forms (O'Brien 1992). Other mathematical models include Linear Models (Stigler 1981), Generalised Linear Models which can transform normalised distributions (Nelder and Wedderburn 1972), Generalised Additive Models to allow non-linearity and add smoothing parameters, Geostatistical Models based on kriging (spatial interpolation developed by Krig (1966)), thin plate spline interpolation methods, (Hutchinson 1989, 1991, 1993), Tree-based Models (Breiman et al 1984) which sample increasingly homogenous subsets, and Bayesian and Neural Network Models (Aspinall 1992) that can be used for decision making under uncertainty.

The Digital Elevation Model (DEM) is a powerful spatial representation from which to construct a mathematical model of the landform (Li Zhang et al 1996). A variety of methods have been developed to produce gridded DEMs in order to delineate and measure drainage networks and basins (Martz and Garbrecht 1998). These methods include the research of Jenson and Domingue (1988), and Hutchinson (1989). Hutchinson and Gessler (1994) indicate that spline methods (incorporated in some DEMs) do not require an estimation of the variogram, and yet may provide similar information about the structure in a more robust way than kriging by utilisation of the generalised cross validation (GCV).
All environmental modelling requires input data to execute, modify, validate, and improve predictions of environmental processes. It has been argued by Brutsaert (1986) that the properties of natural catchments cannot be measured with enough accuracy to treat the hydrologic cycle and its components in terms of detailed descriptions of all its internal mechanisms. It has been argued that at Lockyersleigh Catchment, the modelled vertical processes are far more important than the modelled lateral distribution of water (Guerra 1995, Boulet 1995). Results obtained by Kalma et al (1995) indicated that the variable infiltration capacity (VIC) model of Wood et al (1992) made useful predictions of the soil moisture status at the catchment scale. However, one limitation of the VIC model is that it uses a simple evapotranspiration model that does not include spatio-temporal vegetation distribution patterns. It has been suggested that the statistical distribution of critical parameters can describe the spatial variability of land cover, soil and topography at the catchment scale (Boulet 1995). It was also concluded by Boulet (1995) that in the Lockyersleigh Catchment, topographic attributes have less impact on hydrology than the patchiness of vegetation. Guerra (1995) confirmed that not all components of the water balance are equally important and this has major implications for the modelling approach required. He also stated that model selection must account for all important surface parameters and needs to adequately account for the key processes. Guerra (1995) concluded that

"the challenge ahead lies in adequately representing the spatial and temporal variability in the critical land surface parameters in each of the important land surface processes operating in the particular environment"

1.3.2 Study site, methodologies and tools

This study incorporates stratified data samples from ground meteorological stations, topographic and geologic maps, aboveground biomass and aircraft and satellite platforms. The experimental site is a small, 70% cleared low relief catchment in a temperate climate. The surface cover consists mostly of pasture and grassland. The original dry sclerophyll forest has been cleared with few remaining trees below 690 m. The area of the whole catchment is approximately 27 km² (Figure 1.4). The intensive biomass study covered two seasons (late Summer/Autumn and early spring) over a two-year period from 1993 to 1994.
Figure 1.4  Map of Lockyersleigh Creek Catchment (5 km²)

Lockyersleigh Creek
Catchment

Site 2

Site J

Site A
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The author collected and analysed all the field data. The models used in this thesis are the Australian National University Digital Elevation Model interpolation program (ANUDEM), Australian National University Climate surfaces (ANUCLIM), Estimation of Climate (ESOCLIM), Growth Estimation (GROWEST), Terrain Analysis Program for Environmental Sciences – grid version (TAPES-G), Solar Radiation Model (SRAD), Australian National University Spline Interpolation model (ANUSPLIN), and their gridded outputs. Mapping and plotting software include 1:25,000 maps, microBRAIN, ARC/INFO, Paintshop Pro, XVGR, XV, GNUPLOT, GNU. The statistical analysis packages include ARC/INFO, SPSS, GNU, ANUSPLIN. Mathematical analysis includes linear and multiple regressions, curve fit: linear, exponential, quadratic and cubic polynomials, variance analysis, differential equations, Q-Q plots, thin plate spline interpolation and other equations specified in the text and incorporated in the models.

1.3.3 Model Development and statistical validation

Modelling can deliver a simplified version of a complex system, providing a framework for further understanding of catchment processes from which strategic research and management plans can be devised. One advantage of some models is that catchment averaged values can be obtained from time and space integrated climate data. These values need then to be distributed or disaggregated throughout the catchment. Another desirable feature is the transparency of any model and its direct relationship with the physical properties of the catchment.

Three models are developed in this thesis. These models are referred to as the Sub-catchment, Satellite and Topo-climate models. These models are supported by simple flow diagrams indicating the various inputs and outputs of the models as well as further model developments. Statistical validation and model comparisons are essential parts of model development and these are achieved by comparing model residuals and degrees of parameterisation.

1.3.4 Geographic Information Systems (GIS) Capabilities

GIS support the gridded format of modelled data, useful for the display of modelled data, classification of data into specific groups, statistical outputs, data queries for specific cells, overlaying different data sets, further model development comparison and map production. The map production possibilities from GIS provide outputs that can be readily interpreted by a range of different disciplines, from managers to researchers.
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1.3.5 Summary

Given the limited and variable biomass and climate data (a generic environmental problem), modelling is essential to extend these data in both space and time. To successfully model the spatial and temporal heterogeneity of catchment processes, topographic, climatic, remotely sensed, modelled growth indices and ground biomass data will be investigated. The incorporation of GIS for map production and data interrogation provides added insights and management tools for present and future catchment management of our land resources. Research will continue to embrace modelling as a method of addressing a range of environmental problems and research strategies.

1.4 Thesis Organisation

This thesis is organised into the following sections:

1 Introduction
2 Catchment Characteristics
3 Remotely Sensed Data and Vegetation Data
4 Modelling Plant Growth
5 Terrain Analysis and Vegetation Data
6 Wetness index
7 Spatio-temporal Modelling of biomass
8 Discussion and conclusions

The structure for the modelling components is summarised in a series of flow diagrams. The literature is reviewed in each chapter according to the topics under analysis and discussion. Chapter one introduces the generic problem of limited biomass data and the need for catchment scale spatial data over time. Chapter two describes the experimental catchment. This chapter also includes the field data and remotely sensed data acquisition dates as well as the modelling of the catchment surface using ANUDEM (Hutchinson 1989). Chapter two provides Global Positioning Satellite (GPS) for the locations of point based biomass data. Chapter three introduces the spatial remotely sensed data sets and the inherent need to calibrate these data sets. This chapter analyses both aircraft and satellite data with georeferencing techniques, atmospheric corrections and initial correlations with biomass data.
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Chapter four introduces plant growth modelling and provides a temporal framework for further model development. Plant growth modelling was achieved using GROWEST (Fitzpatrick and Nix 1970, Nix 1981, Hutchinson et al 1997) at the catchment and sub-catchment scale. Sub-catchment modelling allowed the disaggregation of temperature and biomass data. These results produced a sub-catchment model. Chapter five investigates empirical relationships between biomass and spatially disaggregated terrain attributes. The topographic attributes rely on an accurate DEM as input data. Exploratory plots of satellite data correlations to terrain attributes were also investigated. Selected terrain attributes from these tests were incorporated into further model development. Chapter six delves into the relationship between biomass and the static terrain attribute wetness index. This relationship was difficult to determine in a low relief catchment.

Chapter seven investigates ways to disaggregate spatial biomass data on topo-climate inputs. This chapter draws conclusions from all the previous chapters and utilises the spatial and temporal outputs to develop spatio-temporal models of biomass distribution patterns. Further normalisation of the satellite data over time allowed the development of a satellite model. Statistical validation and model comparisons were reviewed to determine the most accurate spatio-temporal model. Maps of selected model outputs are displayed. Chapter eight reviews the thesis hypothesis and broad objectives, suggests model applications, discusses future biomass modelling and further research.

One idiosyncratic feature in this thesis is the figure numbering system and shaded flow diagrams. In order to simplify the numbering of items within chapters, all tables, figures, diagrams and images are referred to as ‘Figures’. Each figure number is prefixed with the same number as the chapter. The modelling chapters include flow diagrams to show a simplified format of the modelling process. The purple shading indicates model development where the outputs of that particular model will be utilised for further model development, while the blue shading indicates a developed model. Chapters 3 and 5 include published papers. One figure (Figure 2.17) is repeated in this thesis.
Chapter 2.

Catchment Characteristics
CHAPTER 2. CATCHMENT CHARACTERISTICS

2.1 Introduction

2.2 Ground-based Data Sources
   2.2.1 Climatic data
   2.2.2 Hydrology
   2.2.3 Biomass data
   2.2.4 Topographic data
   2.2.5 Soil description
   2.2.6 Site locations

2.3 Anthropogenic factors and summary
   2.3.1 Anthropogenic factors
   2.3.2 Summary
2.1 Introduction

This chapter describes the topography, hydroclimatology, vegetation and soils as well as the selected sites and anthropogenic factors of Lockyersleigh Creek Catchment. Lockyersleigh Creek Catchment is a 27 km² largely cleared, grazed catchment which is located on the tablelands on the western side of the Great Dividing Range in southern New South Wales, Australia (Figure 2.1a). It is a low relief catchment, with elevation range 600 to 762 m above mean sea level, covered with grassland/pasture (70%) and woodlands over duplex soils. Lockyersleigh Creek drains from the south to the north in the catchment to join the Wollondilly River.

The aims of this study are to quantify the spatio-temporal variability of the biomass within this catchment, and to consider whether topographic effects determine the spatial variance of biomass in this low-relief catchment. Climate data from 1987 to 1994 were used, but the emphasis is on the years 1993 and 1994. Detailed biomass data were measured on the ground and by airborne and spaceborne sensors, for the months March and September 1993 and March 1994.

Figures 2.1a and 2.1b shows the catchment with 10 m contours, biomass sites and other identifying features such as meteorological stations and weirs. The larger map shows the Lockyersleigh Creek Catchment location in Australia.

2.2 Ground-based Data Sources

2.2.1 Climate data

Daily meteorological data were collected from June 1986 to May 1993 at three locations within the Lockyersleigh Catchment (Figure 2.1a, 2.2). As meteorological data were not collected after May 1993, September 1993 and March 1994 rainfall data were estimated/predicted from nearby meteorological stations via regression methods (chapter 4). Monthly rainfall data were analysed from 113 stations within a radius (0.5 degree and 0.2 degree) about the approximate centre of Lockyersleigh at 149.933, -34.692, elevation 635 m. These 113 stations were regressed against the Lockyersleigh climate data between June 1986 and December 1995 to determine the best fit. September 1993 and March 1994 rainfall data were then calculated. 1987 and 1993 were relatively dry years.
Figure 2.1a – Additional Sites, weirs and structural features.
Figure 2.1a – Additional Sites, weirs and structural features.

Figure 2.1b – 25 DEM with 10m contour.
The geographic locations of the three Lockyersleigh climate stations are listed in figure 2.2.

**Figure 2.2** Geographic co-ordinates of the three climate stations

<table>
<thead>
<tr>
<th>Climate Station</th>
<th>Easting (m)</th>
<th>Northing (m)</th>
<th>Elevation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Climate Station A</td>
<td>768916.9</td>
<td>6154890.4</td>
<td>656.0 m</td>
</tr>
<tr>
<td>Climate Station B</td>
<td>768191.6</td>
<td>6156593.3</td>
<td>626.0 m</td>
</tr>
<tr>
<td>Climate Station C</td>
<td>757168.0</td>
<td>6160471.3</td>
<td>606.2 m</td>
</tr>
</tbody>
</table>

**Figure 2.3** Monthly rainfall data June 1986 - May 1993 using Lockyersleigh average rainfall from three climate stations

<table>
<thead>
<tr>
<th>Year</th>
<th>Jan</th>
<th>Feb</th>
<th>Mar</th>
<th>Apr</th>
<th>May</th>
<th>June</th>
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<td>na</td>
<td>na</td>
<td>na</td>
<td>na</td>
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<td>18.6</td>
<td>108.0</td>
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Missing rainfall data from mid-1993 and 1994 were calculated from the linear regression equations to Lockyersleigh rainfall from nearby rainfall stations (refer to Chapter 4, figure 4.16).

**Daily rainfall data for the months February and March 1993**

Solar radiation variations between March and February show a highly variable daily pattern however, the monthly mean totals were more consistent. Also refer to chapter 6, figures 6.7 and 6.8

2.2.2 Hydrology

The hydrology of Lockyersleigh Creek Catchment is typical of many catchments in Australia. It has low intermittent runoff, where some of the overland flow may be increased due to clearing and erosion. The streams are small and there is a reduction in the water capacity over summer due to high evaporation rates. There are two weirs, one a modified Rimeco water level float transducer (labeled G, Fig 2.1a) and a V-notch weir near the outlet of Lockyersleigh Creek (labeled H Fig 2.1a). The streamflow measuring site at G was established in 1987 and H in mid-1991. Both sites ceased recording streamflow mid 1993.

Figure 2.5 shows monthly runoff for March and September over the six year period 1987-1992 and Figure 2.6 shows daily rainfall and runoff for March 1993. Spring and summer seasons (which incorporate the months of March and September) are relevant to this study as the vegetation is exposed to high solar radiation and variable moisture conditions.
Figure 2.5  Monthly runoff (mm) data between 1987 - 1993

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where: G = runoff (mm) at weir at site G, H = runoff (mm) at weir at site H, G1 = number of days of data collection at site G, G2 = number of days of runoff at site G, H1 = number of days of data collection at site H, H2 = number of days of runoff at site H, na = no data.
Figure 2.6 shows May 1988 as 441 mm (scaled up from runoff Station G x 30). The actual runoff for May 1988 was 79.2 mm and scaled up (x30) would have been 2376 mm, however it is shown as much lower to allow the graph to represent low runoff records for most of the other months. The records of runoff data were not continuous and the mean monthly runoff in figure 2.6 is spasmodic and erratic as evident from the runoff data in same figure.
Figure 2.7 shows the unrealistic measurements of runoff for March 1993, especially between 1 - 21 March. High evaporation would have accounted for minimal runoff during this period, however the straight line suggests that accurate measurements of peak runoff are difficult to obtain during summer and in March in this catchment. The straight line could also represent the base flow and low flows of water, however it still appears that earlier rainfall events were missed.

Measurement and prediction of runoff in catchments with episodic and low runoff events such as Lockyersleigh are difficult. Predicting runoff is also difficult in semi-arid regions and in any catchment that contains ephemeral streams. The modelling of rainfall runoff complex and the calibration and validation of models even more troublesome (Conesa-Garcis and Alonso-Sarria 1997). The randomness of rainfall runoff processes, gauging calibration, and intermittent data and sometimes inaccurate records make preceding rainfall events difficult to measure. In this study, a simple robust water balance method using GROWEST (Fitzpatrick and Nix 1970) has been used.

February and March are significant months in this study as ground and satellite biomass acquisition occurred during these periods. In figure 2.7 the rainfall is negligible for most of March 1993 until a rain event on 25 March 1993 of 21.8 mm. February also had negligible runoff with the highest runoff was 0.03 mm on 10/02/93 and the highest rainfall 18.6 mm on 9
February 1993. Kalma et al (1995) considered the lateral redistribution of water in this catchment to be restricted to surface overflow processes shortly after rainfall. The timestep between rainfall and overland flow is significant as it is known that grasses have high evaporation rates during summer. Tattari and Granlund (1991) found a dense grass field was able to evapotranspirate more than twice as much water as cultivated barley.

2.2.3 Biomass Data

Clearing of native vegetation occurred approximately 150 years ago in eastern Australia with the onset of European settlement. The majority of the clearing occurred in Lockyersleigh after World War II (pers. comm. C Clarke 1998). The replacement of native vegetation with introduced species is widespread. Lockyersleigh Catchment is 70% cleared with 20% open woodland and 10% medium density woodland (Walker and Hopkins 1990). The landcover varies in species composition and structure and density. Lockyersleigh has both medium density and open woodlands, native and introduced grasses, standard and improved pasture, as well as exposed patches of soil. Lockyersleigh Catchment trees consist of dry sclerophyll forest where red stringybark predominate, savanna woodland of yellow box, red gum and some snow gums at higher altitudes near the Wollondilly River. Native Lockyersleigh grasses include spear grasses, kangaroo grass and Poa species, but they have largely been replaced by tussock grass, wallaby grass and wire grass due to grazing and fire pressure (Hird 1991). Weeds within the catchment are not considered within the context of this study.

The above-ground biomass data was collected for two different seasons (summer and spring) in 1993 and in summer in 1994 refer to figure 2.8. The sites within the catchment (figure 2.1a,b) were selected to represent the total variation within the catchment. Sites at transect A (Aₜ) have a relatively high elevation and some sites are north facing, sites at transect B (Bₜ) are low, flat and at times intensively grazed, sites at transect C (Cₜ) are close to the outlet of the catchment, sites at transect J (Jₜ) have the steepest topography, sites at transect K (Kₜ) are partly in open and dense woodlands; and sites at transect L (Lₜ) are random check points for validation and testing.

Biomass samples were collected using electric clippers on the soil surface over a 0.25m² area to represent a square metre on the ground. The site locations were selected for various reasons. Some of the site locations were chosen along a transect perpendicular to the stream lines, others to be on different gradients in the catchment, some near the catchment outlet, sites range between grasses and woodlands, and to synchronise with previous years soil and neutron moisture meter (NMM) data. Each sample was labeled, general site conditions were recorded.
e.g.; density, proximity to trees. Biomass samples were weighed (dry and wet), and samples were divided into brown and green material. Leaf area measurements taken from some samples. And some samples were sieved to determine if any excess soil remained in the samples.

**Figure 2.8 Monthly Data Acquisition Dates**

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<td>56, 1 spatial data (bands 3, 4, 5 and 7)</td>
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The field data collected in 1992 and January 1993 (figure 2.8) were used for the geographical location of sites and general assessment of the catchment. The biomass data collected at these times were not included in the modelling. The following figures (2.9 - 2.11) show the biological productivity and diversity in the landscape. Transect A_x at approximately 665 m is considered to be representative of the higher southern one-third of the catchment and has higher biomass levels. Transect B_x with an approximate elevation of 628 m represents the middle third of the catchment and generally had slightly less biomass than A_x. Transect C_x at approximately 608 m represents the lower third of the catchment where the Lockyersleigh Creek joins the Wollondilly. Transect J_x on the north eastern edge of the catchment (also considered in the upper third of the catchment) consisted of both grass/pasture and woodlands and steeper terrain with elevation of approximately 686 m.
**Figure 2.9**  Biomass Data: March 1993

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Where in figure 2.9:
- site = site within catchment
- TFW = total fresh weight (gms)
- subFW = subsample fresh weight (gms)
- subLAgreen = subsample of the green material (gms)
- TDW = total dry weight (gms)
- LA cm$^2$/0.25m$^2$ = leaf area (cm$^2$/0.25m$^2$)
- LAI = leaf area index
- TDW Kg/ha = total dry weight (Kg/ha)

**Figure 2.10**  Biomass Data: September 1993.
## Spatio-temporal Modelling of Biomass

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### Chapter 2. Catchment Characteristics

#### Spatio-temporal Modelling of Biomass

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**Figure 2.11 Biomass Data: March 1994**

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Figures 2.12a-d, 2.13a-e and 2.14a-d show site-average biomass values at transects in the catchment. Even in this low relief catchment it is evident that biomass varies spatially and temporally (figures 2.12, 2.13 and 2.14). These site-averaged biomass values can be referenced to figures 20a-f, where for example, site 12 transect A, has a relatively high biomass on the east to north eastern slope on the catchment.

**Figure 2.12a**

![Biomass Variability: Transect Ax](image)

March 1993

**Figure 2.12b**

![Biomass Variability: Transect Bx](image)

March 1993

**Figure 2.12c**

![Biomass Variability: Transect Jx](image)

March 1993

**Figure 2.12d**

![Biomass Variability: GPS sites at K](image)

March 1993
Chapter 2. Catchment Characteristics
Spatio-temporal Modelling of Biomass

**Figure 2.13a**
Biomass Variability: Transect Ax
September 1993

**Figure 2.13b**
Biomass Variability: Transect Bx
September 1993

**Figure 2.13c**
Biomass Variability: Transect Cx
September 1993

**Figure 2.13d**
Biomass Variability: Transect Jx
September 1993

**Figure 2.13e**
Biomass Variability: At GPS locations
September 1993
Figure 2.14a

Biomass Variability: Transect Ax
March 1994

Figure 2.14b

Biomass Variability: Transect Bx
March 1994

Figure 2.14c

Biomass Variability: Transect Jx
March 1994

Figure 2.14d

Biomass Variability: GPS sites
March 1994
Wet biomass is highly variable and unreliable due to continuing evaporative process after collection, therefore it is not referred to in a quantitative way. The variation of dry biomass within the catchment demonstrates the spatial variability of the surface cover. This is significant as low relief catchments that have been cleared are often considered to be homogeneous. To a degree this is true. Sites such as Lockyersleigh Creek Catchment are suitable as calibration sites for remotely sensed data due to the homogeneous nature of the catchment. Sites with comparatively complex terrain and diverse vegetation are not usually suitable for such calibration. They are more useful for polygon raster analysis once some regionalisation is established. The nature of this study is twofold a) determine the degree of spatial variability within the catchment, that is to verify homogeneity or regionalise areas of homogenous surface cover and b) to understand (determine, quantify) what determines the spatial variability within the catchment. Could the spatial variability of biomass depend on the terrain in such a low relief catchment?

The Leaf Area Index (LAI) is an important variable for a number of studies (Figure 2.15). It is used as input into many physically based hydrologic models and atmospheric models as it gives important information about the surface area of the vegetation, that is exposed to evaporative processes. Leaf area usually refers to only one side of the leaves and is often referred to as $m^2$ leaf area to $m^2$ on the ground, and is therefore unitless. LAI also is commonly related only to green leaf material but this can vary between studies. In forest systems with dense tree canopies LAI can be underestimated when using remote sensing as the sensor only views the top of canopies. Depending on the tree species ‘browning’ is often not a problem for LAI as trees continue to transpire throughout the year. Eucalyptus species can reflect a red colour with new growth shoots. This is particularly prevalent after a ‘cool’ fire has been through a forest system. In grasses and pasture ecosystems LAI is difficult to measure and can vary with different measuring techniques and climatic seasons (Cusack et al 1997). Laboratory techniques for the determination of LAI can often reflect high LAI values as compared to remotely sensed LAI values due to calibration techniques or the instrument sensitivity to colour and surface area. LAI variability is shown in figure 2.16.

Remote sensing output has been quantitatively related to a number of physiological and growth parameters for vegetation. It has however, rarely been correlated directly to LAI in grasses and pastures (McVicar 1996). The difficulty with estimating LAI for grasses is due to the high density of vegetation to the ground surface and the small leaf sizes. The relationship between LAI and remotely sensed data is an example of upscaling from point data to spatial pixel coverage. This will be discussed in more detail in Chapter 3 on remote sensing.
Chapter 2. Catchment Characteristics
Spatio-temporal Modelling of Biomass

Inevitably ground samples cover a small fraction of the mapped region or satellite viewed area which raises the question of how representative the resulting models are for undersampled areas (Davis and Goetz 1990). Heterogeneity can also occur in the methods of sampling. The sampling technique and number of different samplers can affect the results obtained. In this study these human errors were minimised by using a constant technique and a maximum of two samplers. Leaf area was determined using a leaf-area video measuring instrument which was pre-calibrated for grasses.

Figure 2.15 Table of Leaf Area Index (LAI) functions and applications.

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<td></td>
<td>Growth rates</td>
<td>moisture indices</td>
</tr>
</tbody>
</table>

Figure 2.16 Graph showing the variability of LAI within the catchment in March 1993.

Aᵦ = meteorological station near site A
Figure 2.17 shows biomass (dry weight) correlated with LAI for March 1993 from the study by Cusack et al (1997). The strong correlation between biomass and LAI \( r^2 = 0.78 \) for this small catchment suggests a strong linear relationship between biomass and LAI. However, Boulet and Kalma (1997) suggest LAI has a highly non-linear response throughout different seasons. For management purposes it is expected that a high LAI would occur under fertilised and ungrazed conditions. And conversely, a lower LAI would occur under grazing pressure and dry surfaces, due to low to zero rainfall or high radiation load, southerly aspect, diverging surface water and at erosion sites.

2.2.4 **Topographic Data**

**Digital Elevation Models**

Digital Elevation Models (DEM) provide a 3D map of the landsurface. DEMs are one of the most fundamental inputs to spatial models. They are a powerful tool to spatially construct the land surface using a mathematical model (Zhang et al 1996). However, a DEM only provides accurate representation of the surface shape and drainage structure if it is calculated with high quality interpolation algorithms, that can overcome inherent biases in source topographic data (Hutchinson and Gallant 1998, 2000). Spatial data supplied by the DEM is extremely useful as it allows a better quantitative spatial understanding of surface parameters and their influence on biomass.

The topography modelled by the DEM delineates the surface through which the soil, vegetation, atmosphere interact. Minor changes in the surface geometry can affect the interaction between...
Chapter 2. Catchment Characteristics
Spatio-temporal Modelling of Biomass

surface hydrology and biomass and one of the major aims of this study is to quantify the interaction between biomass and the land surface.

The DEM of the topographic surface produced through a minimum curvature gridding technique (Hutchinson 1996) can also be combined with climate data to produce accurate monthly mean interpolated climate surfaces across Australia (Hutchinson, 1991ab, 1995). These climate variables are essential inputs for plant growth models.

DEM's can be calculated in three ways: contour based (Moore et al 1991), TIN triangulation method (Weibel and Heller 1991) and the grid or raster techniques (Moore et al 1991). The advantages of the contour based DEMs occur when polygon analysis is required and accurate contour data are available, while the TIN method can produce effective models with few data points. The grid based elevation interpolation techniques have a number of advantages, especially compatibility with remotely sensed data. Direct gridding or finite difference methods can produce high quality interpolation methods (Smith and Wessell 1990, Hutchinson 1989). Hutchinson (1989) describes an iterative direct gridding approach that fits discretised bivariate splines using tension. The limitation of contour data is that the source data can undersample the areas between contour lines especially in low relief catchments (Hutchinson and Gallant 1999) and it has a high data storage demand (Moore et al 1991). The TIN method can produce less than optimal results if triangular polygons are not located at critical locations within the catchment. However, high accuracy results can be obtained by combining contour data with a suitable interpolation technique. This is particularly important in low relief catchments where the surface shape and drainage structure are more important than the elevation alone.

For this study the DEM was created using ANUDEM version 4.6 (Hutchinson 1997) using digitised stream, point and contour data (figure 2.18). A grid resolution of 25m was selected to match the information content of the source data. ANUDEM includes a drainage enforcement algorithm to represent the true surface drainage structure. Multiple runs of the program were used to determine sinks (which are rare in most landscapes Band 1986, Goodchild and Mark 1987) and large data residuals that often indicate data errors. These were checked and corrected in figure 2.19. Hutchinson (1988, 1989, and 1993) describes in detail spline-based gridding methods that can provide high accuracy in spatial modelling surface shape. Figure 2.18 shows ANUDEM input options for producing the DEM for the Lockyersleigh catchment.
ANUDEM (Hutchinson (1989) interpolates source topographic data and produces as 3D surface of the elevation (figure 2.19). The ANUDEM flow chart shows the steps and statistical checks involved in producing an accurate DEM. DEM outputs are the basis for further terrain modelling in this thesis.
FIGURE 2.19  ANUDEM FLOW CHART

Topographic Data:
Streams, heights contours. Chapter 2

ANUDEM:
Thin plate interpolation
Chapter 2.

Check sinks and residuals for data errors.

3D surface output of topographic morphology

Map Production

Further modelling & GIS developments. Input for model development, chapters 4, 5, 7
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Figures 2.20a – 2.20f show elevations determined by the DEM for the transects and additional sites in the catchment. The numbers refer to the site numbers within each transect.

**Figure 2.20a** Terrain surface at Transect A*

![Terrain Surface: Transect Ax](image)

**Figure 2.20b** Terrain surface at Transect B*

![Terrain Surface: Transect Bx](image)
Figure 2.20c  Terrain surface at Transect Jx, sites 1 - 6

Terrain Surface: Transect Jx, sites 1 - 6

Figure 2.20d  Terrain surface at Transect Jx, sites 6 - 12

Terrain Surface: Transect Jx, sites 6 - 12
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Figure 2.20e Terrain surface at Transect Cx

Terrain Surface: Transect Cx

Figure 2.20f Elevations at extra GPS sites

Elevations at extra GPS sites

Extra Sites with GPS locations
Chapter 2. Catchment Characteristics
Spatio-temporal Modelling of Biomass

**Correlations between Biomass and Topographic data**

Biomass data were correlated with elevation to determine whether elevation as a single attribute could predict biomass production. Elevation could represent temperature and rainfall in this scenario as temperature generally decreases and rainfall generally increases with increases in elevation (altitude). Since these climatic variables are key variables for biomass growth then, in the simplest form, biomass could be directly correlated to elevation (Figures 2.21a, b and c). However, there was not a statistically significant correlation at the scale of this catchment. Therefore more process based controls on biomass are examined in chapters 4, 5, 6, 7.

Figure 2.21a, b and c  Show graphs of biomass verses elevation for different time periods.

**Figure 2.21a**  
*Biomass vs Elevation (DEM) March 1993*

**Figure 2.21b**  
*Biomass vs Elevation (DEM) October 1993*

**Figure 2.21c**  
*Biomass vs Elevation (DEM) March 1994*

Although there is not a significant correlation between biomass and elevation in this low relief catchment some trends can be seen. For both the March periods biomass appears to decrease with increasing elevation. This trend seems to be ‘driven’ by transect J_x (also labeled as 4.01-4.12). Transect J_x is the steepest site within the catchment. Sites A_x and B_x have lower
Chapter 2. Catchment Characteristics
Spatio-temporal Modelling of Biomass

elevations than \( I_x \) and have similar higher biomass. Theoretically, the wetter and cooler surface conditions could provide a partial explanation for this trend.

Further Analysis using DEMs

Hydrological Applications
Topographic attributes can be determined from the DEM. The accuracy of topographically driven attribute are dependent on the DEM accurately representing the surface shape, (see chapter 5). Once an accurate DEM is established the Terrain Attribute Programs for Environmental Sciences – grid version (TAPES-G) can show the spatial variability of the dominant hydrological processes (Gallant and Wilson 1996) and allow more physically-based secondary attributes to be calculated (Chapter 5). Figure 2.22 shows the 3D terrain surface of the Lockyersleigh Catchment, as created using ANUDEM and TAPES-G. Hydrological applications using a DEM base are greatly improved using the Hutchinson (1989) drainage re-enforcement algorithm which removes spurious depressions in the DEM. Douglas (1986) and Carter (1988) discuss drainage structure in low relief catchments. Hutchinson (1988, 1996) uses a locally adaptive feature and gridded method to produce results with minimal or zero spurious depressions. The procedure developed by Hutchinson (1988, 1989) can be calculated from digitised point, contour, and stream data. This method includes an algorithm that automatically calculates stream, and ridge lines from contour data (Hutchinson 1988). This can alleviate the problems associated with contour data representing drainage in low relief catchments.

2.2.5 Soil Description
The soil profile in this region consists of bleached sandy/silty A horizon and heavy clay B horizon that is usually mottled. Northcoate et al (1975) defined these soils as “mottled-yellow duplex soils”. According to geologic maps (Soil Landscape Series Sheet SI 55-12) these soils are derived from Lockyersleigh Adamellite, an acidic granite intrusive that outcrops in the northern end of the catchment and near the centre lower third of the catchment. Other parts of the catchment are derived from Ordovician-Silurian and Devonian sediments. The north eastern parts of the catchment are characterised by a stony loam texture with rocky outcrops. Guerra (1995) described other properties of the soil profile across the catchment. This study mainly concentrates on the above ground processes and vegetation.

This study examined the surface processes that influence biomass distribution above the clay layer as they are important for the soil moisture, structure and nutrients for plant growth. Grasses and pasture use approximately the top 10 cm for the root system although through
Figure 2.22  Map of the Topographic Surface using a 25 m DEM
Lockyersleigh Catchment
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Hydraulic conductivity properties of the soil and the physiological capacity of the plant, biomass (grass/pasture) can utilise water and nutrients through the soil profile below the clay layer. A summary of the clay layer depths from data collected in September 1994 is shown below. The soil depth can be important to vegetation. The average soil depth within this catchment is approximately 48 cm (Figure 2.23). This agrees with Boulet and Kalma (1997) who described the local duplex soils as 30-50 cm thick.

Figure 2.23 Clay depth at sites in the catchment.

<table>
<thead>
<tr>
<th>Site</th>
<th>Clay layer Depth</th>
<th>Comments</th>
</tr>
</thead>
<tbody>
<tr>
<td>L1</td>
<td>soil layer greater than 60 cm</td>
<td>top - 20 cm fine light brown middle - 20 cm yellowish brown bottom - fine mid-brown small stones no clay layer found at 60 cm depth</td>
</tr>
<tr>
<td>L2</td>
<td>41 cm</td>
<td></td>
</tr>
<tr>
<td>A9</td>
<td>43 cm</td>
<td></td>
</tr>
<tr>
<td>L3</td>
<td>24 cm</td>
<td></td>
</tr>
<tr>
<td>EC2</td>
<td>62 cm</td>
<td></td>
</tr>
<tr>
<td>L4</td>
<td>soil layer greater than 36 cm</td>
<td>36 cm all fine sand &gt; 36 cm small stones could not auger any further</td>
</tr>
<tr>
<td>L6</td>
<td>65 cm</td>
<td></td>
</tr>
<tr>
<td>K6</td>
<td>61 cm</td>
<td>stones collected at 50 cm level clay layer at 61 cm</td>
</tr>
<tr>
<td>K4</td>
<td>50 cm</td>
<td></td>
</tr>
<tr>
<td>K2</td>
<td>soil layer greater than 35 cm</td>
<td>stones at 35 cm too difficult to auger through</td>
</tr>
</tbody>
</table>

Relationships between the clay layer depth and biomass were considered in this study, however, with limited soil depth data these correlations could not be statistically proven. Erodibility of the topsoil based on severity classes for various forms of water erosion shows the topsoil is ‘highly’ erodible and subsoil from low to highly erodible Hird (1991). Therefore, the DEM is used as a surrogate for soil depth changes within the catchment and biomass is correlated to topographic attributes.

2.2.6 Site Locations

All biomass collection sites were entered into ARCINFO Geographic Information System (GIS) with their Global Positioning Satellite (GPS) locations and respective UTM positions. Extra sites were examined in 1994 and their locations were again determined by global position satellite (GPS) and also imported into ARCINFO. The additional sites and their positions are shown in Figure 2.24.
Figure 2.24  Table of GPS positions of the additional sites using the GDA66 co-ordinate system and converted to WGS84

<table>
<thead>
<tr>
<th>Site Name</th>
<th>GPS number</th>
<th>Latitude</th>
<th>Longitude</th>
<th>Elevation</th>
<th>Station Quality</th>
</tr>
</thead>
<tbody>
<tr>
<td>L1 (Trig.station)</td>
<td>0690</td>
<td>34°42'58.86</td>
<td>149°56'58.86</td>
<td>689.90000</td>
<td>Fixed control</td>
</tr>
<tr>
<td>L2</td>
<td>00L2</td>
<td>34°42'42.50</td>
<td>149°56'47.49</td>
<td>652.60616</td>
<td>Baseline</td>
</tr>
<tr>
<td>L3</td>
<td>00L3</td>
<td>34°43'5.89</td>
<td>149°55'21.67</td>
<td>656.17852</td>
<td>Baseline</td>
</tr>
<tr>
<td>L4</td>
<td>00L4</td>
<td>34°41'59.32</td>
<td>149°56'9.71</td>
<td>640.43133</td>
<td>Baseline</td>
</tr>
<tr>
<td>L6</td>
<td>00L6</td>
<td>34°41'31.87</td>
<td>149°57'1.00</td>
<td>676.62585</td>
<td>Baseline</td>
</tr>
<tr>
<td>K6</td>
<td>00K6</td>
<td>34°42'44.05</td>
<td>149°56'17.08</td>
<td>627.79584</td>
<td>Baseline</td>
</tr>
<tr>
<td>K2</td>
<td>00K2</td>
<td>34°39'41.93</td>
<td>149°55'21.06</td>
<td>640.03628</td>
<td>Baseline</td>
</tr>
</tbody>
</table>

* All seconds are rounded to 2 decimal places where 1 second is approximately 25 m.

2.3 Anthropogenic Factors and Summary

2.3.1 Anthropogenic Factors

Anthropogenic factors are also a component of this managed catchment. Figure 2.25 summarises anthropogenic activities and an attempt has been made to describe the activities despite limited information. Kalma et al (1989) noted that the mixed grazing property included 13,000 sheep, 900 cattle and an intensively farmed horse stud. Stocking rates in the Goulburn district between 1978 to 1984 averaged at 1.5-2.5 dry sheep equivalents (dse) per hectare, ranging from 10 dse on improved pasture to 1 dse on cleared unimproved country (Hird, 1991). According to farm manager officials at the time of data collection for this study the grazing regime at Lockyersleigh was 4.5 dry sheep equivalent. For the periods of 1993 and 1994 this grazing regime was constant in all paddocks except site B where, during November and May the numbers increased as it was used as a 'holding' zone for agricultural activities such as shearing and crutching. All dams are hillslope construction and used for water holding and presumed erosion control. Native tree planting of five acres per year has been implemented since 1988. The farm managers determined the location of the tree planting.
Chapter 2. Catchment Characteristics
Spatio-temporal Modelling of Biomass

It makes ecological sense to understand any plausible links between the spatial variability of the biomass with anthropogenic causes as these could affect the relationship between biomass and topographic attributes. From a management perspective an accurate understanding of the dietary requirements of grazing animals could regulate the grazing densities to nutritionally high regions for short periods where necessary. Regional distribution or landscape utilisation may increase biomass and reduce erosion processes, or indicate areas that are susceptible to land degradation.

Remote sensing offers the possibility of recording the actual surface conditions at both regional and local scales (Tucker et al 1986). The Global Inventory Monitoring and Modelling Studies (GIMMS) group has recorded the utility of NOAA/AVHRR data for providing timely information on grazing conditions in the Sahel (Tucker et al 1985). Thus, even without grazing data remotely sensed data can used to assess the condition of the land surface.

Figure 2.25 Table of anthropogenic factors

<table>
<thead>
<tr>
<th>Activity</th>
<th>Descriptions</th>
<th>Quantity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fertilisers</td>
<td>location</td>
<td>3000 acres every 3 yrs starting winter 1994</td>
</tr>
<tr>
<td></td>
<td>type</td>
<td>Superphosphate</td>
</tr>
<tr>
<td></td>
<td>quantity</td>
<td>100 wt/acre. (No fertilizer 1989-1993)</td>
</tr>
<tr>
<td>Grazing</td>
<td>types</td>
<td>sheep, cattle, horses</td>
</tr>
<tr>
<td></td>
<td>numbers</td>
<td>4.5 d s e (dry sheep equivalent)</td>
</tr>
<tr>
<td></td>
<td>location &amp; duration</td>
<td>throughout all paddocks</td>
</tr>
<tr>
<td>Fencing</td>
<td>location Site A and J</td>
<td>1995 fences removed</td>
</tr>
<tr>
<td></td>
<td>Other sites no change</td>
<td></td>
</tr>
<tr>
<td>Driving tracks (major)</td>
<td>location</td>
<td>roads on map</td>
</tr>
<tr>
<td>Walking tracks (major)</td>
<td>location &amp; type</td>
<td>kangaroos north eastern section of catchment sheep, cattle tracks to water and other random patterns</td>
</tr>
<tr>
<td>Animals, people</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Buildings</td>
<td>location</td>
<td>Buildings on map</td>
</tr>
<tr>
<td>Dams</td>
<td>number</td>
<td>86</td>
</tr>
<tr>
<td></td>
<td>when constructed</td>
<td>1988</td>
</tr>
<tr>
<td></td>
<td>type</td>
<td>hillslope</td>
</tr>
<tr>
<td></td>
<td>location</td>
<td>approximately 2/paddock</td>
</tr>
<tr>
<td>Improved pasture</td>
<td>location &amp; planting dates</td>
<td>Native pasture, mostly silver grass, velarius, rye, barley &amp; some clover</td>
</tr>
<tr>
<td>Tree planting</td>
<td>native &amp; non-native</td>
<td>native: eucalyptus &amp; wattle</td>
</tr>
<tr>
<td></td>
<td>purpose</td>
<td>tree wind breaks, stock shelter</td>
</tr>
<tr>
<td></td>
<td>when</td>
<td>1994, 1996</td>
</tr>
<tr>
<td></td>
<td>location</td>
<td>paddock 12 near railway line, near site C</td>
</tr>
<tr>
<td>Clearing</td>
<td>dates</td>
<td>mostly 1940's</td>
</tr>
<tr>
<td></td>
<td>techniques used</td>
<td>mostly clear felling</td>
</tr>
<tr>
<td>Animals</td>
<td>non-native (total)</td>
<td>sheep, cattle, horses</td>
</tr>
<tr>
<td></td>
<td>native (total)</td>
<td>kangaroo, wombat, birds</td>
</tr>
<tr>
<td></td>
<td>feral</td>
<td>rabbits, foxes, birds</td>
</tr>
<tr>
<td>Machinery used</td>
<td>types</td>
<td>cultivated one paddock 1996</td>
</tr>
<tr>
<td></td>
<td>location &amp; duration</td>
<td>tractor direct drilling</td>
</tr>
</tbody>
</table>
2.3.2 Summary

This chapter has described the experimental catchment as low relief and mostly cleared with limited climate and spatio-temporal biomass data. Limited spatio-temporal biomass and climate data are realistic and common problems for environmental scientists. This catchment has a variable climate with extended dry periods and these fluxes are difficult to account for in space/time models. Given the complexity and dynamic behaviour of plant communities across a range of spatial and temporal scales, predicting vegetation patterns is difficult (Rowe and Sheard 1981). The aim of this thesis is to obtain spatio-temporal biomass data that can be linked to the topography. Chapters three to six investigate and determine the relationship between biomass and topographic, satellite, climatic and modelled growth indices via different modelling procedures. In chapters seven and eight, statistical biomass models are developed, validated and compared with each other in terms of their accuracy and modes of application.
Chapter 3.

Remotely Sensed Data and Vegetation Data
CHAPTER 3. REMOTELY SENSED DATA AND VEGETATION DATA

3.1 Introduction
   3.1.1 Introduction to remote sensing
   3.1.2 Instrument variations and specifications
   3.1.3 Atmospheric and geometric corrections
   3.1.4 Limitations to data sets

3.2 Spectral and Spatial Functions
   3.2.1 Introduction to spectral and spatial functions
   3.2.2 NDVI, biomass and LAI

3.3 Airborne Data and Vegetation Data
   3.3.1 CASI data
   3.3.2 Ground-based data
   3.3.3 Correlations between aircraft and biomass data
   3.3.4 Discussions of the airborne data study
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3.4 Satellite Data and Vegetation Data
   3.4.1 Aims
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   3.4.6 Remote sensing and modelling

3.5 Summary
Chapter 3. Remotely Sensed and Vegetation Data  
Spatio-temporal Modelling of Biomass

This chapter

- introduces remotely sensed data
- discusses instrument specifications and variations
- examines hyper-spectral data from airborne data sets
- demonstrates a method of waveband selection from airborne and biomass correlation’s
- determines algorithms for airborne data beyond ground collection points.
- includes satellite data acquisition and waveband selection for biomass data
- calculates atmospheric corrections for normalising satellite data
- correlates remotely sensed data with ground measured biomass data

3.1.1 Introduction to remote sensing

Electromagnetic radiation (or radiant energy) is the source of remotely sensed digital data. Electromagnetic radiation can be considered as a harmonic wave which can be refracted or reflected. These waves are defined in wavelengths (λ) where $\lambda = \frac{c}{v}$ and $c$ is the velocity in of the speed of light (m s$^{-1}$) and $v = \nu$ is the frequency (cycles per second). Wavelengths are usually measured in micrometers (µm) in the infrared and nanometers in the visible and ultra violet region. Where 1 µm = $10^{-6}$ m and 1nm = $10^{-9}$ nm. Spectrometers allow a range of frequencies (or width of spectral lines) to be absorbed (received) by the detector. Within this study these are commonly referred to as wavebands, and in other literature as absorption bands (Banwell 1972).

Remotely sensed data provide a rich source of spatial data when used in conjunction with accurate calibration techniques. Calibration consists of radiometric, geometric and surface cover corrections/recordings. Radiometric calibration is often incorporated into the remote sensor and geometric corrections need to be calculated with the remotely sensed data and prevailing conditions (sun zenith angle etc) and the land surface cover.

Remotely sensed data allows spatio-temporal analysis which can a) provide descriptive interpretation, b) show change over time, c) depict cause and effect, d) be used as input into models or as validation of the outputs of models. Spatially distributed vegetation data are difficult and expensive to collect on the ground. Ground collected data rarely provide complete spatial coverage at a single time. Remotely sensed data provide spatially extended maps of the surface cover, but require calibration. Remotely sensed data can be particularly useful for
distinguishing between trees and grasses however, in this study it is used over a mostly grass/pasture catchment to determine whether subtle topographic differences can be linked to different biomass levels.

Remotely sensed data are represented by digital (numeric) or image format. Digital data can be manipulated, analysed, enhanced or displayed using image processing. Mathematical algorithms allow noise data reduction and interpolation, geometric changes and pattern extractions while image analysis often involves statistical analysis. These calculations vary with the level of accuracy required and the objectives of the study. Remotely sensed data come mainly in raster or grid based form. Each pixel within a remotely sensed data set usually refers to radiance in discrete wavelength bands or channels. This study includes, aircraft data with a 6m spatial resolution and satellite grid-based data with a 25m spatial resolution.

3.2.2 Instrument specifications and variations

Each type of remote sensor requires individual instrument calibration and ground validation. The geometric corrections required to calibrate the sensor depend on the stability of the sensor, geographic location, atmospheric and meteorological influences as well as terrain and biological factors. Geo-referencing refers to the process of using ground points for surface validation. Geo-referencing techniques have been incorporated in this study. Detailed calibration of an aircraft sensor has been described by Louis et al. (1995) who regressed airborne data with reflectance, wavelength, flying height and aperture variables.

Wavelength or bandwidths vary from approximately 7 nm on airborne scanners such as the Compact Airborne Spectrographic Imager (CASI) to wavebands of approximately 100 nm on Thematic Mapper Satellite (TMSAT). TMSAT5 band 3 (red) has a bandwidth of 60 nm covering four CASI channels from channel 5 - 8 as shown in figure 3.3. TMSAT5 NIR band 4 has a width of 140 nm (figure 3.13). The hyperspectral nature of CASI data means CASI NDVI calculations can be determined using different waveband combinations.

Different remote sensing platforms operate at varying distances to the surface and therefore produce different surface resolutions. Advanced Very High Resolution Radiometer (AVHRR) supplies Normalised Difference Vegetation Index (NDVI) data at 1 km surface resolution whereas Compact Airborne Spectrographic Imager (CASI) produces NDVI data at 6 m resolution. The low-altitude aircraft instrument yields considerably more surface detail about the vegetation status than AVHRR. The Thematic Mapper Satellite (TMSAT) can be accurately interpolated to a resolution of around 25 m. In a comprehensive study, Moran et al. (1994)
compared remotely sensed data (aircraft and satellite) and vegetation-related parameters
(biomass, cover) in a semi-arid rangeland in Arizona. They concluded that more research was
required on the relationship between remotely sensed measurements and surface reflectance,
specifically issues relating to variations with sensor spatial resolution.

Other remote sensing devices include; radar data (altimetry and interferometry) with 25 m and
10 m resolutions; laser profiling and altimetry, which can give fine grids of 4 m; and air
photography.

3.2.3 Atmospheric and geometric corrections.

Monitoring vegetation using remote sensing has many difficulties (Dymon and Qi 1997).
Potential errors in raw remotely sensed data (McVicar 1996) include; pitch, roll and yaw
(planes and satellites), altitude (of aircraft and topography), orbital inclinations, earth curvature
and rotation, project of oblate sphere to a flat surface and uncertainty regarding the absolute
position of the satellite.

These errors can be broadly classed under radiometric and georadiometric effects. Teillet
(1986) defines major categories as sensor and scene effects. Sensor effects include calibration
and de-striping and scene effects include atmospheric, georadiometric and target reflectance
properties. Lillesand et al (1994) summarised radiometric corrections as scene illumination,
viewing geometry and instrument response characteristics. They discuss three methods of
correction: sun elevation correction, earth-sun distance correction and haze compensation.
Dymond and Qi (1997) discuss the variation in vegetation radiance in terms of view direction
and sun position. Other difficulties include the hot spot effect where a canopy is viewed from
the same direction as the sun and therefore shadows disappear and that portion of the canopy is
'seen' as sunlit. Dymond and Qi compared three models (physical and empirical), by Roujean
et al. (1992), Verstraete (1990), Dymond and Qi (1997) to predict radiance from pine and
pasture at different sun zenith angles. For low zenith angles (up to 60°) the Dymond and Qi
model predicted the best fit and success was attributed to the hotspot function having a sun
zenith angle dependence, thereby allowing average projected leaf area to vary with off-nadir
view angle (figure 3.2).

It is therefore clear that radiometric and atmospheric corrections can be categorised and in
various ways and the individual categories are inter-related. Different calibration techniques
are also required depending on atmospheric and surface conditions. However, to directly
compare images at different times the normalisation of radiance to a set of standard conditions or conversion of radiance data to reflectance is essential (Teillet 1986) (section 3.4.5).

In this study, the microBRIAN (Barrier Reef Image Analysis) computer package (Jupp et al 1985a, 1987) was used to calibrate the airborne data set. Ground control points (GCPs) were statistically matched to remotely sensed data for stability and complexity. Instability is created by a) systematic distortions are produced in transferring data e.g. co-ordinates must be defined accurately according to their origin of centre or corner, b) converting data e.g. ascii to binary, image to graphics to digital c) map projection and scaling effects, and d) human error. Complexity refers to the algorithm chosen to fit the remotely sensed surface to the ground, points or DEM. That is, a high level polynomial (e.g. a cubic fit as opposed to a linear fit) could have a higher error level (significant level) than a simple fit (e.g. linear) with a lower correlation coefficient reflected in a higher level of significance (figure 3.6).

3.1.4 Limitations

Single remotely sensed data sets (snap shots) can be problematic as they can miss important events and do not show any temporal trends. Multi-temporal analysis is best for assessing vegetative growth. However, single images can be advantageous during an emergency (such as an oil spill) where aircraft data can rapidly supply a collection of high resolution data (Jensen 1986). Bidirectional reflectance is a problem with airborne and satellite sensors but can be overcome with internal sensor calibration or empirical models to take account for off-nadir and solar angle conditions as mentioned under atmospheric and geometric corrections section 3.8 this chapter.

A major restriction of aircraft data is its limited spatial cover or narrow swath-width (Cusack et al 1997). Aircraft data are restricted to local or regional scales only, with multiple flightlines (Wilson 1997). Other limitations include, a limited range of operations due to the aircraft’s capacity (e.g. speed, endurance), complex rectification due to turbulence (although there is less turbulence over grasses than trees), and more complex atmospheric correction due to low altitudes and by using sensors with wide field-of-view (FOVs) (Wilson 1997) (equation 3.8). Barnsley and Curran (1990) however, considered the potential to vary the altitude of the plane as an advantage as the spatial resolution could be varied, unlike satellite-borne sensors where the resolution is fixed.
Temporal limitations for aircraft data are sensor availability, while satellite data are limited by their orbital dates (Curran 1985). Both satellite and aircraft data sets require computer facilities that store and manipulate large data sets.

**Effects of Clouds**

Clouds and topography modulate remotely sensed data, which is derived from incoming shortwave radiation (Dubayah and Loechel 1997). Satellite data are of a much superior quality if the conditions are cloud free. Clouds obscure reflectance and close the atmospheric window due to their high absorptivity in the infrared region. Under cloudy conditions, the atmospheric window prevents significant loss of longwave radiation. Therefore, cloudy conditions trap heat which increase the surface temperature and alters the reflectance patterns received by satellite and airborne sensors. Kontoes and Stakenborg (1990) concluded from regression estimates that an image suitable for sampling agricultural vegetation was if cloud coverage was less than 10% of total sky coverage. Conversely, meteorologists may specifically use remote sensing data to determine the amount of cloud cover and the radiative effects produced by clouds.

### 3.2 Spectral and Spatial Functions

#### 3.2.1 An introduction to spectral and spatial functions

Spectral functions in remote sensing refer to the value of individual pixels and spectral responses to channels. Spatial responses refer to groups of pixels used to identify shape, size or a value. Image processing can use both spectral and spatial analysis. (Tunstall et al 1984) There often is a degree of spatial association between spectral classes. Classes which are spectrally homogeneous can be spatially aggregated. However, Okabe (1981) said improved spatial aggregation is usually achieved at the expense of spectral homogeneity. Spectral response comparisons between CASI and SPOT HRV (multi-spectral linear array sensor) over a pine forest have shown that models based on SPOT HRV variables were poorer estimates of individual and stand-level tree parameters than CASI. This was attributed to the decreased spatial resolution of the SPOT sensor (Franklin and McDermid 1993).

Spectral characteristics vary with cover type (Karaska et al 1986). Spectral reflectance of vegetation varies with wavelength (Curran 1985). NDVI (Normalised Difference Vegetation Index) is a calculated spectral response. NDVI is a primary tool for detecting, green leaf biomass, leaf area, vegetation changes and the interpretation of the impacts of environmental phenomena (Curran 1980, Holben et al 1980, Justice et al 1985, Kogan 1990, Bonifacio et al. 1993, Van De Griend and Owe 1993). NDVI is defined as the ratio of the difference of the
near infrared minus the red channels divided by the sum of the near infrared and red channels. It can be referred to as a greenness index. Satellite data shows how much radiation is available to the surface and green vegetation absorbs the photosynthetically active radiation (PAR 0.4 - 0.7µm). This energy is used in the exothermic photosynthetic reactions and vegetation appears green. It is referred to as a spectral response as each band or channel responds differently to the vegetation (figure 3.1). The red wavebands reflect the absorption of solar radiation by chlorophyll and the NIR wavebands reflect the multiple scattering by the leaf tissue. Hoffer and Johannsen (1969) noted that reflectance in the middle infrared region increases as the moisture content of leaves decreases. Satellite derived NDVI not only provides estimates of photosynthetic capacity (Sellers 1985) but can also be used to estimate biomass accumulation via integration over time (Tucker and Sellers 1986). NDVI can also help to compensate for changing illumination conditions, surface slope, aspect and other extraneous factors (Lillesand and Kiefer 1994, Baret and Guyot 1991).

### Figure 3.1  Colour and Wavebands recorded by TMSAT 4 and 5

<table>
<thead>
<tr>
<th>Colour</th>
<th>Wavelength Micrometers (µm)</th>
<th>Band Width</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>blue /green</td>
<td>0.45 -0.52</td>
<td>0.07</td>
<td>water penetration, strong</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>vegetation absorption</td>
</tr>
<tr>
<td>green</td>
<td>0.52 - 0.60</td>
<td>0.08</td>
<td>strong vegetation reflectance</td>
</tr>
<tr>
<td>red</td>
<td>0.63 - 0.69</td>
<td>0.06</td>
<td>very strong vegetation absorbance</td>
</tr>
<tr>
<td>near infrared</td>
<td>0.76 - 0.90</td>
<td>0.14</td>
<td>high land /water contrasts, very strong vegetation absorbance</td>
</tr>
<tr>
<td>near /middle infrared</td>
<td>1.55 - 1.75</td>
<td>0.20</td>
<td>very moisture sensitive</td>
</tr>
<tr>
<td>middle infrared</td>
<td>2.08 - 2.35</td>
<td>0.27</td>
<td>very sensitive to soil moisture and vegetation</td>
</tr>
<tr>
<td>thermal infrared</td>
<td>10.40 - 12.50</td>
<td>2.10</td>
<td>good geological discrimination</td>
</tr>
</tbody>
</table>


### 3.2.2 NDVI, biomass and LAI

The NDVI method was first used by Jordan (1969) to measure biomass and LAI, and has since been widely adopted (Rouse et al. 1973; Tucker 1979 a,b; Guoliang 1989). NDVI is a
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A vegetation index that can be correlated to parameters such as biomass, leaf-area index, percent cover and, in some cases, leaf water content, crop yield and leaf nitrogen content. It has been suggested that NDVI may also be a useful indicator of soil moisture (Choudhury and Golus 1988, Liping Di et al. 1994). More recently, Crapper and Kalma (1996) discussed the relationship between NDVI and vegetative cover using NOAA/AVHRR. NDVI can be referred to as a “greenness” index although the relationship between NDVI and greenness may depart from linearity under conditions of high rainfall, saturated soils and low solar radiation or where leaf chlorosis occurs.

NDVI is related to LAI but the calibration of remotely sensed NDVI to LAI is difficult to effect at sub-regional scales where the spatial variability of LAI is high (Nemani et al. 1993). LAI strongly influences evapotranspiration and photosynthetic rates which are important functions of biomass. Nemani et al. (1993), have shown that LAI derived from TMSAT NDVI has a strong correlation with microclimate and soil water conditions in forest ecosystems where soil moisture levels are high. Dry regions, which prevail over much of the Australian continent show high spatial variability in surface moisture and vegetation cover due to erratic rainfall, and spatial representation of vegetation is therefore difficult. Variable rainfall patterns also affect the surface hydrology by altering biomass production and thereby influencing soil infiltration as well as runoff. High evapotranspiration rates cause rapid surface drying resulting in less growth and thus potentially decreasing greenness. Grazing is an additional pressure on such comparatively dry soils.

McCloy et al. (1993) discusses two difficulties in transforming remotely sensed data into a vegetation index by means of regression equations. One is that the vegetation index can estimate only one independent parameter; the other is that the occurrence of brown material impairs the value of the regression. The same authors suggest that multiple independent parameters can be used to develop regression equations to estimate multiple independent physical parameters. Anderson et al. (1993) also failed to find a strong relationships between clipped-plot biomass estimates of green biomass and 9-pixel averaged NDVI values. Further, the type of vegetation cover can affect the precision of remotely sensed data sources. Variations in vegetation species and percentage cover produce different reflectance’s which can change the relationship between aircraft NDVI and biomass. Bare ground, ephemeral and perennial vegetation all have slightly different linear relationships with NDVI as determined by CASI bands. Lewis and Wood (1994) noted that the correlation between field percent cover and Landsat TM waveband data overestimated the spatial coverage of bare ground and underestimated the spatial coverage of ephemeral vegetation. Kauth and Thomas (1976) used
linear transformation 4 MSS bands and derived 4 new axis of spectral data used for vegetation analysis. They refer to this as the ‘tasselled cap’.

Peters et al (1991) refers to AVHRR course satellite resolution. He summaries the interaction between vegetation and NDVI by stating that "...because vegetation is such a good integrator of the physical variable that make up drought, the normalised difference vegetation index from the course resolution satellite data may offer a useful "composite signal" for a region of interest.". However, depending on the season, other wavebands may be of interest. For example, TMSAT band 3 detects brown vegetation.

3.3 Airborne Data and Vegetation Data

3.3.1 CASI airborne data set
Two distinctive features characterise the CASI data: firstly, the pixel size is small, approximately 6 x 6 m; and secondly, wavebands can be selected from a large number of narrow bands. The spectral reflectance data from CASI were converted to NDVI. Six combined CASI bands were chosen for comparison with the ground vegetation data to display 'greenness'; to give additional information on plant function through LAI; and to avoid bands with water vapour and oxygen absorption features. The CASI is based on an imaging spectrograph. Repeated sensor records can create a detailed spectrum for every point in a two-dimensional scene image as the aircraft moves along its flight path. The ground resolution (pixel length) is determined by the aircraft speed and frame rate, while the across-track ground resolution (pixel width) is a function of the aircraft altitude. The CASI spatial operating mode was chosen to maximise the spatial resolution (figure 3.3). Directional distortion was minimised by the speed of the CASI scanner. The CASI sensing head employs a fast (f/2) reflection grating spectrograph (Franklin and McDermid 1993). Two flightlines were flown in the catchment starting at 11:48 EST 20 March 1993. The preferred swath width was 2000 m at aircraft height of (3000 m). The maximum flight height was 3300 m.

The CASI data were processed using roll correction (geometric) methods developed at COSSA (CSIRO Office of Space Science and Applications) that eliminated erroneous data due to plane movement (pitch, roll and yaw). Further processing with microBRIAN (an image processing package) at CSIRO Division of Water Resources (DWR) allowed rectification of the roll-corrected data (Jupp et al. 1985a, 1987). This process removes the lateral distortion of the images. Both the sun’s zenith angle and its relative off-nadir position affect the CASI sensor. Therefore, both geometric and radiometric calibration were essential to produce directional radiances distributions. Figure 3.4 from Dymond and Qi (1997) shows the angles
discussed. Re-processing within microBRIAN involved radiometric corrections, a scaling procedure and data file management. During radiometric correction the spectral radiance units SRUs were calculated for each pixel in the data. This was derived from the analysis of four factors, the signal generated by the incident light, the contributions of dark current and electronic offset and any instrument non-uniformity's. Next the CASI data (collected at a resolution of 12 bits) were scaled to match the dynamic range of the image-processing software (either 8 or 16 bits) by radiometric corrections based on user-selected peak spectral radiance units. Finally the data were rectified and geo-referenced to the surface using ground control points (GCPs). The CASI scan look angle is known to range between 12 degrees on one side to 18 degrees on the other. However, any angular variations due to the (generally clear) Australian atmosphere are not large (pers. comm. D L B Jupp 1997). Figure 3.2 is a schematic diagram of vegetation radiance, (i.e., brightness), view directions and the sun position. The CASI data were recorded near 12 noon, in this low relief catchment with mostly grasses and pasture and this reduces measurement errors. In addition, the CASI had instrument geometric and radiometric calibration of the camera to reduce directional radiance distribution differences.

Figure 3.2 Diagram of an example of the angle-lens of a mounted camera (Dymond and Qi 1997)

\[ \theta = \text{sun zenith angle} \]
\[ \phi = \text{off-nadir view angle} \]
Figure 3.3  Table 1. CASI channels and wavebands.

<table>
<thead>
<tr>
<th>CASI Channels</th>
<th>Wavebands (nm)</th>
<th>Range (nm)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>lower - upper</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>526.4 - 535.7</td>
<td>9.3</td>
</tr>
<tr>
<td>3</td>
<td>546.0 - 555.3</td>
<td>9.3</td>
</tr>
<tr>
<td>4</td>
<td>604.9 - 614.3</td>
<td>9.4</td>
</tr>
<tr>
<td>5</td>
<td>657.0 - 662.0</td>
<td>5.0*</td>
</tr>
<tr>
<td>6</td>
<td>677.8 - 682.6</td>
<td>4.8*</td>
</tr>
<tr>
<td>7</td>
<td>682.2 - 686.2</td>
<td>4.0*</td>
</tr>
<tr>
<td>8</td>
<td>689.4 - 693.4</td>
<td>4.0*</td>
</tr>
<tr>
<td>9</td>
<td>693.0 - 697.0</td>
<td>4.0</td>
</tr>
<tr>
<td>10</td>
<td>698.4 - 702.4</td>
<td>4.0</td>
</tr>
<tr>
<td>11</td>
<td>703.8 - 707.8</td>
<td>4.0</td>
</tr>
<tr>
<td>12</td>
<td>709.2 - 713.2</td>
<td>4.2</td>
</tr>
<tr>
<td>13</td>
<td>738.1 - 743.9</td>
<td>5.8</td>
</tr>
<tr>
<td>14</td>
<td>743.5 - 749.4</td>
<td>5.9</td>
</tr>
<tr>
<td>15</td>
<td>751.5 - 756.6</td>
<td>5.1</td>
</tr>
</tbody>
</table>

1 = standard  
* = TMSAT5 Band 3 (red)

where

red : 600 -700 nm  
near infrared : 700 - 1100 nm  
near middle infrared : 1100 - 2000 nm  
middle infrared : 2000 - 2500 nm

Figure 3.4  Optical conditions at the time of CASI data acquisition.

Sun zenith angle approximately 85°  
View angle = nadir viewing  
Leaf angle distribution = ellipsoidal
The above radiometric conditions minimise the effects of the CASI look angle. Bidirectional reflectance is of a canopy is usually higher if the sensor is looking into, as opposed to away from the sun (Curran 1985). This study site has low-relief terrain and approximately 65% low dense grass. These environmental conditions combined with and high solar angles reduce shadow effects from the CASI sensor (figures 3.2, 3.4).

CASI data are suitable for vegetation description because the radiation detector used is a silicon-based sensor with a sensitivity between 430-870 nm (figure 3.3). Most of the photosynthetic activity in plants occurs in the region of photosynthetically-active radiation between 400-700 nm. Fourteen bands from red to near-infrared (NIR), as shown in Table 1, were used in the study. Channel 1 was used as a standard. The exclusion of other wavelengths prevented any influence of atmospheric water vapour on NDVI values.

3.3.2 Ground-based vegetation data
The narrow swathe width and the sometimes unpredictable flight path made the selection of ground data points difficult. Twenty-five sites were chosen for ground measurements within the catchment on 20 March 1993 when the CASI flight occurred (figure 3.7). Final processing left only ten of the ground points under the flight path. Sample duplicates gave six averaged ground points. The 'clip-method' of sampling was used for 0.25 m² biomass quadrats. The vegetation was removed down to soil level, and wet and dry weights were obtained. Some samples were divided into green and brown matter, and descriptions of all samples were recorded. The average sward height of the biomass was 5cm. The grass layer consisted of C₃ and C₄ grass species. Any leaf litter from surrounding trees was also recorded. Leaf area was determined for the 25 samples using a leaf-area video measuring instrument which was pre-calibrated for grass-type vegetation. Biomass refers to dry weights only. The soil was not irrigated and conditions were relatively dry at the time of sampling.

The growing season for this region is characterised by high rainfall and intense radiation periods. It can extend from October to March. Since this experiment was aimed at establishing relationships between satellite bands (including NDVI) and ground biomass under conditions of minimal rainfall, it was performed in mid-March 1993 after a recorded rainfall of just 0.2 mm in the preceding week.

Figure 3.7. Flight path and spatial image of NDVI values.
Diagram from north (top right) to south (bottom left) with images overlapping at the road depicted at bottom of the first flight path and top of second flight path.

3.3.3 Correlations between biomass and aircraft data

Three CASI bands in the red and two in the near infrared (NIR) were examined in this study. NDVI (figure 3.6) was calculated using the formula below from bands 4, 5 or 6 in the red region, and bands 14 or 15 from the NIR. Channels 4, 5 and 6 are characterised by strong chlorophyll absorption. Channels 14 and 15, with longer wavelengths in the near infrared, have high reflectance due to internal reflectance involving the mesophyll structure of green leaves. Chlorophyll-absorbed light is used for photosynthesis, and greenness is associated with strong photosynthetic activity.

\[
NDVI = \frac{(X-Y)}{(X+Y)}
\]

(3.1)

where:

\[
X = \text{channel 14 or 15} \\
Y = \text{channel 4, 5 or 6.}
\]
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The resulting NDVI ratios (equation 3.1) were regressed with the ground biomass data. Relationships in the red and near-infrared regions were examined using a multi-channel vegetation index to account for variations of image brightness and of soil background or standards. Soil reflectance was assumed to be constant at all sites and to not have influenced NDVI recordings. The selected bands avoid water reflectivity.

Three regression equations were used:

Linear: \[ Z = b_0 + b_1C \]  \hspace{1cm} (3.2)

Quadratic: \[ Z = b_0 + b_1C + b_2C^2 \]  \hspace{1cm} (3.3)

Exponential: \[ Z = b_0 (\exp b_1C) \]  \hspace{1cm} (3.4)

where

- \( Z \) = dependent variable (above-ground biomass, kg ha\(^{-1}\))
- \( b_0 \) = constant
- \( b_1, b_2 \) = regression coefficients
- \( C \) = independent variable (CASI NDVI)

Figure 3.6 Correlations of above-ground biomass (kg ha\(^{-1}\)) to CASI NDVI for different wavebands combinations.

<table>
<thead>
<tr>
<th>CASI channels for NDVI</th>
<th>Linear regression</th>
<th>Quadratic regression</th>
<th>Exponential regression</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>( r^2 = 0.41 )</td>
<td>( r^2 = 0.41 )</td>
<td>( r^2 = 0.62 )</td>
</tr>
<tr>
<td></td>
<td>( \text{sig F} = 0.17 )</td>
<td>( \text{sig F} = 0.46 )</td>
<td>( \text{sig F} = 0.06 )</td>
</tr>
<tr>
<td>14 - 4</td>
<td>( r^2 = 0.36 )</td>
<td>( r^2 = 0.40 )</td>
<td>( r^2 = 0.56 )</td>
</tr>
<tr>
<td></td>
<td>( \text{sig F} = 0.21 )</td>
<td>( \text{sig F} = 0.46 )</td>
<td>( \text{sig F} = 0.09 )</td>
</tr>
<tr>
<td>14 - 5</td>
<td>( r^2 = 0.30 )</td>
<td>( r^2 = 0.43 )</td>
<td>( r^2 = 0.50 )</td>
</tr>
<tr>
<td></td>
<td>( \text{sig F} = 0.26 )</td>
<td>( \text{sig F} = 0.43 )</td>
<td>( \text{sig F} = 0.12 )</td>
</tr>
<tr>
<td>14 - 6</td>
<td>( r^2 = 0.35 )</td>
<td>( r^2 = 0.38 )</td>
<td>( r^2 = 0.55 )</td>
</tr>
<tr>
<td></td>
<td>( \text{sig F} = 0.22 )</td>
<td>( \text{sig F} = 0.49 )</td>
<td>( \text{sig F} = 0.09 )</td>
</tr>
<tr>
<td>15 - 4</td>
<td>( r^2 = 0.36 )</td>
<td>( r^2 = 0.40 )</td>
<td>( r^2 = 0.57 )</td>
</tr>
<tr>
<td></td>
<td>( \text{sig F} = 0.21 )</td>
<td>( \text{sig F} = 0.47 )</td>
<td>( \text{sig F} = 0.08 )</td>
</tr>
<tr>
<td>15 - 5</td>
<td>( r^2 = 0.37 )</td>
<td>( r^2 = 0.40 )</td>
<td>( r^2 = 0.58 )</td>
</tr>
<tr>
<td></td>
<td>( \text{sig F} = 0.20 )</td>
<td>( \text{sig F} = 0.47 )</td>
<td>( \text{sig F} = 0.08 )</td>
</tr>
</tbody>
</table>
Linear, quadratic and exponential correlations for six waveband combinations are shown in figure 3.6. The correlation coefficient for each of the six combinations represents the strength of the linear, quadratic or exponential relationship, respectively between various combinations of wavebands and the above-ground biomass. Biomass is the dependent variable and the CASI NDVI data are the independent variable in the regression analysis. CASI channels 14 and 4 produced the NDVI data with the highest correlation with biomass (kg ha\(^{-1}\)). The significant F values (figure 3.6) suggest that these data cannot support linear or quadratic fits (equations 3.2, 3.3) with CASI NDVI (at present biomass levels). The fitted quadratic and exponential curves (equations 3.3, 3.4) are almost identical but the fit of the exponential curve was considered to be significantly better because the exponential curve has one less parameter than the quadratic curve and the number of data points was small. Site conditions varied and this had an impact on biomass levels (see Fig 3.7a). Site A12 (a relatively elevated site) in figure 3.9 was slightly 'dry' at the time of data collection and had a vegetation height of 25 cm with intermittent sedges up to 80 cm and thistles up to 100 cm. Site B (relatively low site) was slightly 'wet' at the time of sampling and consisted of flat short grass up to 5 cm. Site B had also been recently grazed. At the time of sampling, B11 was dry with short dense grasses up to 10 cm and some thistles up to 100 cm. It also had been grazed. The biomass sample at B11 consisted of 43% brown material. All other sites under the flight path consisted of 100% green biomass. Figure 3.7a also displays the high degree of biomass variability in the observed data. Nevertheless, CASI NDVI represents the surface biomass reasonably well for channels 14 and 4 using an exponential curve. Sites A12 and B contributed to the lack of significance of the linear and quadratic regressions.

Fig 3.7a Biomass vs NDVI CASI Channel 14 and 4 and fitted exponential curve
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Figure 3.7b Equation for the exponential fit of biomass to CASI bands 14 and 4

\[
\text{Biomass (kg ha}^{-1}\text{)} = 1371 (\exp 3.34 \text{NDVI}) \tag{3.5}
\]

The statistical correlation coefficients between biomass and LAI are shown in figure 3.8. The high \(r^2\) values are a validation of the measuring technique. There were 18 grassland sites within the catchment, eight sites of which are under the CASI flight path. Point correlations between LAI and biomass were calculated at collection sites. Averaged biomass values were correlated with the aircraft data.

**Table 3.8** Linear regression of biomass on LAI at 18 grassland sites within catchment and eight sites under CASI flight path.

<table>
<thead>
<tr>
<th>Linear regression at 18 sites within catchment</th>
<th>Linear regression at 8 sites under CASI flight path</th>
</tr>
</thead>
<tbody>
<tr>
<td>Biomass vs LAI</td>
<td>(r^2 = 0.78)</td>
</tr>
<tr>
<td></td>
<td>sig F = 0.0000</td>
</tr>
<tr>
<td></td>
<td>(r^2 = 0.78)</td>
</tr>
<tr>
<td></td>
<td>sig F = 0.0028</td>
</tr>
</tbody>
</table>

**Fig 3.9** Correlation of biomass to LAI at 18 sites in catchment

\[
r^2 = 0.78 \quad \text{sig F} = 0.0000
\]
Fig 3.10 Correlation of biomass to LAI at 8 sites under the CASI flight path.

\[ r^2 = 0.78 \quad \text{sig F} = 0.0028 \]

Fig 3.11 Correlation of LAI to NDVI CASI 14-4
Poor correlation between LAI and CASI NDVI (channels 14 and 4) is shown in Figure 3.11. The outlier in figure 3.11 is site B11. Site B11 contained 43% brown material and CASI channels 14 and 4 are specifically designed to detect green material, resulting here in a relatively low NDVI value. Site B11 however, has a high LAI value due to both green and brown biomass recorded against the instrument’s white background. Laboratory conditions for determining LAI were more sensitive to a range of colours of the biomass than was the airborne data with specialised channels for the determination of ‘greenness’. Although CASI NDVI and LAI are not well correlated with these few ground points, it was possible to obtain a correlation between CASI NDVI and biomass. By removing B11 (figure 3.11) the relationship between NDVI and green LAI appears linear in agreement with (Holben and Tucker 1980, Hatfield et al 1985, Curran 1982, Clevers 1989) although the correlation is not statistically significant. There is limited published research on the relationships between Landsat TM and LAI for grasses, crops or pastures in Australia (McVicar et al 1996). Cusack et al (1997) highlighted problems with brown biomass interfering with any relationship between Landsat TM and LAI.

3.3.4 Discussion of the Airborne Data Study

The principal aim of this study was to determine the spatial distribution of vegetation data, by calibrating remotely sensed and ground based vegetation data. Three steps are required: a) the selection of suitable wavebands which best represent the vegetation index, in this case NDVI; b) correlation of ground and airborne data, in this case biomass and LAI with selected NDVI bands (equation 3.5); and c) extrapolation of the surface cover (biomass) beyond the ground collection points using equation 3.5, noting the errors in this calibration.

From the band-correlation coefficients, the best relationship was exponential using bands 14-4 where the proportion reflectance between the NIR and red bands predicted the best relationship with ground biomass. Sites A12 and B in figure 3.11 were outside the 95 percentile. Site A12 had high biomass due to the large proportion of ‘taller vegetation. The aircraft sensor could however only ‘view’ the surface biomass and therefore airborne NDVI value appeared lower than the ground-collected taller biomass. Site B was a grazed green site, with some ‘damp’ patches. As a consequence site B had a low biomass recording due to grazing yet a high NDVI value due to the new green growth. Site B11 consisted of 43% dry, ‘brown’ biomass which confirms the results of Johnston (1994) who viewed NDVI as a poor predictor of dry biomass. Johnston showed that this was a significant problem in semi-arid
and arid regions. Gross et al. (1986) also found that vegetation index (VI) regression models were a poor predictor of total biomass in marsh ecosystems due to the dead biomass component. The results of the present study indicate that NDVI may also be less useful in predicting green biomass outside the growing season in some less arid regions since rainfall is a primary determinant for greenness. Therefore, it is not surprising that vegetative cover and biomass were highly variable during this experiment in March when rainfall was low. The driest sites were not able to maintain surface moisture and therefore their intensity of greenness and its correlation with the airborne sensors was low. As with all remote sensing or ground sampling, the data necessarily represent the time of sampling, providing a 'snapshot' view of spatial biomass data. The greenness relationship varies therefore with rainfall, antecedent surface moisture, radiation, and vegetation species and nutrient availability to the vegetation.

Figure 3.5 highlights the narrow swathe-width of CASI in terms of the whole catchment. CASI does, however, give an accurate and detailed surface description (as indicated by fencelines and treelines) which is important for management purposes. The surface biomass is very variable (as shown in Figure 3.9) and it is therefore difficult to represent the surface using coarse-resolution remotely sensed data. This high biomass variability leads to loss of information with decreasing resolution. Aircraft data show the finest resolution of all types of remotely sensed data and this is very useful in highly variable land cover conditions.

Although the quadratic regression analysis of biomass to NDVI can be theoretically rationalised by a saturated NIR band, the data does not support this, possibly due to very few ground points aligning with the airborne data. More ground data may show that the linear relationship is asymptotic to high biomass densities very green vegetation. The threshold for these grasses and CASI data may be reached at densities of greater than 1.0 kg m⁻²; however, more data would be needed to ascertain the critical biomass value.

Grazing is an external factor which can have a direct influence on the biomass and NDVI regardless of the climatic conditions. Some degree of biomass and greenness variability could also be due to both terrain and drainage variability. Previous studies in this region indicated that topography is not strongly correlated with soil moisture (Boulet et al. 1995).

3.3.5 Conclusions from biomass to airborne correlations

Calibration of remotely sensed and ground data is an important step towards model application. This study confirms that remotely sensed NDVI with 6 meter pixels does correlate with surface biomass in a 27 km² catchment, notwithstanding the limited number of
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ground data points. The optimum calibration between NDVI and biomass occurred in CASI channels 14 and 4. Given this calibration of NDVI to biomass, biomass may be extrapolated using equation 3.5 to estimate spatial coverage of biomass at the time of the overpass. However, caution must be taken due to few data points and due to the influence of site A12 and B. To extend the relationship to other times atmospheric corrections of the CASI data to give spectral reflectance would be required. Grazing appears to have a significant impact on both LAI and biomass. The elevated dry sites produced an increase in the estimates of biomass and a decrease in estimates of LAI, possibly due to a higher percentage of ‘taller’ biomass.

Simple linear, quadratic and exponential regressions with limited ground points may not fully explain the complex relationship between biomass and airborne NDVI; however, additional biomass data from larger data sets at different seasons, and wider coverage from remotely sensed data sources such as TMSAT, may clarify and confirm the nature of the relationship. Further research into the relationship between airborne and satellite vegetation data would provide an assessment of biomass and vegetation dynamics for the whole catchment.

3.4 Satellite Data and Vegetation Data

3.4.1 Aims
The aims of this study are:
• to relate satellite data with biomass and determine the nature and physical reasons for any correlations
• use satellite data to help determine the spatial and temporal variations in primary production (biomass) by incorporating ground sample biomass correlations with remote sensing data

3.4.2 Thematic Mapper Satellite (TMSAT)

In this study Landsat 4 and 5 data are used and its specifications are shown in figures 3.13 and 3.15. Landsat 5 incorporates both MSS Multispectral Scanner and TM Thermatic Mapper. The TM sensor has a number of spectral radiometric and geometric design improvements relative to the MSS sensor. TM has 7 bands which incorporate the mid-infrared and thermal portions of the spectrum. TM Bands 4 through to 7 are useful for vegetation analysis due to the narrow bands and reflective capacity (figure 3.13). The TM sensor also accounts for movement of the satellite and has an internal radiometric calibration system. TMSAT band 5 and 7 observations are shown in figures 3.23 – 3.28.
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Figure 3.12 Summary of Orbital Characteristics of TMSAT 4 and 5

<table>
<thead>
<tr>
<th>Information on Landsat 4 &amp; 5</th>
<th>Quantity, distance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Orbital distance from earth</td>
<td>705 km</td>
</tr>
<tr>
<td>Inclination angle</td>
<td>$98.2^\circ$ (8.2° from normal) with respect to the equator</td>
</tr>
<tr>
<td>Orbit times</td>
<td>99 mins</td>
</tr>
<tr>
<td>1 day orbits</td>
<td>approx. 14.5 orbits</td>
</tr>
<tr>
<td>Time intervals between orbits</td>
<td>16 days</td>
</tr>
<tr>
<td>Sensor swath</td>
<td>2752 km</td>
</tr>
<tr>
<td>MSS Multispectral scanner</td>
<td>79 m ground resolution</td>
</tr>
<tr>
<td>TM Thermatic Mapper</td>
<td>bands 3, 4, 5, 6 and 7 ground resolutions 30 m and 25 m</td>
</tr>
</tbody>
</table>

The satellite coverages used in this study are listed below. These are the closest cloud free days to the acquisition dates of the ground biomass. The coverages centre on $34^\circ 39'$ S and $149^\circ 55'$ E. The orbital pass is over path 90 row 84 with pixel size 25m.

TM coverage dates:

21 February 1993 time of overpass approximately 11 am EST
4 October 1993  time of overpass approximately 11 am EST
30 April 1994  time of overpass approximately 11 am EST

Curran (1984) correlated radiometric temperature against sensor look angle and found variations with the time of the day and in particular with remote sensing and LAI correlation’s. All satellite overpasses in this study are at approximately the same time of day.

Figure 3.13 Spectral bands and their wavelengths from Thermatic Mapper 4 and 5.

<table>
<thead>
<tr>
<th>Band</th>
<th>Spectrum</th>
<th>Wavelength $\lambda$ (µm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>3</td>
<td>visible red</td>
<td>0.63 - 0.69 µm</td>
</tr>
<tr>
<td>4</td>
<td>near infrared</td>
<td>0.76 - 0.90 µm</td>
</tr>
<tr>
<td>5</td>
<td>middle infrared</td>
<td>1.5 - 1.75 µm</td>
</tr>
<tr>
<td>7</td>
<td>long/middle infrared</td>
<td>2.08 - 2.35 µm</td>
</tr>
</tbody>
</table>
Vegetation can be assessed by remote sensing devices using a number of different wavebands. In this study NDVI was calculated from bands 3 and 4. Le Roux et al (1997) used a range of sensors to overcome problems associated with sparse grass canopies. These included amorphous silicon cells that included PAR 400-700nm and shortwave radiation 400-1000nm where near infrared was calculated as the difference between total shortwave radiation and PAR radiation. They also examined spectral reflectance where they subdivided red 610-680 nm and near infrared 790-890 nm.

Figure 3.14 The co-ordinate system used in this study

<table>
<thead>
<tr>
<th>Co-ordinate System Description</th>
<th>Units, projection system</th>
</tr>
</thead>
<tbody>
<tr>
<td>Projection</td>
<td>UTM</td>
</tr>
<tr>
<td>Zone</td>
<td>55</td>
</tr>
<tr>
<td>Units</td>
<td>Metres</td>
</tr>
<tr>
<td>Spheroid</td>
<td>Australian National</td>
</tr>
<tr>
<td>X shift</td>
<td>0.0</td>
</tr>
<tr>
<td>Y shift</td>
<td>10000000.0</td>
</tr>
</tbody>
</table>

Figure 3.15 Statistics for the Satellite data used in this study.

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Cell size</td>
<td>25</td>
<td>25</td>
<td>25</td>
</tr>
<tr>
<td>No of rows</td>
<td>720</td>
<td>719</td>
<td>719</td>
</tr>
<tr>
<td>No. of columns</td>
<td>720</td>
<td>719</td>
<td>719</td>
</tr>
<tr>
<td>X min</td>
<td>758311.5</td>
<td>758311.5</td>
<td>758311.5</td>
</tr>
<tr>
<td>X max</td>
<td>776311.5</td>
<td>776286.5</td>
<td>776286.5</td>
</tr>
<tr>
<td>Y min</td>
<td>6152858.5</td>
<td>6152883.5</td>
<td>6152883.5</td>
</tr>
<tr>
<td>Y max</td>
<td>6170858.5</td>
<td>6170858.5</td>
<td>6170858.5</td>
</tr>
<tr>
<td>Min value</td>
<td>12</td>
<td>13</td>
<td>8</td>
</tr>
<tr>
<td>Max value</td>
<td>158</td>
<td>101</td>
<td>86</td>
</tr>
<tr>
<td>Mean value</td>
<td>31.198</td>
<td>28.755</td>
<td>19.525</td>
</tr>
<tr>
<td>Standard Deviation</td>
<td>8.016</td>
<td>5.854</td>
<td>4.384</td>
</tr>
</tbody>
</table>

Results from correlating TMSAT NDVI wavebands 3 (red) and 4 (NIR) against biomass using linear, quadratic and exponential equations are shown in the figure 3.16.
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Figure 3.16 Correlation’s of biomass (kg ha\(^{-1}\)) to TMSAT for selected Wavebands for March 1993

<table>
<thead>
<tr>
<th>TMSAT channels &amp; NDVI</th>
<th>Linear regression</th>
<th>Quadratic regression</th>
<th>Exponential regression</th>
</tr>
</thead>
<tbody>
<tr>
<td>3 (Red)</td>
<td>(r^2 = 0.52)</td>
<td>(r^2 = 0.72)</td>
<td>(r^2 = 0.50)</td>
</tr>
<tr>
<td></td>
<td>sig F = 0.009</td>
<td>sig F = 0.003</td>
<td>sig F = 0.010</td>
</tr>
<tr>
<td>4 (NIR)</td>
<td>(r^2 = 0.26)</td>
<td>(r^2 = 0.36)</td>
<td>(r^2 = 0.20)</td>
</tr>
<tr>
<td></td>
<td>sig F = 0.09</td>
<td>sig F = 0.13</td>
<td>sig F = 0.14</td>
</tr>
<tr>
<td>NDVI</td>
<td>(r^2 = 0.02)</td>
<td>(r^2 = 0.08)</td>
<td>(r^2 = 0.06)</td>
</tr>
<tr>
<td></td>
<td>sig F = 0.64</td>
<td>sig F = 0.70</td>
<td>sig F = 0.44</td>
</tr>
</tbody>
</table>

The best correlation from figure 3.16 (figure 3.17) are where biomass resulted in a quadratic regression with the red waveband of TMSAT.

Figure 3.17 Correlation of biomass to TMSAT Band 3 (Red): March 1993.

It has been noted that most forage (vegetation palatable to animals) loses its high near-infrared reflectance (MSS6, MSS7) far more rapidly than it declines in quality and acceptability to grazing animals (Graetz et al 1988). Therefore, the red waveband may be indicating browning vegetation that still has a high biomass and is edible by grazing animals. Figure 3.17 shows high biomass with the increasing red waveband (ie, increases in biomass with more ‘yellow/brown’ vegetation). Gross et al (1986) found dead biomass substantially increases reflection in the red (TM band 3). CASI NDVI (figure 3.7a.) shows increasing biomass with increasing NDVI or greenness. Such different results were produced by differences in sensor-resolution and waveband widths. The coarser resolution satellite data the showed yellow/brown
vegetation correlated with high biomass at the A sites and a greener tone at the B sites with less biomass.

\[
\text{Biomass} = 45476 + (-2876.3 \text{ NDVI}) + (47.4 \text{ NDVI}^2) 
\]

Equation 3.6 (derived from the data in Figure 3.17) would not be used for the spatial determination of biomass unless the climatic conditions were similar to this study and the vegetation was beginning to senesce. This quadratic biomass relationship suggests dry conditions where NIR is decreasing with increases in temperature, and the red waveband reflection is increasing with the reduction in photosynthesis and chlorophyll production. The TMSAT data in figure 3.17 confirm that the driest sites were not able to maintain surface moisture and therefore their intensity of greenness and its correlation with airborne sensors was low. Site A (high elevation) displayed yellow/brown values and site B (lower elevation) was mostly green except for intensely grazed patches. As discussed previously hyperspectral high-resolution sensors are very useful at fine scale resolutions, while, the TMSAT data does supply greater spatial coverage to give total catchment coverage and has more coarse wavebands. TMSAT NDVI and elevation or slope-based radiation may show some relationship under these dry conditions.

3.4.3 Biomass and satellite correlations: September/October 1993, March 1994

Further correlations between biomass and satellite data were investigated during September/October 1993 and March 1994 (figures 3.21a,b and 3.22a, b). There were no relationships during the September/October period, as biomass levels were low and there was little greenness due to senescence. There also was not a relationship between biomass and satellite observations during the March 1994 period (figure 3.22a, b). Figures 3.23 to 3.28 show the middle and long/middle infrared observations for TMSAT bands 5 and 7. TMSAT band 5 for March 1993 and September 1993 show high moisture while March 1994 had lower moisture levels. These values are valid for the time of the overpass and in agreement with the moisture indices calculated in chapter 4.
Figure 3.21a Correlations of Biomass to Satellite Data: September/October 1993

**Biomass vs Satellite Data**

**Figure 3.21b: Statistical Summary of Biomass to Satellite Data Correlations**

<table>
<thead>
<tr>
<th>TMSAT NDVI Band 3</th>
<th>TMSAT Band 4</th>
<th>TMSAT Band 5</th>
<th>TMSAT Band 7</th>
</tr>
</thead>
<tbody>
<tr>
<td>( r^2 = 0.028 )</td>
<td>( r^2 = 0.042 )</td>
<td>( r^2 = 0.007 )</td>
<td>( r^2 = 0.074 )</td>
</tr>
<tr>
<td>( L = 0.009 )</td>
<td>( L = 0.095 )</td>
<td>( L = 0.009 )</td>
<td>( L = 0.211 )</td>
</tr>
<tr>
<td>( Q = 0.038 )</td>
<td>( Q = 0.097 )</td>
<td>( Q = 0.013 )</td>
<td>( Q = 0.233 )</td>
</tr>
<tr>
<td>( C = 0.025 )</td>
<td>( C = 0.043 )</td>
<td>( C = 0.008 )</td>
<td>( C = 0.259 )</td>
</tr>
<tr>
<td>( E = 0.025 )</td>
<td>( E = 0.043 )</td>
<td>( E = 0.008 )</td>
<td>( E = 0.200 )</td>
</tr>
</tbody>
</table>

L = Linear, Q = Quadratic, C = Cubic, E = Exponential
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Figure 3.22a  Correlation of Biomass to Satellite Data: March 1994

Biomass vs Satellite Data

Figure 3.22b  Statistical Summary of Biomass to Satellite Data Correlations

<table>
<thead>
<tr>
<th>TMSAT NDVI $r^2$</th>
<th>TMSAT Band 3 $r^2$</th>
<th>TMSAT Band 4 $r^2$</th>
<th>TMSAT Band 5 $r^2$</th>
<th>TMSAT Band 7 $r^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>L = 0.002</td>
<td>L = 0.022</td>
<td>L = 0.036</td>
<td>L = 0.001</td>
<td>L = 0.005</td>
</tr>
<tr>
<td>Q = 0.048</td>
<td>Q = 0.024</td>
<td>Q = 0.061</td>
<td>Q = 0.036</td>
<td>Q = 0.005</td>
</tr>
<tr>
<td>C = 0.107</td>
<td>C = 0.026</td>
<td>C = 0.061</td>
<td>C = 0.036</td>
<td>C = 0.005</td>
</tr>
<tr>
<td>E = 0.004</td>
<td>E = 0.049</td>
<td>E = 0.082</td>
<td>E = 0.011</td>
<td>E = 0.020</td>
</tr>
</tbody>
</table>

L = Linear, Q = Quadratic, C = Cubic, E = Exponential
Figure 3.23
Satellite Observations
TMSAT Band 5
Lockyersleigh: March 1993

Raw Reflectance Values:

- 0 - 15
- 15 - 20
- 20 - 25
- 25 - 30
- 30 - 35
- 35 - 40
- 40 - 45
- 45 - 50
- 50 - 65
- 65 - 108
Figure 3.24
Satellite Observations
TMSAT Band 5
Lockyersleigh Catchment
September/October 1993
Figure 3.25
Thematic Mapper Satellite
TMSAT Band 5
Lockyersleigh Catchment
March 1994
Figure 3.26
Satellite Observations
TMSAT band 7
Lockyersleigh: March 1993

Raw Reflectance Values.

- 0 - 15
- 15 - 20
- 20 - 25
- 25 - 30
- 30 - 35
- 35 - 40
- 40 - 45
- 45 - 50
- 50 - 65
- 65 - 108

1km
Figure 3.27
Satellite Observations
TMSAT band 7
Lockyersleigh:
September/October 1993

Raw Reflectance Values.

- 0 - 15
- 15 - 20
- 20 - 25
- 25 - 30
- 30 - 35
- 35 - 40
- 40 - 45
- 45 - 50
- 50 - 65
- 65 - 108

1 km
Figure 3.28
Satellite Observations
TMSAT band 7
Lockyersleigh: March 1994
3.4.4 Resolution

Resolution can be both spatial and temporal. Spatial resolution relates to the spatial accuracy of digital or image data produced by sensor or GIS package. Spatial resolution is often referred to as the 'grain'. Atkinson (1997) suggests there is a need for a guide to the range of spatial resolutions that may be appropriate for airborne remote sensing investigations. The spatial frequency of the ground depends on the photographic resolution. The fidelity of the film can vary depending on the density of the lines and rows. Lillesand and Kiefer (1994) define ground resolution distance (GRD) as the photographic scale divided by the dynamic resolution. For example,

\[
\text{GRD} = \frac{50000}{40} = 12450 \text{ mm}
\]

where:
photographic scale = 50 000

dynamic resolution = 40 lines/mm

Therefore the ground resolution is equal to 12.5 m.

To calculate the spatial resolution of an aircraft spectral image Curran (1985) uses equation 3.7

\[
D = H\beta
\]

(3.7)

where:
\(D\) = diameter of ground sampling element (metres)
\(H\) = flying height of aircraft above ground (metres)
\(\beta\) = instantaneous field of view (IFOV) radians

The CASI overpass at Lockyersleigh had an average flying height of 3000m with an IFOV (\(\beta\)) of approximately 2.0 milliradians, therefore according to this calculation the ground sampling was 6m. The \(D\) can be calculated using equation 3.8

\[
D = \text{ground resolution at nadir in the above equation, to calculate the swath width } W \text{ then}
\]

\[
W = 2H\tan\theta
\]

(3.8)

where
\(W\) = swath height
\(H'\) = flying height above terrain
\(\theta\) = one-half the total field of view of the scanner

Different sampling methods provide information about the surface, which can be used, for specialised purposes. At the hillslope scale, hydraulic conductivity may be important and can be most accurately assessed by means of ground samples. Catchments of less than 50 km² may require resolution finer than that of 1 km grids for accurate determination of biomass. CASI data, provides such a finer resolution, between that of satellite and ground data. Satellite data
with a coarser resolution, may provide optimal coverage at a regional scale where ecosystem diversity may be important. Lillesand and Kiefer (1994) state that Thematic Mapper satellites have been extensively used to prepare image maps over a range of mapping scales, while Atkinson (1997) states that for satellite-borne sensors the spatial resolution of the images are fixed. The investigator is limited to different sensors and pre-determined resolutions with satellite data. However, for airborne sensors the spatial resolution is determined by the combination of the instantaneous field of view of sensor and the altitude of the aircraft (which is variable). Therefore, the spatial resolution can be varied by varying the altitude of the aircraft (Atkinson 1997). This is considered a major advantage of the airborne remote sensing (Barnsely and Curran 1990).

Spectral resolution refers to bandwidths. Spectral data has many forms such as NDVI, TVI (Transformed vegetation index), SAVI (Soil Adjusted Vegetation Index). Spectral resolution types can be used in varied ways Lillesand and Kiefer (1994) uses TVI for calibration purposes. Lilliesand and Kiefer (1994) refer to DN numbers to calibrate ground samples of biomass with satellite data (equation 3.9). The TVI needs to be calibrated for each vegetation type.

\[ TVI = \left[ \frac{(D_{N4} - D_{N3}) - (D_{N4} - D_{N3}) + 0.5}{0.5} \right] \times 100 \]  

where:

DN = original digital number of pixel input image

DN3 = bands in TM3

DN4 = bands in TM4

### 3.4.5 Atmospheric corrections to satellite data

There can be substantial atmospheric effects on satellite reflectance (Chavez 1996). Some researchers believe satellite data require an accurate slope-aspect correlations with an atmospheric model for elevation (Woodham and Lee 1985), and a reflectance model for slope effects on radiance (Teillet 1986, Sjoberg and Horn 1983). Tanre et al (1979) identified three main mechanisms by which the atmosphere perturbs ground reflectance from space as (1) aerosol and molecular backscattering (2) at nonuniform sites the reflectance is affected by the contribution of the target background and (3) bidirectional properties (figure 3.2).

To account for sensor and atmospheric changes many different methods can be used depending on the availability of supporting input data required for correction analysis. Within this study clear sky days have been used and therefore aerosol and backscattering has been kept to a
minimum. Bidirectional properties have also been reduced by the remotely sensed data collection times occurring close to noon and therefore, the high zenith angles minimise view angle differences. Target backgrounds variation has been standardised by rescaling the reflectance values for the full image by using a selection of invariant pixels. The two major modifications to TMSAT data are (as mentioned) caused by atmospheric effects and sensor calibration. These atmospheric corrections are known to be additive while the sensor calibrations are multiplicative. Atmospheric additive corrections are usually positive and caused by lots of aerosols creating scattering. This scattering of light increases the brightness of the pixel.

Red wavebands are most suitable for reflecting chlorophyll and land cover, however, these red wavebands are also most affected by atmospheric scattering (due to their positions in the spectrum). Therefore they can be greatly modified by aerosols in the atmosphere. Q-Q plots were used on the red waveband scenes as a tool to determine whether these scenes needed to be normalised. From the Q-Q plots the trend varies from one side of the normal distribution to the other suggesting corrections to these data sets are necessary, although the curve show a linear fit. Using this method there is an assumption that there is a linear relationship between brightness and reflectance. Other assumptions, (reference to potential errors section 3.2.3 this chapter) are:

1. that the geometry of the earth is a sphere (radius approximately 6370 km)
2. that the satellite does has an absolutely circular orbit
3. that there is a stable relationship between the altitude and the satellite orbit
4. that the earth is non-rotating (Kontoes and Stakenborg 1990)

Determining solar elevations is crucial, as it is highly variable at different times of the year. However, (D. Graetz per. comm.) suggested that the differences in solar elevation between March and September/October were not large and are less than about 10%. Canopy shading affects the overall brightness. Woody vegetation can change the reflectance with differences in sun angles of just 10 degrees different. Low sun, dark vegetation is reflected poorly and this is not a linear process with the changes in the sun angle. Lockyersleigh consists mostly of pasture and grasses and therefore this error is greatly reduced.

Often the reference scene chosen to registrate TMSAT data has the least aerosols in the atmosphere for example, after a rain period. The method used for atmospheric corrections is shown below. It has been chosen as more accurate than the DOS (dark object subtraction)
method as it addresses both the atmospheric additive (brightness) effects as well as the multiplicative sensor calibration effects which can incorporate darkness effects.

**Methodology for Atmospheric Corrections to TMSAT Data**

1. Select a reference image and specify the waveband and orbital date.
2. Identify 5% of the darkest objects (invariant pixels) in the reference image (Figure 3.36).
3. Identify 5% of the lightest objects (invariant pixels) in the reference image (Figure 3.36).
4. Normalise other wavebands and orbital dates using correlations.
5. Repeat this for each waveband with the reference image that needs correction.
6. Normalise the data according to the curve fits of the reference scene.

In this study, TMSAT October 1993 Band 3 was selected as the reference scene. The 10 invariant pixels are shown in Figure 3.36. The individual correlations between October 1993 TMSAT satellite data with corresponding wavebands at different time periods are shown in the following graphs (figures 3.29 – 3.35).

**Figure 3.29 Atmospheric Corrections to TMSAT Band 3 March 1993**
Figure 3.30  Atmospheric Corrections to TMSAT Band 3 March 1994

Figure 3.31  Atmospheric Corrections to TMSAT Band 4 March 1994

Figure 3.32  Atmospheric Corrections to TMSAT Band 5 March 1993
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Figure 3.33 Atmospheric Corrections to TMSAT Band 5 March 1994
Figure 3.34 Atmospheric Corrections to TMSAT Band 7 March 1993

Atmospheric Corrections to Satellite Data
TMSAT Band 7: Oct '93 vs March '93

\[ \text{Rsq} = 0.8226 \]

TMSAT Band 7 March 1993

Figure 3.35 Atmospheric Corrections to TMSAT Band 7 March 1994

Atmospheric Corrections to Satellite Data
TMSAT Band 7: Oct '93 vs March '94

\[ \text{Rsq} = 0.8090 \]

TMSAT Band 7 March 1994
Figure 3.36
Atmospheric Correction Sites
Thematic Mapper Satellite
TMSAT Band 3, October 1993
10 Invariant Pixels = ×
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3.4.6 Remote sensing and modelling

Accurate spatial vegetation data are essential for hydrological modelling since vegetation processes are directly related to biomass and affect the distribution and redistribution of surface water. Generally biomass has two impacts on the hydrologic system: in terms of evapotranspiration and percolation. Given vegetation dynamics are an important determinant of the water balance, spatial and temporal vegetation data are often required for the initialisation of many hydrological models. Biomass, percent coverage, and Leaf Area Index (LAI) are all important descriptors of the vegetation cover. Hydrologic models such as TOPOG (OLoughlin et al. 1986, ACCH 1990) make use of vegetation indices to calculate soil moisture patterns. Even simpler lumped-parameter water-balance models such as SWRRB (Williams et al. 1985) require LAI data for the partitioning of water and the estimation of biomass. Weltz et al. (1994) also suggest that it is important to understand the temporal distribution of vegetation in terms of biomass and LAI before significant improvements can be made in modelling hydrological outputs (such as surface runoff, erosion and evapotranspiration) and plant growth.

The normalisation of the satellite data to standard atmospheric corrections using invariant target data improved the data quality and allowed spatial comparison between scenes. These data allow further model development when each scene could be normalised to a reference scene (chapter 7). The correlation of satellite data to terrain attributes is the subject of chapter 5 and 6.

3.5 Summary

One of the major advantages of remotely sensed data is its availability for areas where ground data cannot be collected. Remotely sensed data provides unique data to complete or enhance ground data, confirm or correct existing data, and to aid spatial interpolation and map production for management purposes. The remotely sensed data however, need to be calibrated and atmospherically corrected to provide an accurate spatial data set.

In this study, values of the airborne Normalised Difference Vegetation Index (NDVI), obtained with Compact Airborne Spectrographic Imager (CASI), and a red waveband of Landsat Thematic Mapper (TMSAT) were calibrated with ground biomass samples in a largely cleared grazed catchment. Linear, quadratic and exponential regressions were applied to six waveband combinations of CASI NDVI and two selected TMSAT wavebands. The best relationships were an exponential correlation of $r^2 = 0.62$ for the airborne data and $r^2 = 0.72$ quadratic curve for the
Chapter 3. Remotely Sensed and Vegetation Data
Spatio-temporal Modelling of Biomass

TMSAT red data. There was no correlation between ground biomass and TMSAT NDVI. Calibration was affected by vegetation type and height, grazing, possible saturation of the near infrared (NIR) bands and the narrow swathe-width of aircraft data. The TMSAT calibration produced different results due to the broader wavebands and the courser spatial resolution. Ground validation between Leaf Area Index (LAI) and biomass gave an \( r^2 = 0.80 \) but no significant correlation was found between LAI and airborne or satellite NDVI. A significant fractions of non-green biomass at some sites, due to dry conditions, was seen as a contributing factor.

The linear relationship between biomass and LAI and the exponential relationship between red reflectance and biomass during March 1993 could help to determine the spatial and temporal variations in primary production (biomass) using ground sampling and remote sensing data (chapter 7). However, this trend did not have statistical significance at other time periods. Figures 3.23 to 3.28 show TMSAT bands 5 and 7 over the three scenes. Although there was not a statistical correlation between biomass and the satellite data, structural features can be seen such as the railway track, trees and some paddock boundaries. Using the wavebands of the middle and long/middle infrared the seasonal differences are not obvious without further calibration. TMSAT bands 5 and 7 are moisture sensitive (figure 3.1) and therefore they record the surface moisture and reflectance at the time of satellite overpass and not necessarily plant growth over the previous six months (figures 3.23 – 3.28).

As discussed in chapter 1 land management affects many processes within a catchment. Spatial biomass information is very important for understanding the grazing condition of the land, highlighting area/s of degradation, or when supplementing stock feed is required and assisting in setting realistic stocking densities. This is where satellite data could help by supplying spatial data on the condition of the land surface with an aim to reduce the tendency to overstock; allow time for pasture/grass growth and seed regeneration. Time series NDVI data derived from AVHRR sensors have been used to monitor vegetation condition in the rangelands of Western Australia (Cridland et al. 1995). They classified four broad grazing condition classes. Other anthropogenic factors effect runoff generation, which change the soil hydraulic properties particularly at the surface (Coles et al 1997, McFarlane et al., 1992). Compaction of the soil surface by livestock reduces the effective hydraulic conductivity and storage capacity of the soil (Coles et al., 1997) causing less water available for pasture and grasses and reducing biomass. All these influences on biomass distribution could be aided by spatio-temporal modelling of biomass to determine the best future management strategies.
Chapter 4.

Modelling Plant Growth
CHAPTER 4. MODELLING PLANT GROWTH

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Spatio-temporal Modelling of Biomass

4.1 Introduction

4.1.1 Introduction to this chapter

This chapter introduces a plant growth model (GROWEST), which uses weekly or monthly climate data to produce outputs that include a simple water balance and a growth index which, represents biomass growth. The model contains a simple hydrological model and it allows the temporal extension of biomass data via growth indices. Growth indices data can be examined both retrospectively and into the future provided appropriated climate data are available. The GROWEST models inputs and outputs will be reviewed and integrals of growth indices over different time periods will be evaluated. This chapter also includes an examination of the spatial variability of radiation effects on biomass and the development of a sub-catchment model for biomass distribution. The results from this chapter support the development in chapter 7 of a spatio-temporal biomass model using GROWEST outputs.

4.1.2 Plant growth modelling

Climate and terrain are major determinants of plant growth and biomass production. Australia has been largely cleared and therefore this altered environment needs management to prevent further land degradation, to maintain productivity levels and for biodiversity. Assessment and monitoring of the land surface is essential for ongoing management strategies. Crop weather and crop growth models have been studied since at least the 1950’s. The principles underpinning crop growth models are to quantity physical, chemical and physiological processes of plant/crop growth (Baier 1977). Basic plant processes include photosynthesis, respiration, translocation and transpiration, all of which are influenced by climatic variables such as solar energy, temperature and water. The shape of the land surface can also directly affect the way in which plant processes interact with climate.

The important requirements for the type of hydrological model best suited to this project are simplicity, uniformity, data availability and an ability to model biomass outputs. There are many different types of hydrologic models such as physically based, conceptual, 1D, 2D, 3D, and theoretical. Most models use mathematical equations to calculate outputs, which can be used directly, tested against other data sets and/or interpolated for different scales. Models for plant growth have been used for almost three decades. Examples of plant growth models include: Fitzpatrick and Nix (1968) and Nix and Fitzpatrick (1968) for wheat, grain and sorhum growth; Paltridge (1970) for pasture growth; Rose et al. (1972) for seasonal growth patterns in pasture; Stewart (1970) for simulated net photosynthesis of corn, Nix and Fitzpatrick (1970),
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Donnelly et al (1987), Arnold et al (1990); McKeon et al. (1990) for simulating hydrologic and related processes including biomass. Two distinctive types of hydrologic models that are important for this study are distributed hydrologic models and ‘lumped’ or catchment averaged hydrologic models. From previous work in this catchment (Guerra 1995) it seems that a catchment averaged water balance model is the most suitable.

GRAZPLAN developed by CSIRO’s Division of Plant Industry (Canberra, Australia) contains a series of computer programs that examine optimum grazing regimes in temperate Australia. Within GRAZPLAN a GrassGro sub-program exists which predicts the level and quality of feed expected in a paddock at any given time according to the type of pasture, soil characteristics and historical records of temperature and rainfall. The GRASP (GRASs Production) can model 4 layer soil moisture levels and is sensitive to atmospheric moisture and nitrogen availability (McKeon et al. 1990). It is point based but can incorporate a spatial domain by interpolating weather inputs and linking to static water models in a GIS system.

The GROWEST (GROWth ESTimation) has been selected for this study and can be run on monthly mean climate using an umbrella program ANUCLIM (Hutchinson et al 1997). ANUCLIM can produce command files which contain can be incorporated (as input) into the ESOCLIM (Estimation of CLIMate) model to produce monthly mean climate estimates at specific locations. These climate estimates are calculated from thin plate smoothing surfaces fitted to point data by the ANUSPLIN package (Hutchinson 1997). GROWEST was first developed by Fitzpatrick and Nix (1970) with further developments by Nix (1981). Hutchinson et al (1992) have used it to produce a global agroclimatic classification. GROWEST determines growth as a function of light, moisture and temperature. To predict cover GROWEST integrates the growth response over the growing period at time intervals suitable for the particular application (figure 4.6).

This study uses monthly mean maximum and minimum temperature (°C), solar radiation (MJ m⁻²), evaporation (mm day⁻¹) and actual monthly totals of rainfall (mm). The experimental site consists of a grass/pasture cover from which biomass growth was determined at a catchment average scale over 13 weeks periods using GROWEST. The grass/pasture coverage has not been divided into different species as previous studies have shown that without large data inputs concerning specific management strategies it is not possible to account for this variation. Other research by Williamson and Eldridge (1993) concluded that three different types of pasture were not significantly different when using a regression model between reflectance and pasture variables to estimate biomass.
4.1.3 Objectives

The objectives being explored in this chapter are to:
1. Examine catchment averaged biomass variability over two seasons
2. Explore relationships between biomass and radiation
3. Use a plant growth model to determine weekly growth indices
4. Development a sub-catchment biomass model and determine a suitable period for integrating weekly growth indices

4.2.1 Average biomass variability at two seasons

Biomass variability was examined in March and September to indicate growth over summer and winter.

Figure 4.1 Biomass variability over the 3 time periods.

Boxplots are useful to show the variability of distributions of different cohorts. These boxplots show the spatial variability of measured biomass across the sample sites at three time periods. The lower section of the box is the 25\textsuperscript{th} percentile of biomass and the upper boundary is the 75\textsuperscript{th} percentile. The horizontal line is the median. The lines at either end of the box are the largest and smallest biomass values. The length of the boxplot shows the spatial variability of the biomass as determined by the interquartile range (i.e., difference between the 25\textsuperscript{th} and 75\textsuperscript{th} percentiles). March 1993 has the largest spatial variability of biomass. The medians for March
and September 1993 show the biomass distributions are skewed, as they are not in the centre of each box. The March 1993 median shows that the biomass distribution is negatively skewed as the median is closer to the bottom of the box whereas September 1993 shows the opposite trend where the biomass distribution is positively skewed. September 1993 had the least spatial variation in biomass because the growth was generally less. Environmental variables such as rainfall and temperature in September were also lower. This seasonal difference between March and September shows that the biomass is reflecting the temporal variation in the physical environment.

4.2.2 Average biomass verses rainfall

A preliminary examination of biomass verses rainfall was reviewed to determine whether such a simplistic approach would be possible at seasonal or annual timescales.

Figure 4.2  Biomass Vs modelled Growth Index at site A1 over 3 time periods

This graph examines biomass at an individual site (A1) and its relationship to rainfall as distinct from other climatic and terrain variables and their influence on biomass. Rainfall is often considered the most dominant climatic factor in determining biomass. It is also known that moisture; temperature and light also have an influence on biomass quantity. It is the balance between the climatic variables, which is critical to biomass distribution. Figure 3.2 shows that the biomass at site A1 was high and that March 1993 and 1994 had similar biomass.
levels. March 1994 was slightly higher than 1993 and this indicates that other factors contribute to growth and these could include terrain effects (see chapter 5).

Figure 4.3 Averaged biomass verses averaged rainfall.

Figure 4.3 shows the relationship between averaged biomass and rainfall. Biomass and rainfall for March 1993 are higher than for September where biomass and rainfall are lower. The higher temperatures in March 1993 allow vegetative growth to better utilise the rainfall available in March 1993. The higher rainfall in the six months preceding March 1993 produced higher biomass than March 1994. In particular the low rainfall in January 1994 contributed to lower accumulated biomass by March 1994. Site A1 has biomass similar to the averaged biomass except for September 1993 where the biomass is lower than the catchment average. There is however, a limitation to the direct use of instantaneous rainfall. It is evident that catchment averaged biomass variability cannot be fully explained by rainfall alone, however, a distinct seasonality in plant growth can be seen. As discussed in this chapter plant growth is a function of multiple climatic variables (equation 4.7), and therefore rainfall alone has limited impact on biomass distribution.

4.3 Biomass and solar radiation

4.3.1 Introduction
Solar radiation was also examined as an independent climatic variable to determine its impact on biomass. Although solar radiation is not a limiting environmental factor in Australia, it has been incorporated to determine its role in plant growth. Simple crop growth modelling commonly only include rainfall and temperature and it is assumed that solar radiation is closely linked with temperature (Henderson-Sellers and Robinson 1986).

The dominant mechanism for surface heating is through surface absorption of solar radiation and re-radiation from that surface. At the microscale the role of geometry in radiation exchange is evident between horizontal and the ridged surface of agricultural furrows. The subtle impacts of topography on radiation are important especially in low relief catchments as they can be ignored or treated as insignificant. Figure 4.4 demonstrates the radiative effect on a sloping surface.

Figure 4.4 (a) Diagrammatic representation of the angle $\Theta$ between the surface and the incident direct-beam short-wave radiation, $S$. (b) The form of the cosine law of illumination (Oke 1987).

It is known the effects of surface shape on that direct short-wave radiation can be calculated using the cosine law of illumination. Since direct shortwave radiation is a direct beam it is approximated as a parallel beam and therefore irradiance of a surface depends on its orientation to that beam by the following equation

$$S = S_i \cos \Theta$$

Equation 4.1

where:

$S =$ flux density of the beam at the surface
\[ S_i = \text{flux density normal to the beam} \]
\[ \Theta = \text{angle between the beam and normal to the surface} \]

4.3.2 Modelling solar radiation

Solar radiation can be modelled in a number of different ways. GROWEST uses radiation surfaces described by Hutchinson et al 1984, which incorporate both measured radiation and Anstrom (1924) estimates. The late Professor Ian Moore (Moore et al 1993) first developed the solar radiation model (SRAD) used in this study (figure 4.5). Wilson and Gallant (1997) have developed it since. The model includes two programs: CLOUDY (Fleming 1987) and the fast horizon algorithm of Dozier et al (1981). The SRAD model calculates radiation at each cell of the DEM grid. The incoming short-wave radiation accounts for direct, diffuse and reflected components, and it computes a range of radiative outputs including radiation on a sloping surface and a short-wave radiation ratio (figure 4.6).

The SRAD solar radiation model calculates total short-wave radiation on the sloping surface to total short-wave radiation on a horizontal surface corrected for cloud effects and including topographic shading. The horizontal surface calculation is optimised and computed forward and backward on horizon angles (at 16 steps) along a profile (Dozier et al., 1981). The sky view \( v \) is the proportion of the sky hemisphere visible from a point on the surface and computed from horizon angles, where the ground view is \( 1 - v \) (Gallant 1997). Slope and aspect at each point on the surface were calculated from the DEM and were used to determine the direction of the normal to the surface (Gallant and Wilson, 1996). Similar to the cosine equation and diagram \( w \) (above) the angle of incidence of the direct radiation component is the angle between the surface normal and the direction of the sun (Iqbal, 1983).

4.3.3 Slope-based verses short-wave radiation

SRAD outputs were evaluated to determine their relationship with biomass. Two radiation outputs were selected (from 14 possible outputs) for further examination: short-wave radiation ratio and short-wave radiation on a sloping surface. The short-wave radiation ratio is the ratio of total short-wave radiation on the sloping surface to the total short-wave radiation on a horizontal surface, corrected for cloud effects. The short-wave radiation on a sloping surface (slope-based radiation) to the total short-wave radiation on a horizontal surface corrected for cloud effects but not including topographic shading.
Figure 4.5  Spatially Disaggregated Solar Radiation Modelling

DEM:
25 m scale
Chapter 2.

SRAD:
Input data
Climatic
Atmospheric
Astronomic
Chapter 4

Scale match

SRAD:
Solar radiation
modelling.
Chapter 4.

GIS development
ARCINFO for gridded surfaces
Chapter 4.

Examine all surfaces.
Select suitable surface

Correlations between biomass and selected radiation surfaces.
Output equations

Map production

Further modelling.
Chapter 7.
Figure 4.6    An example of a map of spatially distributed slope-based radiation using SRAD. March 1993 Lockyersleigh Catchment
Figures 4.7a and 4.7b have very similar correlations. This reflects the small gradient variability within this catchment. It also confirms that biomass increases with increasing exposure to radiation.

Figure 4.7 (b) Biomass verses short-wave radiation
Chapter 4. Modelling Plant Growth
Spatio-temporal Modelling of Biomass

The linear relationship (figure 4.7a, b) did not adequately describe the real fit between biomass and radiation on a sloping surface therefore, quadratic function has been applied (figure 4.8). Solar radiation is a key variable in determining biomass production (Monteith 1972). However, a fundamental problem with radiation data is that it cannot account for biomass which accumulates over months. Therefore, monthly radiation values have been calculated. Monthly timesteps for radiation data may still need reviewing. A study in Japan relating phytomass (above ground biomass) to solar radiation discovered a negative relation between plant and solar radiation indicating that some environmental stress suppressed growth irrespective of the levels of solar radiation (Ikeda et al 1999). Ikeda et al noted that in their study the sum of solar radiation was not calculated over the growth period but only for the dates between the landsat observation and the hay harvest of 4-51 days and therefore this result did not directly imply that solar radiation suppressed plant growth.

**Figure 4.8** Biomass vs Radiation: March 1993

Biomass vs Slope-based Radiation

March 1993

![Biomass vs Slope-based Radiation](image)

The quadratic fit describes the increase in slope-based radiation with increasing biomass well. However, the lower levels of radiation (slope-based) at sites J3 and J9 appear to show an increase in biomass with decreasing radiation and this does not make physical sense in this environment. The true relationship is probably an exponential fit.
Chapter 4. Modelling Plant Growth
Spatio-temporal Modelling of Biomass

Biomass vs Slope-based Radiation
September 1993

![Graph showing Biomass vs Slope-based Radiation for September 1993](image)

Figure 4.9  Biomass vs Radiation: September 1993

Biomass vs Slope-based Radiation
March 1994

![Graph showing Biomass vs Slope-based Radiation for March 1994](image)

Figure 4.10 (above)  Biomass vs Radiation: March 1994
4.3.4 Discussion of Radiation Modelling

In September most sites have high moisture levels and low radiation as compared with March levels. The lack of a correlation is a combined climatic effect, where low solar radiation produces low evaporation and prevents effective utilisation of soil moisture by plants. March 1994 has a similar trend to March 1993 however, a lower correlation coefficient. Site A12 had lower biomass than in March 1993 and site A2 has higher than in March 1993. The other sites respond in a similar fashion. Biomass appears to be sensitive to radiation changes during the March periods when the biomass is growing. It is not surprising that radiation alone had limited correlation to biomass in such a low relief catchment, just as there was not a statistical correlation between biomass and elevation (chapter 2). Therefore, temperature disaggregation is pursued later in this chapter.

Biomass needs to be examined over its growth period and GROWEST allows the growth to be modelled via growth indices over a range weekly intervals. These functions represent the biomass growth according to their dynamic, non-linear responses to solar radiation, temperature and available soil moisture into three dimensionless indices on a linear scale from zero to unity (Hutchinson et al 1992). Solar radiation is not generally a limiting variable for plant growth in Australia, other than in the humid tropics and high latitudes. Hutchinson (1987) states that errors in estimates of solar radiation are likely to be less restrictive for estimating plant growth. He gives an example of research where Richardson (1985) where monthly mean solar radiation values used in CERES-wheat crop model (Ritchie and Otter 1985) produced results almost identical to those obtained by stochastically varying values. Conversely, temperature (daily minimum and maximum) can be significant. Richardson (1985) also demonstrated that wheat crop yields obtained from monthly mean daily minimum and maximum in the CERES-wheat model did affect predicted yields. However, temperature data at Lockyersleigh were collected only at one site in the catchment. Therefore, given the lack of spatial and temporal temperature data (no data after April 1993) and the potential significance of such data, temperatures were determined from interpolated monthly mean surfaces (Hutchinson 1999) at three locations within the catchment. These inputs were used to examine GROWEST outputs at he sub-catchment scale. The outputs of this methodology are presented as sub-catchment A, B, and I, (section 4.6).

Solar radiation and temperature are important environmental variables as they are determinants of the surface energy budget. Evapotranspiration is calculated from these energy balances. Evapotranspiration in catchments such as Lockyersleigh account for a major part of the total water budget. It has been suggested that the vertical processes contribute more to the water balance than the horizontal process in the Lockyersleigh catchment (Guerra 1995). However, seasonal differences are critical to evapotranspiration rates and therefore for biomass growth, which accumulates over months, could also be sensitive to terrain variation.
Chapter 4. Modelling Plant Growth
Spatio-temporal Modelling of Biomass

4.3.5 Conclusion

Radiation as a sole determinant of biomass is limited with the linear fit $r^2 = 0.4$ (figure 4.7a). However, given the general trend shown in March 1993 and in combination with other climatic variables it will be investigated further. The slope-based radiation is the preferred radiative parameter, given that one of the key objectives in this study (chapter 1) is the investigation of terrain effects on biomass. Since the relationships between the short-wave radiation on a sloping surface and the short-wave ratio radiation were similar, the total short-wave radiation on a sloping surface was selected for further investigation throughout this study (chapter 7).

4.4 The GROWEST model

The limited extent of climate data in Australia and the frequent requirement of daily data for most hydrologic models compounds data problems when only spatially sparse and temporally variable data are available for modelling purposes. Therefore for the purpose of this study a simple robust model with monthly input climate variables would be suitable. The GROWEST model was selected and monthly climatic input data was utilised and interpolated to weekly values. Unlike the dynamic nature of rainfall and runoff, which vary within a day and are spatially erratic in their intensity and quantity, biomass changes occur over a longer time period (weeks to months) and therefore monthly climate data were optimal for this study. Monthly timesteps are also appropriate for this study as this ‘matches’ the frequency of data collection for the satellite and biomass data. GROWEST inputs include rainfall, temperature and evaporation (figure 4.11). The four principle weekly outputs produced by GROWEST are the Light Index, Thermal Index, Moisture Index and the Growth Index.

Assumptions within the model are:

- when water is non-limiting, evapotranspiration ($E_t$) is equal to potential evaporation ($E_o$)
- the default drying curve used in estimating actual evapotranspiration ($E_a$) divided by potential evapotranspiration ($E_t$) is represented by a medium-textured clay loam soil where available water storage in the root zone is 150 mm.
- the thermal response curves distinguish between temperate and tropical vegetation groups. The median positions in the series of overlapping curves are derived for individual species characteristic of each group.
Chapter 4. Modelling Plant Growth
Spatio-temporal Modelling of Biomass

Figure 4.11 Temporal Growth Indices for Model Development

Input data:
- max, min temp., radiation, evaporation

Monthly mean climate surface

ESOCLIM from ANUCLIM data
Chapter 4.

Monthly Rainfall
Chapter 4.

GROWEST:
Integrated weekly growth indices, over time. Chapter 4.

GI
TI
MI
LI
LI x TI

Regressions of biomass to GI:
Output equations

Catchment model.

Development of Sub-catchment models

4.4.1 Rainfall data

One of the most critical input parameters for biomass is rainfall. The model (equation 4.2) for determining monthly rainfall for the missing months is a linear model where six years of Lockyersleigh rainfall is regressed against nearby rainfall stations. The mean root sum of squares (MRSS) (Equation 4.2), was used to examine the significance of the correlation's of the nearby rainfall stations. All meteorological stations within a 0.2 degree radius of the approximate center of Lockyersleigh were selected (Figure 4.12). Data availability and quality was accessed (Figure 4.13). The rainfall station most similar to Lockyersleigh was selected by choosing the lowest MRSS calculated by fitting the Lockyersleigh rainfall data against individual rainfall stations (Figure 4.14). The most representative monthly mean rainfall at Lockyersleigh has been applied (Figure 4.10).

Figure 4.12 Summary of meteorological stations examined.

<table>
<thead>
<tr>
<th>Station Number</th>
<th>Longitude</th>
<th>Latitude</th>
<th>Elevation</th>
<th>Name</th>
</tr>
</thead>
<tbody>
<tr>
<td>070020</td>
<td>149.883</td>
<td>-34.557</td>
<td>860.0</td>
<td>Chatsbury (Maryland)</td>
</tr>
<tr>
<td>070063</td>
<td>150.000</td>
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<td>645.0</td>
<td>Marulan Post Office</td>
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<td>070119</td>
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<td>-34.569</td>
<td>648.0</td>
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</tr>
<tr>
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<td>149.950</td>
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<td>610.0</td>
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</tr>
<tr>
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<td>740.0</td>
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</tr>
<tr>
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<td>650.0</td>
<td>Goulburn composite (Progress St)</td>
</tr>
<tr>
<td>070269</td>
<td>149.988</td>
<td>-34.667</td>
<td>630.0</td>
<td>Marulan (Johniefields)</td>
</tr>
</tbody>
</table>

Figure 4.13 Data assessment on rainfall stations

<table>
<thead>
<tr>
<th>Station Number</th>
<th>Total no. of monthly data points for station</th>
<th>Total no. of data points for Lockyersleigh</th>
<th>Comments</th>
</tr>
</thead>
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<tr>
<td>70020</td>
<td>114</td>
<td>84</td>
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</tr>
<tr>
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<td>120</td>
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<td>77</td>
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<tr>
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<td>84</td>
<td>missing data</td>
</tr>
</tbody>
</table>
**Chapter 4. Modelling Plant Growth**  
*Spatio-temporal Modelling of Biomass*

---

**Linear Model for Lockyersleigh Rainfall Regression**

\[ Y_i = a + bx_i + E_i \]  \hspace{1cm} (4.2)

where  
\[ Y_i = \text{Lockyersleigh monthly rainfall for time } i \]
\[ X_i = \text{Rainfall station for time } i \]
\[ \text{var}(E_i) = \sigma^2 \]

and  
\[ \sigma^2 = \frac{\text{RSS}}{df} \]
\[ = MRSS \]

\[ \text{RSS} = \text{residual sum of squares} \]
\[ df = \text{degree of freedom} = n - 2 \]

\( MRSS \) was then summed to obtain a mean monthly annual output using

\[ n \sum_{i=1}^{n} \sigma^2 / n \quad (i = 1, \ldots, n) \]

\( n = 12 \) (i.e. 12 months of the year)

and producing an output shown below

---

**Figure 4.14 Statistical analysis on rainfall stations**

<table>
<thead>
<tr>
<th>Station number</th>
<th>MRSS between Lockyersleigh &amp; other rainfall stations</th>
</tr>
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<tr>
<td>70147</td>
<td>381.0619</td>
</tr>
</tbody>
</table>

** *** = lowest MRSS**

It is known that the MRSS can be converted to the standard error by determining its square root. MRSS values have thus been used to calculate standard errors for the selected station.
Figure 4.15 Statistical Summary for Station 70143 (Brayton) selected to represent Lockyersleigh monthly rainfall.

<table>
<thead>
<tr>
<th>Month</th>
<th>Correlation coefficient</th>
<th>Standard Error</th>
<th>Number of data points</th>
</tr>
</thead>
<tbody>
<tr>
<td>January</td>
<td>0.46649</td>
<td>14.66190</td>
<td>9</td>
</tr>
<tr>
<td>February</td>
<td>0.89931</td>
<td>17.31230</td>
<td>10</td>
</tr>
<tr>
<td>March</td>
<td>0.96132</td>
<td>13.96359</td>
<td>10</td>
</tr>
<tr>
<td>April</td>
<td>0.91720</td>
<td>24.53371</td>
<td>10</td>
</tr>
<tr>
<td>May</td>
<td>0.96731</td>
<td>8.15440</td>
<td>10</td>
</tr>
<tr>
<td>June</td>
<td>0.99586</td>
<td>3.60448</td>
<td>9</td>
</tr>
<tr>
<td>July</td>
<td>0.62994</td>
<td>18.9934</td>
<td>10</td>
</tr>
<tr>
<td>August</td>
<td>0.95212</td>
<td>15.04019</td>
<td>10</td>
</tr>
<tr>
<td>September</td>
<td>0.93462</td>
<td>6.93442</td>
<td>10</td>
</tr>
<tr>
<td>October</td>
<td>0.90311</td>
<td>10.71992</td>
<td>10</td>
</tr>
<tr>
<td>November</td>
<td>0.77922</td>
<td>16.84845</td>
<td>10</td>
</tr>
<tr>
<td>December</td>
<td>0.94948</td>
<td>7.65395</td>
<td>10</td>
</tr>
</tbody>
</table>

Given the linear modelling and regression outputs, some rainfall stations, as opposed to regression equations were applied to missing data. June 1994 for this climate station (70143) had a missing value therefore June 1994, (as did station 70147) therefore climate station (70263) was used for June 1994 as input for the GROWEST model. The monthly rainfall data from 1986 to 1995 were then used as input into GROWEST.

Figure 4.16 (below) Rainfall from 1986 – 1995 for Lockyersleigh. Regressed rainfall data from Station 70143 included where data was missing from Lockyersleigh.

<table>
<thead>
<tr>
<th>Year</th>
<th>Jan</th>
<th>Feb</th>
<th>Mar</th>
<th>Apr</th>
<th>May</th>
<th>June</th>
<th>July</th>
<th>Aug</th>
<th>Sep</th>
<th>Oct</th>
<th>Nov</th>
<th>Dec</th>
</tr>
</thead>
<tbody>
<tr>
<td>1986</td>
<td>72.1</td>
<td>0.0</td>
<td>0.0</td>
<td>45.5</td>
<td>34.1</td>
<td>6.2</td>
<td>41.8</td>
<td>124.8</td>
<td>33.1</td>
<td>53.6</td>
<td>114.4</td>
<td>45.4</td>
</tr>
<tr>
<td>1987</td>
<td>23.8</td>
<td>52.0</td>
<td>78.0</td>
<td>32.2</td>
<td>61.8</td>
<td>16.6</td>
<td>60.0</td>
<td>83.2</td>
<td>18.6</td>
<td>108.0</td>
<td>64.6</td>
<td>91.4</td>
</tr>
<tr>
<td>1988</td>
<td>67.6</td>
<td>54.0</td>
<td>27.0</td>
<td>228.8</td>
<td>42.8</td>
<td>28.2</td>
<td>72.0</td>
<td>43.4</td>
<td>74.8</td>
<td>12.6</td>
<td>98.8</td>
<td>74.6</td>
</tr>
<tr>
<td>1989</td>
<td>105.4</td>
<td>31.4</td>
<td>209.0</td>
<td>105.2</td>
<td>32.2</td>
<td>72.8</td>
<td>44.8</td>
<td>27.6</td>
<td>12.4</td>
<td>28.8</td>
<td>75.6</td>
<td>52.8</td>
</tr>
<tr>
<td>1990</td>
<td>54.0</td>
<td>126.2</td>
<td>57.4</td>
<td>131.6</td>
<td>138.6</td>
<td>24.2</td>
<td>76.8</td>
<td>201.6</td>
<td>75.0</td>
<td>35.8</td>
<td>17.8</td>
<td>18.2</td>
</tr>
<tr>
<td>1991</td>
<td>68.8</td>
<td>28.2</td>
<td>8.6</td>
<td>52.4</td>
<td>31.2</td>
<td>154.8</td>
<td>102.8</td>
<td>43.2</td>
<td>43.2</td>
<td>29.0</td>
<td>41.0</td>
<td>89.2</td>
</tr>
<tr>
<td>1992</td>
<td>87.8</td>
<td>155.4</td>
<td>67.6</td>
<td>33.2</td>
<td>31.4</td>
<td>52.0</td>
<td>14.6</td>
<td>42.8</td>
<td>39.0</td>
<td>61.2</td>
<td>65.0</td>
<td>107.2</td>
</tr>
<tr>
<td>1993</td>
<td>79.0</td>
<td>45.2</td>
<td>88.4</td>
<td>4.0</td>
<td>16.6</td>
<td>35.4</td>
<td>74.2</td>
<td>19.9</td>
<td>58.6</td>
<td>50.8</td>
<td>64.3</td>
<td>53.2</td>
</tr>
<tr>
<td>1994</td>
<td>41.7</td>
<td>107.1</td>
<td>90.5</td>
<td>82.3</td>
<td>13.8</td>
<td>45.7</td>
<td>22.5</td>
<td>12.1</td>
<td>6.5</td>
<td>43.0</td>
<td>49.5</td>
<td>55.2</td>
</tr>
<tr>
<td>1995</td>
<td>92.6</td>
<td>0.0</td>
<td>31.6</td>
<td>8.5</td>
<td>90.2</td>
<td>20.8</td>
<td>44.0</td>
<td>9.7</td>
<td>94.9</td>
<td>75.5</td>
<td>95.1</td>
<td>76.5</td>
</tr>
</tbody>
</table>
The shaded areas in figure 4.16 show the calculated rainfall from the regression equation between Lockyersleigh and Rainfall Station number 70143. The three dark shaded cells show the rainfall at the data acquisition times. Figure 2.3 (Chapter 2) shows Lockyersleigh rainfall data with incomplete data for the years 1986, 1993 and 1994. The other four inputs (monthly mean maximum and minimum temperature, solar radiation $\text{MJ}^2$ and evaporation mm day$^{-1}$) were obtained using ESOCLIM. ESOCLIM is a software package at CRES, ANU which calculates climate values using a digital elevation model (DEM) and thin plate spline climate surface functions.

### 4.4.2 Light Index

All plants use incident solar radiation for photosynthesis, which is required for plant growth. Although solar radiation is one of the determinants for plant growth, temperature and available moisture are often the limiting factors in Australia (Fitzpatrick and Nix 1970). Total solar radiation can be used as the maximum potential energy available to plants, when other radiation data are not available. The light index in GROWEST transforms the non-linear response of plant biomass to incident solar radiation into a linear scale with values ranging from 0 to 1 (figure 4.17).

The Light Index in GROWEST is the fractional increase in biomass as a function of total daily solar radiation. The light index equation was developed from theory by (Davidson and Philip 1958, de Wit (1959) and experimentation by (Hesketh 1963, Cooper 1996, Tanaka Kwano and Yamaguchi 1966).

Light Index ($LI$) is calculated by the following expression

$$LI = 1.03 - \exp^{-3.5R/Q_{\text{sat}}} \quad (4.3)$$

where $R$ = total solar radiation and $Q_{\text{sat}}$ is maximum possible solar radiation at any point on the earth’s surface. From theory this is 31.401 MJ m$^{-2}$ day$^{-1}$ or 750 cal cm$^{-2}$ day$^{-1}$.

Further examination of the light index and biomass are discussed in chapter 7.

Figure 4.17 shows the modelled response of biomass to radiation.
4. Modelling Plant Growth

Spatio-temporal Modelling of Biomass

Figure 4.17
The modelled response of biomass to radiation

Source: Nix 1981

4.4.3 Thermal Index

Biomass exhibits a strong response curve to temperature. The proportion of dry matter accumulation to mean daily temperature is a combination of a power function determined by derivatives in temperature above or below the optimum temperature. The Thermal Index varies with biome/species type/ photosynthetic pathway as determined by the critical temperature ranges as described by Nix (1981).

The plant thermal response regimes types have been divided into: microtherm (typical cold-climate conifers); mesotherm (including wheat, barley and oats); megatherm (C₃ photosynthetic pathway) includes broad leafed plants; and the megatherm (C₄ photosynthetic pathway), which includes tropical grasses, (see figure 4.18).

Figure 4.18 Values for the plant groups and constants used in the thermal index calculations

<table>
<thead>
<tr>
<th>Plant species</th>
<th>T₀ (°C)</th>
<th>T₉ (°C)</th>
<th>Tₒₚ (°C)</th>
<th>a</th>
<th>b</th>
</tr>
</thead>
<tbody>
<tr>
<td>microtherm</td>
<td>0</td>
<td>10</td>
<td>25</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>mesotherm</td>
<td>5</td>
<td>19</td>
<td>35</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>megatherm C₃</td>
<td>10</td>
<td>28</td>
<td>40</td>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td>megatherm C₄</td>
<td>10</td>
<td>35</td>
<td>50</td>
<td>2</td>
<td>2</td>
</tr>
</tbody>
</table>
The thermal index (TI) has a maximum unity at $T_0$, is equal at zero below $T_0$, and above $T_{up}$ decays according to a power law relationship which is possibly different on either side of the optimum.

Therefore TI used by GROWEST is given by:

\[
\begin{align*}
  T < T_0 & \quad \bar{T} = T_0 - T / T_0 - T_{lo} \\
  \bar{T} < 0.5 & \quad TI = 1 - 0.5(2^* \bar{T}) \\
  \bar{T} > 0.5 & \quad TI = 0.5(2(1 - \bar{T})^a) \\
  \bar{T} > T_0 & \quad \bar{T} = T - T_0 / T_{up} - T_0 \\
  \bar{T} < 0.5 & \quad TI = 1 - 0.5(2^* \bar{T})^b \\
  \bar{T} > 0.5 & \quad TI = 0.5(2(1 - \bar{T}))^b
\end{align*}
\]  

where:

- $T_{lo}$ = low temperature threshold, below which no growth occurs
- $T_0$ = optimum temperature
- $T_{up}$ = upper temperature threshold, above which no growth occurs

The coefficients $a$ and $b$ are equal for the microtherm and mesotherm while the megatherms distributions are skewed.

**Figure 4.19**

The modelled (GROWEST) response

Function of biomass to temperature

Source:

Nix 1981
4.4.4 Moisture Index

In Australia moisture can be the most limiting environmental variable for biomass growth. Australia has large areas where water is limited. Therefore, simple water balance models have been used for many years in different environments and have produced reasonable results. Previous studies (Guerra 1995, Bouglet 1995) in this catchment confirm that an averaged water balance model would be suitable to model soil and moisture changes within this catchment. GROWEST incorporates an integrated water balance model where growth is a response to the ratio of $E_a / E_t$ (actual evaporation/potential evaporation). In this study a linear 1:1 relationship between $E_a / E_t$ was assumed and a weekly water balance was calculated (Figure 4.20). A simple exponential function is used to relate $E_a / E_t$ to the relative available water storage in the root zone. Soil moisture is also estimated as a function of maximum storage in the root zone, AET/PET and actual water storage (Figure 4.21). MI is therefore represented by:

$$M_I = C - \exp^{-kx}$$

(4.5)

where $k$ is a coefficient based on soil type and $x$ is the ratio of actual to maximum available soil-water storage the three moisture extraction classes (a, b and c) are shown in figure 4.21 (Nix 1981). In this study soil moisture extraction curve b was selected.

Figure 4.20: GROWEST function for the moisture index

Figure 4.21: GROWEST function for the soil extraction index

**MOISTURE INDEX**

**SOIL MOISTURE EXTRACTION**

Figure 4.21 where:

- **a** = sandy loam with $C = 1.0$, $k = 7.5$
- **b** = clay loam with $C = 1.02$, $k = 3.5$
- **c** = clay with $C = 1.21$, $k = 1.5$
4.4.5 Growth Index

According to Baier (1977) a typical crop weather model is based on the assumption that crop yield or biomass depends on three agrometeorological variables: solar energy, temperature and soil moisture (or evapotranspiration). The typical model is

$$ Y = \sum_{t=0}^{m} V_1 \cdot V_2 \cdot V_3 $$

(4.6)

where:
- $Y$ is the dependent variable (e.g. biomass)
- $\sum$ summation of daily (or monthly) $V$ values from time $t = 0$ to $t = m$
- $V_1, V_2, and V_3 = indices$ in model e.g. rain, temperature and radiation.

A function such as this can be evaluated by using regression analysis. Fitzpatrick and Nix (1970) proposed the multiplicative model, which was expanded and more fully described by Nix (1981). The GROWEST model therefore is the multiplication of light, temperature and moisture indices at timestep $i$. The GI value also ranges from zero to unity as do the separate moisture, temperature and light indices.

$$ GI_i = LI_i \cdot TI_i \cdot MI_i $$

(4.7)

Where $LI_i = light\ index$
- $TI_i = temperature$
- $MI_i = moisture\ index$

Optimal growth occurs when all three indices are equal to unity. On the other hand if any of the growth indices ($TI, MI$ or $LI$) equals zero then the GI is also equal to zero.

4.5 Analysis of outputs: Total catchment scale

Initially weekly growth indices were examined over the three year period from 1992 to 1994 (figures 4.22 - 4.24). Next individual indices were examined during 1993, using a 13 week growth accumulation period to review the growing process (figures 4.25 - 4.27). Finally accumulated GI was regressed against catchment averaged biomass at a 13 weekly timestep (figure 4.28). All catchment scale growth indices were calculated from a center point in the catchment, specifically at longitude 149.9330 -34.6920.
4.5.1 Annual comparisons of the modelled growth indices

The following graphs show instantaneous weekly values of growth, light, moisture and temperature indices based on monthly mean temperature, solar radiation evaporation and actual monthly rainfall for Lockyersleigh during 1992, 1993 and 1994. This first examination is at weekly timesteps to examine the different processes at this temporal scale.

Figure 4.22 1992 Weekly Growth indices

Figure 4.22 shows that growth follows the moisture index during summer and responds to the temperature index during winter. The moisture index increases during winter but this appears to have little influence on growth. Figure 4.23 shows a sharp decline in growth at week 16, which is concurrent with a steep decline in moisture. When the growth index (equation 4.6) equals zero then one or all of the key indices (TI, MI or LI) is/are also equal to zero. The September biomass is lower than the March biomass, which is in agreement with the three graphs (figures 4.22-24) where the GI is still low September at approximately week 36.

Figure 4.23 1993 Weekly Growth indices
In Figure 4.23 the colour of the light and moisture index are different than figure 4.16 and figure 4.24.

**Figure 4.24 1994 Weekly Growth indices**

Figure 4.22, 4.23 and 4.24 all indicate that growth recommences at approximately week 37, with 1994 having the latest starting date for growth. High growth occurred in all years between weeks 7-12, which is at the end of summer. This is in agreement with the Lockyersleigh biomass data, that were high in March and low in September. Since monthly mean temperature and solar radiation were used it is evident that the light and temperature indices have no variation between years but the growth and moisture indices are vary considerably.
because actual monthly rainfall was used. Both light and temperature vary within the year demonstrating a strong seasonal component. Light and temperature provide the energy for photosynthesis and the ‘timing’ for plants to initiate growth. That is, day length and seasonal temperature changes mark the onset or decline in growth patterns. Moisture varies from year to year with rainfall. Although growth is a function of all climatic variables there is a distinct winter/summer pattern.

4.5.2 Growth indices at 13 weekly intervals

To examine the cumulative effects of climate on biomass the resultant growth indices were integrated over 13 weeks periods. Temperature, moisture and light indices were compared with the growth index at 13 weekly growth integrations during 1993.

Figure 4.25 1993 13 Week Integrated Growth and temperature indices

Figure 4.19 displays a marked decline in the temperature index during winter. This decline restricts growth.

Figures 4.25 and 4.26 show that in mid-June moisture increased and biomass remained constant or senesced during winter. At approximately week 26 moisture increases, temperature decreases and the growth index declines to zero. This process indicates that increased moisture does not increase biomass unless there is sufficient temperature and light to utilise the water for plant growth.
Figure 4.26 1993 13 week integrated Growth and moisture indices

Figure 4.27 1993 13 week integrated Growth and temperature x light indices

Figure 4.27 shows a fine scale response between growth, temperature and light during weeks 19 to 26, where the integrated growth index declines more slowly than the temperature x light index. This indicates that the biomass utilised photosynthetic energy that was obtained during the previous months to continue to grow. This indicates that the process of plant growth occurs over several months. Therefore, the true growth interval for grass and pasture in this catchment, may be longer that 13 weeks and this will be explored further in this chapter.
4.5.3 Total catchment response of biomass to growth indices

Figure 4.28a shows GI at a 13 weekly growth accumulation period against averaged biomass. This total catchment scale response used modelled outputs from GROWEST to show the seasonal response of biomass. At this 13 weekly timestep September’s biomass is high which suggests further analysis is required at a different timestep to incorporate the origin in accordance with GROWEST principles.

Figure 4.28a Catchment scale: Biomass vs the 13 week integrated growth index

![Catchment-averaged Biomass](image1)

Figure 4.28b Catchment scale: Biomass vs the 26 week integrated growth index

![Catchment-averaged Biomass](image2)
Figures 4.28a and 4.28b show that at the catchment scale GI reflects plant growth with greater accuracy at 26 weeks \( r^2 = .99 \) than the 13 week growth accumulation interval \( r^2 = .93 \). The proximity to the origin is also better represented at the 26 week growth accumulation interval (figure 4.22b).

### 4.6 Development of a sub-catchment model

GROWEST models were examined at three different locations within the catchment and at two different timesteps. The three locations are referred to as sub-catchment A_x (longitude 149.9360, -34.7130), sub-catchment B_x (longitude 149.9280, -34.6970) and sub-catchment C_x (longitude 149.8060, -34.6650). The two accumulation periods are 13 weeks and 26 weeks. The objective of developing a sub-catchment model was capture distinct sub-catchment variations in biomass and to determine the most suitable growth interval at this study site.

#### 4.6.1 Examination of different growth intervals at sub-catchment A_x

Sub-catchments A_x, B_x and J_x were examined at 13 and 26 week growth intervals using the modelled growth indices. Statistical summaries show the graphs and goodness of fit for GI at 13 and 26 weeks.

**Figure 4.29 Sub-catchment A_x (GI : 13 week)**

Biomass at Sub-catchment Ax

Modelled Growth Index (13wk)
This 13 week growth period makes physical sense for biomass growth however, in this catchment the winter period has shown reduced growth (Figure 4.16-4.19). Antecedent soil moisture conditions are important for biomass, and the growth response curve is well represented over a 3-month (13 week) period for March growth intervals but not for the September period producing $r^2 = 0.94$. Growth indices are integrated over 13 or 26 weeks. The measured biomass however, better matched accumulated GI over a greater than 13 week time period as verified by the regression at 26 weeks with $r^2 = 0.99$. The 26 week integration period also fitted closer to the origin giving confirmation of a better fit than the 13 week interval. Therefore, GROWEST was executed at a 26 week period to better represent the biophysical growth pattern in this catchment (Figure 4.30).

**Figure 4.30** Sub-catchment A, (GI : 26 week)

Biomass at Sub-catchment

Modelled Growth Index (26 wk)

From the weekly plots of temperature (Figure 4.22 - 4.24) it is clear that both March 1993 and 1994 the temperature index is constant but during September the temperature index is much lower restricting growth. Generally there is higher growth in March 1993 than March 1994 and this is partly due to higher moisture levels in the preceding five months (figure 4.22 - 4.24). This higher growth rate during March 1993 may increase the relationship between biomass and terrain attributes (chapter 5).
Sub-catchment A is moisture limited during both the March periods. During these summer and autumn periods biomass is limited by moisture under high March temperatures and temperature limited in September. Biomass growth at sub-catchment A also appears to be temperature driven, where high biomass responds to high temperatures and low biomass in September is a function of low temperature and high moisture levels.

Figure 4.32 Sub-catchment Bx, (GI: 13 week)
Chapter 4. Modelling Plant Growth
Spatio-temporal Modelling of Biomass

The 26 week integration period represents biomass growth with greater accuracy $r^2 = 0.98$ than the 13 week integration period with $r^2 = 0.92$. Sub-catchment Bx demonstrates the need for the longer growth period. This sub-catchment has less topographic relief (relatively flat) and therefore it is less influenced by terrain. Sub-catchment Bx also has a lower averaged biomass than sub-catchment A, or J. The ease of grazing could contribute to the lower biomass recordings.

Figure 4.33 Sub-catchment Bx, (GI : 26 week)

Overall biomass was less (approximately one third less) at site B than at Site A. These lower fertility levels suggest that site B was less able than site A to take full advantage of the high temperatures, even though biomass and temperature were highly correlated at site B. Site B had lower moisture levels and higher temperatures during September than site A and this lowered the site-averaged biomass at site B.
Figure 4.34 Sub-catchment B, : 13 week integrations

Biomass Sub-catchment B vs Growth & Moisture Indices (13 wk)

Weeks: 1993 - 1994

Figure 4.35 Sub-catchment Jx : GI = 13 week integration

Biomass at Sub-catchment Jx
Modelled Growth Index (13 wk)

Rsq = 0.80 thru origin
The greatest difference between the 13 and 26 integration periods was produced at sub-catchment Jx, where the correlation coefficient ranges from $r^2 = 0.80$ to $r^2 = 0.91$. This again supports the 26 weekly growth accumulation period as a better representation of biomass. Biomass for sub-catchment Jx has three distinct features, both the March periods have very similar and low biomass, and the difference in biomass between March and September is the least. Figure 7.23 and 7.24 also show that September's biomass is not well represented. The site-averaged biomass at sub-catchment Jx is lower than at sites A, and B, and this could be due to terrain effects and encroaching open woodlands.

**Figure 4.36 Sub-catchment Jx: 26 week integrations**
Biomass Sub-catchment J vs Growth & Moisture Indices

Figure 4.37 Sub-catchment J, : 13 week growth indices

Sub-catchment J, shows the least seasonal difference between the March and September. At sub-catchment J, September biomass was 82% of the averaged March biomass at the same sub-catchment. At sub-catchment A, September was 36% of March '93 biomass and 45% of March '94 biomass. Sub-catchment B, September was 54% of March '93 biomass and 49% of March '94 biomass. This high September biomass is difficult to explain. The lower temperature index alone in September at sub-catchment J, cannot account for this degree of variability. Limited access for grazing animals could have contributed to the high September biomass. The surrounding open woodlands could influence low biomass levels and lack of variation between seasons. Accessibility to sub-catchment J, is not as easy as to other parts of the catchment and therefore the grazing pressure could have been reduced.

4.6.4 Conclusions to sub-catchment modelling

From the sub-catchment analysis it is evident that the 26 week integration period captured the growth of the biomass during 1993 and 1994, with greater accuracy than the 13 week integration period. Comparisons between the sub-catchment and catchment averaged (catchment scale) (figures 4.28 - 39) responses of biomass to the 13 and 26 week growth
accumulation interval confirms that the 26 weekly integration time was appropriate. Figure 4.28b shows that the catchment scale response of biomass to GI at 26 weeks produced $r^2 = 0.99$, which is as high as the highest sub-catchment ($A_x$) response. Further comparisons between catchment averaged biomass and sub-catchment modelling are required to determine which model has more statistical significance (chapter 7).

### 4.7 Biomass modelling using temporal growth indices

Modelled growth indices provide climatic information on temporal plant growth patterns as well as supplying outputs on biomass growth. Initial understanding of the connection between plant growth and climate within a catchment are important before further modelling of the spatio-temporal dynamics can be achieved.

#### 4.7.1 Summary of findings

- Biomass levels were lower during September than the March periods
- There was less temporal variability in biomass during September than the March periods
- Rainfall could not be directly correlated to biomass to produce meaningful results
- Rainfall is highly variable between months and years
- A strong seasonal relationship exists between biomass and temperature
- Temperature is very limiting to biomass in winter
- Spatial invariance of the biomass correlations to sub-catchment rainfall data, given the data sets and outputs required in this study
- Sub-catchment temperature data provided appropriate spatial disaggregation. Further statistical analysis on the sub-catchment modelling will be reviewed in chapter 7.
- Modelled biomass was possible at three sub-catchments and at the catchment scale
- A range of intervals for growth index accumulation, from weekly to integrated weekly growth index over a six month growing season was tested. The 26 week integration period captured the most accurate biomass results during 1993 and 1994.
- Modelled biomass was higher during March 1993 than March 1994 due to the higher moisture levels in the preceding five months. These higher biomass levels may allow better discrimination with biomass and terrain attributes (chapter 7).
- Monthly solar radiation did not directly limit biomass over a six month period. This was included during September when the growth was suppressed because of low temperature.
4.7.2 Discussion

Even with the small data sets available here, the relationship between biomass and the modelled growth index integrated over 13 and 26 week periods was consistently evident for all sites and catchments. There is seasonal variation in spatial variability of biomass between September and March as shown in the averaged biomass correlation to the modelled growth index. This makes physical sense in this catchment where the 'drying out' in drier periods such as March produce higher and more spatially variable biomass. September had both less biomass and smaller variability of biomass. This is confirmed by the modelled growth outputs from GROWEST where growth is suspended during winter and throughout most of September. Terrain attributes could also contribute to the understanding of site variability of biomass (chapter 7). The high level of significance from $r^2 = 0.91$ to $r^2 = 0.99$ (26 week integration period) confirms that modelled GI represented the environment for biomass production with reasonable accuracy. Other considerations could include dynamic terrain attributes, that can vary over time such as slope and aspect modified solar radiation produced by SRAD.

In summary, climate data can be used via a plant growth model to determine temporal growth patterns. GROWEST has shown that rainfall, which is spatially and temporally erratic can be limiting over the summer periods, while temperature is limiting over the winter periods. However, before spatio-temporal modelling of biomass is possible other terrain influences on biomass need to be accounted for.

The combination of terrain attributes with modelled outputs of biomass for predictive purposes may seem a problematic task. However, if meaningful results could be established they could aid management within the catchment to prevent further land degradation. Bertram and Reynolds (1998) discuss various sources of errors and limitations using their predictive vegetation model used in Alaska. The topographically driven vegetation model (TVM) was based on slope and discharge, which were derived from digital terrain data. Plant growth models have also been coupled with satellite radiance data. The modelled plant growth outputs are converted through a radiative transfer model to give an estimate of reflectance (Moulin et al. 1995, Kergoat et al. 1995, Fisher et al. 1996 a, b). All these remotely sensed methods require atmospheric corrections to the satellite data and independent calibration via either empirical or physical ground measurements. Chapter 7 shows how spatial disaggregation using a combination of terrain attributes and growth outputs from the GROWEST model can produce meaningful results.
4.7.3 Conclusions

Conclusions to the four objectives are that:

1. there is distinct biomass variability between the two seasons within this catchment, that cannot be determined by a single climatic variable. There is also biomass variability within one season. Further investigation into terrain influences on biomass will be explored in chapters 5 and 6.

2. there is a correlation between biomass and radiation during the March and summer growth period. This will be investigated further in chapter 7.

3. plant growth modelling via GROWEST produced sensible growth indices which provide temporal data on growth within the catchment. This temporal component can be utilised for spatio-temporal modelling.

4. sub-catchment modelling produced sensible results using a 26 week integration period. Further investigation on the statistical significance of the sub-catchment and catchment scale biomass models will be reviewed in chapter 7.
Chapter 5.

Terrain Analysis and Vegetation Data
CHAPTER 5. TERRAIN ANALYSIS AND VEGETATION DATA

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5.1 Introduction

This chapter explains the modelling of terrain attributes and explores their links to vegetation data in the Lockyersleigh Catchment. A Digital Elevation Model (DEM) provides gridded elevation data that is essential input for the estimation of terrain attributes. DEM accuracy in determining surface shape is discussed, as well as a sensitivity analysis in comparing two hydrologic algorithms for routing water flow over the surface. Correlations between biomass, satellite data and selected terrain attributes are investigated at three time periods covering the end of summer and the end of winter.

Terrain attribute data can be used in developing terrain indices that characterise spatial biosphysical patterns. Terrain indices can represent some of the underlying physics of terrain, biological, soil and atmospheric processes. Ideally terrain indices take into account the dominant controlling principles such as topographic controls on water flow. Terrain attribute data can provide information about surface hydrology, enable the prediction of spatially distributed biomass, and facilitate the disaggregation of biomass data from lumped hydrologic models. Correlations between biomass and terrain attributes can provide a basis for management of native vegetation or of agricultural catchments by providing more spatial data about biomass.

5.1.1 Spatial modelling of the land surface and its biomass

Process-based hydrological modelling should include the role of vegetation. For example, Chehbouni et al (1994) considers vegetation-related information as critical for modelling hydrological processes. They also argued that remotely sensed spectral data provide a powerful means to characterise vegetation status. Many plant growth models exist and most produce lumped or point values for biomass. Two point models which can produce catchment-averaged biomass outputs are GROWEST (Nix, 1981) and SWRRB (Williams et al. 1985). GROWEST is derived from climate determinants for plant growth and development while the SWRRB hydrological model has a biomass component based on radiation and leaf area index (LAI).

Spatial models are becoming more common as research tools in many scientific applications where data collected from different locations need to be modelled or interpolated to regions where data cannot be directly sampled (Cressie 1991). Spatial modelling in hydrology has
increased since the mid-to-late eighties and remotely sensed data sets have become more accessible (Moore et al 1991). Many hydrological models incorporate topography. Topographic data allow the determination of drainage areas, area specific slopes (length and shape) and channel networks.

Landscape geometry can be determined from a DEM (Moore et al 1992) and, once calibrated and geo-referenced to the surface, relationships between the topography and biomass can be determined. From correlations between terrain attributes and biomass, spatial coverage of biomass may be obtained or modelled outputs of averaged biomass data may be disaggregated.

5.1.2 Digital Elevation Models and terrain analysis

The generation of a DEM for the Lockyersleigh Catchment is discussed in Chapter 2. A DEM can provide an accurate representation of the surface shape and drainage structure if produced by a technique, which overcomes inherent biases in source topographic data (Hutchinson 1997). Models such as the terrain analysis program for environmental sciences -grid version (TAPES-G), use DEMs to obtain primary terrain attributes (figure 5.0). The utility of terrain attributes depends critically on the accuracy of the landscape representation by the DEM. Hutchinson (1988, 1989) has played an important role in DEM interpolation methods with his development of suitably accurate DEMs. DEMs can be calculated from digitised point, contour or stream data. This method includes a drainage enforcement algorithm, which automatically calculates stream and ridgelines from contour data (Hutchinson 1988). This alleviates the problems associated with contour data representing drainage in low relief catchments. Once an accurate DEM is established, TAPES-G can show the spatial variability of the dominant hydrological processes (Gallant and Wilson 1996) and allow more physically-based secondary attributes to be identified.

Terrain attributes determined by a DEM can be divided into two types: (viz.) primary, and secondary or compound attributes. Primary terrain attributes consist of topographic factors such as drainage area, slope, aspect, tangential curvature and flow path length. In this study primary terrain attributes have been correlated individually with biomass and reflectance data. Terrain attributes have been applied to this catchment to determine the influence that these topographic features have on biomass. Slope and aspect may influence the rate of biomass or plant growth even in low and mid-latitudes and in relatively flat landscapes, which are common in Australia.
Figure 5.0  Spatial Disaggregation of Terrain Attributes

DEM: at appropriate resolution

TAPES-G: Terrain modelling

Scale match

GIS development in ARC/INFO:
Gridded topographic surfaces

Map production of terrain surfaces

Topographic attributes at specific sites or areas

Correlations between biomass & topographic attributes. Terrain selection. Output equations

Further model development. Chapter 7.
Minor changes in the surface geometry can affect the interaction between surface hydrology and biomass. Tangential curvature for example, is useful for determining flow convergence and divergence, thereby indicating where water is available for uptake by vegetation.

Secondary or compound terrain attributes combine primary terrain attributes and may be used to represent some hydrologic processes more directly. Topographic wetness index is a secondary terrain attribute defined by \( \ln(a/tanB) \) where \( a \) is the specific catchment area, and \( B \) is the local surface slope angle. Zheng et al. 1996 compared the available soil water capacity estimated from topography using \( \ln(a/tanB) \) to the available water capacity calculated from soil series information and found a strong linear relationship.

### 5.1.3 Remotely sensed data

The type and resolution of a remote sensor determines its use and sensitivity to the surface parameters being measured. Spatial resolution is determined by the optical aperture of the sensor and the sampling rate (chapter 3). Remote sensors integrate the response of the landscape elements within an area. Use of remotely sensed data also requires an understanding of the view angle over the surface and its interactions with solar zenith angles (Jackson et al. 1990). Off-nadir position and view angle can affect the bidirectional reflectance factors. Canopy spectra and seasonality due to wet and dry seasons may also influence the reflectance values (Qi et al. 1994).

Calibrations of biomass to remotely sensed data can allow direct correlations between remotely sensed reflectance data and terrain attributes data. Remotely sensed NDVI data are important when measuring vegetation as they minimise the effects of season, sun angle and soil background on reflectance (Smith 1997). Studies in this experimental catchment by the author yielded a correlation of biomass to LAI with \( r^2 = 0.78 \) Cusack et al. (1997,1999). Biomass to TMSAT NDVI also produced an exponential regression with \( r^2 = 0.62 \). Given such correlations between remotely sensed data and biomass, improvements of these correlations should be pursued by including terrain attribute data.

While TAPES-G is a useful tool to represent topography-driven surface hydrology, a satellite image is a single ‘snapshot’ of the surface reflectance of biomass. In both terrain and satellite data the antecedent soil moisture are not known. Caution needs to be taken, as temporal variation in both the climate and biomass are not taken into account. Recent research by Running and Thorton (1996) uses estimates of the relationship between meteorological variables and elevation for each grid cell to generate interpolated temperature and precipitation.
based on daily observations. They are also exploring the potential for incorporating remotely sensed thermal infrared data as a way to constrain the regressions of observed meteorological variables against elevation.

This paper examines the correlation between biomass, reflectance data and primary terrain attributes. The study also identifies the type of correlations and their implications in a small catchment. The need for secondary terrain analysis is also demonstrated.

5.1.4 Modelling terrain attributes

An accurate DEM is a critical input to modelling accurate terrain attributes from the landscape. The DEM was calculated using the Australian National University interpolation program (ANUDEM) (Hutchinson 1989) from digitised point, contour and stream data derived from a 1:25,000 map sheet. UTM position co-ordinates were stipulated, and 25 m and 30 m DEMs resolution was generated by the ANUDEM program (Hutchinson 1996).

The late Professor Ian Moore originally developed the terrain analysis program for environmental sciences -grid version (TAPES-G) (figure 5.0) used in this study. It calculates eleven primary terrain attributes from a DEM. These eleven attributes were then correlated to biomass, TMSAT NDVI, red and NIR wavebands. Five terrain attributes were selected from their correlations to biomass and reflectance data: drainage area, slope, aspect, tangential curvature and flow path length. Moore et al (1992) describes the calculation of these attributes in detail.

The assumptions within the TAPES-G model are that terrain shape determines water flow and drainage, and the catchment does not have depressions. In low relief catchments such as Lockyersleigh subsurface drainage velocity is not fast due to the small gradients but it is assumed that there is some subsurface lateral flow under 'wet' conditions. The Lockyersleigh catchment has been assessed for depressions and using ANUDEM version 4.6 25 m and 30 m DEMs were produced.
**Brief description of selected terrain attributes**

Slope and aspect (Figure 5.1 and 5.2) can be determined by two methods: steepest descent slope and the finite difference method. The finite difference method is far superior, with more accurate representation of the surface shape and subsequent water flow. In some studies the steepest descent slope could be used for the calculation of slope if the study was concerned with slopes within channels. Slope determines flow velocity of surface and subsurface water and therefore affects many processes such as erosion and soil formation. Aspect was measured in degrees clockwise from north using the finite difference technique. Aspect indicates the impact of the solar radiation and wind, which often impact on plant growth.

Drainage area (Map 5.3) is the upslope contributing area or the area draining through each cell. The maximum slope as a ratio can be calculated from (multiple flow paths) FD8 (‘F’ from Freeman’s (1991) research) or from the D8 (single flow) approach, which calculates the gradient as the steepest slope to one of the eight nearest neighbours using flow direction. Depending on the scale of the study site the FD8 is a superior algorithm to the D8 algorithm. The D8 method cannot disperse flow from one cell to multiple cells on divergent surfaces. Also on planar surfaces with relatively constant aspect flow the D8 method does not precisely match the parallel lines instead flow has a bias towards the cardinal directions. The computational time for the FD8 is much higher than the D8 method due to the FD8 iterative accounting of flow at each cell from its source with the bulk of its flow in the direction of the steepest descent. The main disadvantage of the FD8 is its artificial dispersion pattern in valleys associated with mildly convergent topography.

Other methods include the Rho8 algorithm (Fairfield and Leymarie 1991) and the (Digital Elevation Model Networks) DEMON method (Costa-Cabral and Burges 1994). The Rho8 method is a stochastic version of the D8 algorithm (O’Callaghan and Mark 1984) with a random flow method. In the DEMON flow is generated areally, not at point sources. Flow generated over a pixel is projected downslope over a two-dimensional flow strip, analogous to a flow tube (Costa-Cabral and Bruges 1994). The results of sensitivity tests comparing the two algorithms are discussed later in this chapter.
Figure 5.1
Spatially Distributed Slope
Using a 25 m DEM
Lockyersleigh Catchment
Figure 5.2
Spatially Distributed Aspect
Using a 25 m DEM
Lockyersleigh Catchment
There are three curvature parameters: plan, profile and tangential. All the curvature parameters/attributes demonstrate the rate of change of a first derivative such as slope or aspect, usually in the one direction. The curvature of a line is the inverse of the radius of curvature. Profile curvature represents the process of flow acceleration and deceleration rates, which relate to erosional and depositional processes within the catchment. Moore and Burch (1986a) demonstrated that profile curvature was a determinant of erosional and depositional processes at the hillslope scale. Plan and tangential curvature relate to converging/diverging flow and soil water content. The usual nomenclature is positive values for convex and negative values for concave. In this thesis positive tangential curvature as calculated by the TAPES-G package indicates the divergence of water and negative tangential curvature is convergent water flow.

Tangential curvature is the curvature of the line formed by intersection of surface with plane normal to flow line. Flow path length is the longest flow path from the catchment divide or edge of the DEM to the cell. Tangential curvature $K_t$ is plan curvature multiplied by the sine of the slope angle which is very important in low relief landscapes where small changes in the surface curvature can be detected. Mitasova and Hofierka (1993) suggest that tangential curvature is more appropriate than plan curvature for studying flow convergence and divergence. The equation for tangential curvature (equation 5.1) is the same as plan curvature, except the denominator is multiplied by the sine of the slope angle.

All the curvature parameters (and other terrain attributes) are determined from derivatives of the topographic surface which are estimated using centered finite differences (equations 5.2, 5.3, 5.4, 5.5 and 5.6). Therefore in $K_n$, the finite difference equations and $h$ the grid spacing are calculated from the edges and across the DEM in varying directions.

Equation (5.1) from Mitasova and Hofierka (1993)

$$K_t = \frac{Z_{xx}Z_y^2 - 2Z_{xy}Z_xZ_y + Z_{yy}Z_x^2}{pq^{1/2}}$$

Equation (5.1)

Where:
Chapter 5. Terrain Analysis and Vegetation Data  
Spatio-temporal Modelling of Biomass

\[ Z_x = \frac{\partial Z}{\partial x} \equiv \frac{Z_2 - Z_6}{2h} \quad \text{i.e., the } Z \text{ value in the } x \text{ direction using 2 grid spacings} \quad (5.2) \]

\[ Z_y = \frac{\partial Z}{\partial y} \equiv \frac{Z_8 - Z_4}{2h} \quad \text{i.e., the } Z \text{ value in the } y \text{ direction using 2 grid spacings} \quad (5.3) \]

\[ Z_{xx} = \frac{\partial^2 Z}{\partial x^2} \equiv \frac{Z_2 - 2Z_6 + Z_4}{h^2} \quad Z \text{ value in the } x \text{ direction using 2 grid spacing & 3 } x \text{ values} \quad (5.4) \]

\[ Z_{yy} = \frac{\partial^2 Z}{\partial y^2} \equiv \frac{Z_8 - 2Z_4 + Z_2}{h^2} \quad Z \text{ value in the } y \text{ direction using 2 grid spacing & 3 } x \text{ values} \quad (5.5) \]

\[ Z_{xy} = \frac{\partial^2 Z}{\partial x \partial y} \equiv \frac{Z_2 - Z_4 - Z_4 + Z_2}{4h^2} \quad Z \text{ value in the } x \& y \text{ directions around a } 3 \times 3 \text{ sub-grid} \quad (5.6) \]

In tangential curvature (\(K_t\)) the other 2 variables are

\[ p = Z_x^2 + Z_y^2 \quad \text{and} \quad (5.7) \]

\[ q = p + 1 \quad (5.8) \]

The grid spacing is defined by \(h\) and the arrangement of a \(3 \times 3\) sub-grid of a DEM with node numbering convention are shown below (Figure 5.4)

Figure 5.4 Node numbering sequence for calculations using a sub-grid DEM

TAPES-G inputs can use DEM files in several different formats. ANUDEM (version 4.6a 1998) was used to produce two DEMs at a 30 m and 25 m grid resolution.
Figure 5.3  Map of Drainage Area (sq metres) using a 25 m DEM and DEMON algorithm in the TAPES-G model
Chapter 5. Terrain Analysis and Vegetation Data
Spatio-temporal Modelling of Biomass

Hydrologically, specific catchment area \( A_s \) is a measure of the surface or near subsurface runoff at a given point and it integrates the effects of upslope contributing area and catchment divergence and convergence (Moore et al 1991). The critical area describes the topographic attribute known as the wetness index, where the specific catchment area \( A_s \) is divided by \( \tan \beta \). The wetness index assumes uniform soil properties. Soil water content has been related to many topographic attributes including wetness index, profile and plan curvature, slope, aspect, specific catchment area, (Moore et al 1988b, Burt and Butcher 1986, Moore and Burch 1986a, Guerra 1995).

5.1.5 Methods for analysing correlations between Biomass and Terrain Attribute

Three regression models have been used in this analysis: linear (and exponential), quadratic and cubic (equations 5.9, 5.10, 5.11, 5.12). Linear, quadratic and cubic equations form a series of nested models. The simplest regression model is the linear trend model. Applying the linear model \( Y \) (biomass) will change linearly according to changes in \( T \) (terrain parameter). \( B_1 \) is the slope of the regression line and \( B_0 \) is the intercept. \( Y \) (biomass) can also increase with constant percentage increases, rather than absolute increases. This assumption is the basis for the simple exponential growth curve.

Linear \[ Y = b_0 + b_1 T \] (5.9)

Exponential \[ Y = b_0 \exp(b_1 T) \] (5.10)

Quadratic \[ Y = b_0 + b_1 T + b_2 T^2 \] (5.11)

Cubic \[ Y = b_0 + b_1 T + b_2 T^2 + b_3 \] (5.12)

Where:

\( Y = \) dependent variable biomass (kg ha\(^{-1}\)), TMSAT NDVI, red and NIR wavebands

\( b_0, b_1, b_2, b_3 = \) regression coefficients

\( T = \) independent variable terrain attributes

These equations were used to examine a range of possible responses between biomass and surface hydrology derived from the topography. The number of model parameters need to be considered carefully as increasing the number of parameters can increase the standard error of
the regression. An observed increase in the $r^2$ does not necessarily reflect a better fit of the model (Norusis 1993).

5.2 Terrain Attributes and March 1993 Vegetation data

5.2.1 Modelled results from March 1993 using the Rho8 algorithm with a 30 m DEM as input specification in the TAPES-G model

Biomass and satellite data were correlated against the five selected terrain attributes generated by TAPES-G. As mentioned the selected terrain attributes are drainage area, slope, aspect, tangential curvature and flow path length. The satellite data incorporates the red, near infrared wavebands as well as the NDVI and the biomass units are kg ha$^{-1}$. Statistically analysed results are shown in Figures 5.5 a, b. Three TAPES-G models were produced using different inputs or by varying the model specifications. One TAPES-G used a 30 m DEM and the Rho8 algorithm (Fairfield and Leymarie 1991), another used a 30 m DEM and a DEMON algorithm (Costa-Cabral and Burges 1994), and the last model used a 25 m DEM and the DEMON algorithm. The Rho8 method attempts to solve the D8 (O’Callaghan and Mark, 1984) propensity to model flow paths toward cardinal or diagonal directions resulting from grid orientation. The Rho8 includes a stochastic component into the D8 yielding flow paths that reflect more closely the true aspect of hillslopes (Costa-Cabral and Burges 1994). However, the introduction of randomness does not ensure reproducible results and flow can converge laterally with one another. The DEMON computes the specific contributing areas and specific dispersal areas of DEM pixels. That is the DEMON downslope flow takes one pixel at a time and makes it a source pixel. The assignment of flow direction is according to aspect angle, as given by Lea (1992). The flow path is two dimensional, allowing the effect of terrain topography on flow path width.

Figure 5.5 a, b shows $r^2$ values for Linear (L), Quadratic (Q), Exponential (E) and (C) Cubic regressions for biomass versus terrain parameters. The dependent variables are biomass, TMSAT red, NDVI or NIR. The independent variables are the five terrain attributes.

The equations for Figure 5.5 a, b are described in the methods section 5.1.5 in this chapter.

Figure 5.5a, b Statistical Summary of Biomass and Satellite correlations to five selected terrain attributes from TAPES-G results using a 30 m DEM with Rho8 algorithm
Chapter 5. Terrain Analysis and Vegetation Data
Spatio-temporal Modelling of Biomass

### Table

<table>
<thead>
<tr>
<th>Variables below include constant</th>
<th>Drainage Area $m^2$ $r^2$ values</th>
<th>Slope (%) $r^2$ values</th>
<th>Aspect degrees $(^\circ)$ $r^2$ values</th>
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</thead>
<tbody>
<tr>
<td>Biomass</td>
<td>$L = 0.05$</td>
<td>$L = 0.28$</td>
<td>$L = 0.07$</td>
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<tr>
<td></td>
<td>$Q = 0.05$</td>
<td>$Q = 0.29$</td>
<td>$Q = 0.67$</td>
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<tr>
<td></td>
<td>$E = 0.06$</td>
<td>$E = 0.49$</td>
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<tr>
<td></td>
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</tr>
<tr>
<td></td>
<td>$Q = 0.02$</td>
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</tr>
<tr>
<td></td>
<td>$E = 0.01$</td>
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<tr>
<td></td>
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<td></td>
<td>$E = 0.07$</td>
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<td></td>
<td>$C = 0.58$</td>
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**Figure 5.5b**  Biomass and Satellite data versus Terrain Attributes using TAPES-G with 30 m DEM and Rho8 algorithm

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<thead>
<tr>
<th>Variables below include a constant</th>
<th>Tangential Curvature $1/(100 \text{ m})$ $r^2$ values</th>
<th>Flow Path Length (m) $r^2$ values</th>
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<td>$L = 0.19$</td>
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<td></td>
<td>$C = 0.27$</td>
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</tr>
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<td>TMSAT NIR</td>
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</tr>
<tr>
<td></td>
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<td>$C = 0.03$</td>
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Figures 5.6 through to Figure 5.11 display selected relationships between the land surface and terrain attributes. The NDVI values used in this study have not been rescaled between zero and one. Figures 5.6 to 5.11 were calculated using a 30 m DEM and Rho8 algorithm in the TAPES-G model.
Figure 5.6  TMSAT NDVI vs Drainage Area

![TMSAT NDVI vs Drainage Area](image)

Figure 5.7  TMSAT NDVI versus Slope

![TMSAT NDVI vs Slope (%)](image)

Figure 5.6 shows increasing NDVI with increasing drainage area up to a drainage area between approximately 5000 and 7000 sq m. This quadratic correlation ($r^2 = 0.60$) suggests that NDVI eventually decreases with increasing drainage area at some critical point between these values. Site B11 with a large upslope contributing area influences the quadratic curve by showing a different trend or indicating some saturation point where increasing drainage area actually decreases NDVI. In reality, some annual species of grass and pasture may survive with zero drainage area and rely totally on intermittent rainfall to sustain photosynthesis and produce chlorophyll. Site B11 does consist of 43% brown material which explains its low TMSAT NDVI value. Other queries remain with regarding site B11. In the sensitivity study (section 5.2.5) site B11 has a much lower drainage area when using a different algorithm to calculate drainage.
Although a very weak relationship, Figure 5.7 has a slight trend of increasing NDVI for increasing slope values. An increasing slope allows higher intensity of solar radiation for the production of ‘green’ biomass. NDVI and biomass correlations with slope show different trends. Further analysis using composite attributes may explain some of these differences. Sites J10 and J11 in Fig 5.7 show less greenness than would be expected from their slope and this is possibly due to their proximity to the open woodlands which do not reflect the same intensity of greenness as the surrounding grassland. In addition, the woodland canopy may also be providing some shading on these sites.

Figure 5.8 shows a complex relationship where most sites (except sites A12 and A9) show decreasing biomass with increasing slope. This is possibly due to more moisture on the flatter slopes where the biomass is higher. The interaction between aspect and slope could be influencing biomass even though the gradient within this catchment is slight. Site A9 is on a western slope and A12 is close to north (Fig 5.9a and 5.9b) and therefore their biomass readings are even higher. Site A12 has utilised its northerly aspect to produce higher biomass.
Figures 5.9a and 5.9b describe two ways to examine the effect of aspect on biomass. Figure 5.5 shows a cubic regression between proximity to north and biomass. The ground biomass data is highly variable but has $r^2 = 0.74$ whereas the TMSAT reflectance data has a cubic fit but with less statistical significance $r^2 = 0.58$ (Table 5.2).

Figure 5.9b shows biomass as a function of aspect interpreted as ‘departure from south’ (equation 5.13)

\[
Y = \text{Biomass (kg/ha)} \\
X = \text{Aspect (absolute value -180 degrees)}
\]

as departure from south (degrees)  

(5.13)
Figure 5.9b produced a correlation with a \( r^2 = 0.70 \), whereas Fig 5.9a had a cubic fit with \( r^2 = 0.74 \). This difference confirms the asymptotic nature of fitting a radiation-based surface where, the cubic fit on the western slopes (at approximately 250 degrees) had an effect on biomass production due to the diurnal cycle radiation load and associated positive sensible heat flux. The significance of showing both equation 5.13 and cubic fits for aspect was to demonstrate the impact of northern aspects, and to a much lesser degree the relative effect of western and eastern aspect effects on biomass values. The standard F ratio test would confirm which equation (linear, quadratic or cubic) more accurately describes the statistical best curve-fit by analysing the degrees of freedom, number of independent variables and the difference in the residual sum of squares. Further investigation of aspect influences on biomass are included in chapter 7.

Figure 5.10a  TMSAT red waveband vs tangential curvature.

Table 5.10b: Statistical significance levels for Fig 5.10a

<table>
<thead>
<tr>
<th>Model</th>
<th>( r^2 )</th>
<th>Significant F</th>
</tr>
</thead>
<tbody>
<tr>
<td>Linear</td>
<td>0.69</td>
<td>0.003</td>
</tr>
<tr>
<td>Quadratic</td>
<td>0.78</td>
<td>0.005</td>
</tr>
<tr>
<td>Exponential</td>
<td>0.70</td>
<td>0.002</td>
</tr>
<tr>
<td>Cubic</td>
<td>0.78</td>
<td>0.020</td>
</tr>
</tbody>
</table>

Tangential curvature is useful for studying flow convergences and divergences. Site J3 is a convergent site whereas site A9 is divergent. Figure 5.10a shows with an increase in tangential curvature and subsequent flow divergence, as the biomass appears as more “brown”. TMSAT red wavebands reflect ‘brown’ biomass, and this correlation with tangential curvature suggests
that with more divergent flow the biomass is becoming ‘drier’ and giving increased red reflectance indicating brown, dry biomass. Site B11 contradicts this with convergent flow and a relatively low brownness value, suggesting this site is a small localised ‘patch’ within the grid which the TMSAT red reflectance pixel. Sites J10 and J11 have been excluded from Figure 5.10a as the TMSAT red waveband reflects ‘brown’ biomass which is only relates to grassland and pasture as the woodland sites do not change colour (from green to brown) to the same degree. The significant F test indicates the most statistically accurate curve-fit is the exponential curve with the $r^2 = 0.70$ and the lowest significant F of 0.002, although the linear curve has almost equal significance.

Figure 5.11 shows a map of Tangential Curvature shows the spatial patterns of water flow. This is very useful in low relief catchments (such as this study site), as the terrain shape determines not only water quantity but it also indicates the location of water available for plant growth. Figure 5.11 was produced using the 25 m DEM in TAPES-G. It clearly shows that negative tangential curvature is convergent flow and positive tangential curvature is divergent flow. The red shading of convergent flow is following the streamlines and valleys in the catchment.

5.2.2 Discussion (March 1993)

Potential correlations between biomass, primary terrain attributes and remotely sensed reflectance data were evaluated. The association between slopes and NDVI as well as between drainage area and NDVI showed that primary terrain attributes were correlated to NDVI for the climatic conditions of this study. NDVI was also weakly correlated to flow path length (Figure 5.5), and in dry (non-rainfall periods) the flow path length could be critical to the NDVI value.

Figure 5.5 and Fig 5.8 show that an increase in slope produced an increase in NDVI and a decrease in biomass respectively. These opposite effects need to be examined more fully to understand what dominant processes/s are responsible for these results. Further examination using secondary terrain attributes (such as radiation and wetness index) could give greater insight into the dominant forces or environmental conditions responsible for the spatial variability in biomass. In low relief catchments it is often assumed that terrain attributes such as aspect and slope do not have a significant effect on biomass. However, this study shows that even minor changes in the terrain can have an impact on landcover in grasses and pastures. This is confirmed by the fact that biomass was correlated to slope and aspect. Some correlations between biomass and aspect were as high as $r^2 = 0.74$ with significant F = 0.002.
Figure 5.11  Spatially Distributed Tangential Curvature (x 100)
Chapter 5. Terrain Analysis and Vegetation Data
Spatio-temporal Modelling of Biomass

The relation between biomass and slope may indicate a number of physical processes (Fig 5.9). The increased slope could reduce runoff and therefore biomass could decrease with increased slope due to lack of surface moisture. Sites A however, may indicate increasing slope producing increasing solar radiation and therefore increasing biomass assuming there is sufficient rainfall or soil moisture. In summary, biomass vs slope could show three different curves where, the A sites are radiation driven, B sites becoming water saturated and the J sites in the woodlands area represent a different biome. Alternatively both terrain and climatic differences (chapter 7) could affect the sites.

Aspect has two specific impacts, it increases in solar intensity due to its proximity to north and in combination with slope it can give more complex accurate spatial disaggregation of solar radiation. Figure 5.9a shows high biomass values for northerly aspect.

As previously stated, minor undulations in the landscape are easy to ignore. However, even small depressions, inclines and other features in the terrain appear to affect the vegetative cover in this small catchment. However, direct comparison between topography and remotely sensed data can only be represented provided the DEM accurately represents surface shape at a sufficiently fine resolution (Hutchinson and Gallant 1999).

The correlation of TMSAT red waveband to tangential curvature ($r^2 = 0.78$), is an example of surface shape influencing the remotely sensed signal. Given tangential curvature combines plan curvature and slope, it is important to understand plan curvature. Plan curvature measures the convergence and divergence thereby indicating the concentration of water in the landscape (Gallant and Wilson 1996). Tangential curvature is particularly useful in low relief catchments where the slope parameter accounted for small changes to the surface shape and thereby gave higher correlations with reflectance data. Plan curvature produced $r^2 = 0.75$ (quadratic fit) with TMSAT red but the correlations were lower than tangential curvature using exponential and linear regressions (Figure 5.11b).

Tangential curvature is negative in valleys where water converges and positive on ridges where water diverges. Sites J3, J6, B11 and B show negative curvature with sites J3 and J6 having the steeper slope and sites B11 and B possibly low flat ground. The remaining sites are positioned on ridges, (confirmed by flow path length), have divergent flow and therefore reflected red wavebands indicating 'brown' biomass.
The climatic determinants for biomass are possibly best examined at a monthly timescale, given vegetative growth rates. Therefore, the different data acquisition dates between the satellite and biomass collection times (1 month) did not seriously impede the outcomes of this study (Table 5.2). Both biomass and satellite vegetative information can be correlated to primary terrain attributes given the prevailing monthly climatic conditions of this study. However, the climatic impacts on the correlation between vegetation and the primary terrain attributes during a summer/winter seasonality would be a worthwhile study.

This chapter has shown it is possible to correlate biomass and TMSAT data to five primary terrain attributes under the climatic conditions present in this catchment. However, the accuracy of this correlation is dependent on the accuracy of the DEM (Hutchinson 1996) and the prevailing climatic conditions. Given the difficulties in determining the spatial distribution of rainfall, the temporal sensitivity of dependent hydro-ecological processes (such as biomass) should be carefully considered (Hutchinson 1995a). Further research is necessary to determine which correlations are best to use for the spatial distribution of biomass.

The use of TAPES-G made it possible to identify the key primary terrain attributes, as well as to identify the type and accuracy of their correlation to land cover data. TAPES-G also indicated which secondary terrain attributes could be investigated.

5.2.3 Conclusion (March 1993)

This study concludes that there is a correlation between landcover (biomass and remotely sensed reflectance data) and primary terrain attributes. The correlations vary with some curve estimations producing $r^2$ values up to 0.78 (Figure 5.10a and 5.10b). Tangential curvature is a particularly useful terrain parameter in low relief catchments due to its sensitivity to minor changes in curvature. Secondary terrain attributes and landcover data could be determined to provide important additional information for the spatial disaggregation of localised or lumped biomass data.

In view of the correlations between biomass and slope and aspect further analysis between solar radiation (a secondary terrain attribute) and NDVI could yield worthwhile results. Similarly, secondary terrain attributes such as the wetness index could be related to biomass values.
From a climatological perspective the comparison between biomass or reflectance data with terrain attributes in a different season could indicate different degrees of spatial variability of landcover between different seasons.

All correlations within this study are dependent on the initial DEM resolution and accuracy. The DEM accuracy determines the usefulness of TAPES-G outputs and therefore the validity of the correlations with ground and satellite data. The implications of this study are that primary terrain attributes do have impacts on biomass in low relief catchments and sufficient accuracy in the DEM is therefore essential.

5.2.4 Summary of results from March 1993 using the Rho8 algorithm and a 30 m DEM

Ground based biomass and satellite measures of land cover data were correlated with five primary terrain attributes calculated from a 30 m DEM yielding a range of responses with $r^2$ values up to 0.78. The primary terrain attributes were obtained using a grid-based Digital Elevation Model (DEM) and Terrain Analysis Program for Environmental Sciences -Grid version (TAPES-G). Drainage direction was calculated using the Rho8 algorithm and catchment area was computed using a multiple drainage direction technique with a slope-weighting algorithm. Although the Rho8 does not represent flow dispersion very accurately, it does simulate more realistic flow networks. However, the breaking up of parallel flow paths introduces many more cells without an upslope connection and this distorts the distribution of the contributing area. In addition, the randomization within the model potentially results in different flow directions with each model execution, which reduces the 'repeatability' of experimental data.

The five primary terrain attributes selected were drainage area, slope, aspect, tangential curvature and flow path length. Only drainage area and flow path length depended on the choice of drainage directions algorithm. The land cover data were ground measured biomass, and Landsat Thematic Mapper (TMSAT) derived Red and Near Infrared (NIR) reflectance data. NDVI values were included in the landcover data and were calculated by the ratio of NIR to Red reflectance values. A cubic correlation between biomass and aspect produced a $r^2 = 0.74$ (Figure 5.9a) and a quadratic correlation of TMSAT red waveband to tangential curvature gave a $r^2 = 0.78$ (Figure 5.10a).

The study concludes that in this low relief catchment there is a strong association between primary terrain attributes and both observed biomass and reflectance data. The terrain...
attributes depended on the DEM providing an accurate representation of surface shape and the choice of algorithm chosen within the TAPES-G model.

5.2.5 Sensitivity Analysis for March 1993 using different algorithms and DEM resolutions

Sensitivity study: Comparison between the Rho8 and DEMON algorithms in the TAPES-G model.

The DEMON (Digital Elevation Model Networks) developed by Costa-Cabral and Burges (1994) uses aspect defined from the DEM to route flow along stream tubes located in a spatially continuous manner to expand and contract with converging and diverging topography (Costa-Cabral and Burges 1994). Although it cannot allow flow dispersion in different directions, it does allow divergence and convergence and has no preferential directions. The assumptions in routing water using the DEMON method are arguably a better representation of actual flow.

The next two sections 5.2.5.1 and 5.2.5.2 examine the sensitivity of Rho8 and DEMON algorithm using a 30 m and 25 m DEM. Figure 5.12 shows water flowing in a stream tube (using the DEMON algorithm) where partial grids (depending on convergent and divergent surfaces) contribute to a specific grid cell.

**Figure 5.12 Water flow movement in a stream tube**

![Diagram of water flow movement in a stream tube](image)

Figure 5.12 (a) Example of two-dimensional, aspect-driven flow movement using the DEMON algorithm. (b) Influence matrix of pixel (1, 1). The numbers show the fraction of the area within pixel (1, 1) that is drained by a pixel. (c) Illustration of the physical meaning of the value 0.58 of pixel in figure 5.12b. (Costa-Cabral and Burges 1994)

5.2.5.1 Direct Sensitivity Test: Comparisons between the Rho8 and DEMON algorithm using a 30 m DEM

This section 5.2.5.1 is a direct sensitivity analysis where Rho8 and DEMON algorithms are compared with the same 30 m DEM. Results from TMSAT NDVI versus drainage area using a 30 m DEM and DEMON algorithm (figure 5.13).
Sites J6, B11 and B8 are distinctively different from Figure 5.6. Site J6 (Figure 5.13) is a better representation of the landscape as its position is at the base of a (south) facing slope and therefore would have a high drainage area. Site B8 (figure 5.13) is also considered to be a more accurate representation of the landscape as it is situated very close to the Lockyersleigh Creek and would therefore have a high drainage area. Site B11 is unusual and could represent a shallow depression in the landscape with a well drained soil substrate due to high percentage of brown biomass. At the 30 DEM resolution site B11 is unreliable and reduces the statistical significance of a curve fit. The cubic fit from Figure 5.9a is too dependent on extreme outliers such as site B11 (figure 5.13), therefore a model based on this statistical relationship would be unrealistic. The drainage algorithm Rho8 or DEMON does not influence the determination of slope or aspect. DEM accuracy and resolution determines the slope and aspect in terrain attribute models.
Figure 5.14 shows sites B11, B8, and J6 are producing different drainage areas depending on the algorithm chosen. These three sites are significant in that B11 and B8 are located close to streamlines (figure 2.20b), B8 and site J6 is located at the bottom of a slope (convergent site). It has been noted by Moore et al (1991) that primary terrain attributes can become unstable (i.e. have increasing error) close to the drainage lines. The DEMON algorithm is therefore considered a superior algorithm for this catchment as the three sites mentioned above gave higher drainage area values consistent with their physical location or proximity to streamlines, and convergent areas in this catchment.

The DEMON algorithm produced very similar correlation coefficients and statistical significance from TMSAT red and drainage area correlations as did the Rho8 algorithm. This is to be expected as the calculation of tangential curvature would not change between these two algorithms. This does confirm that the more divergent the flow (positive tangential curvature) the 'browner' the biomass.
Figure 5.15: Selected Results from the Sensitivity Analysis using a 30 m DEM and Two Different Water Routing (Drainage) Algorithms in TAPES-G

<table>
<thead>
<tr>
<th>Correlation</th>
<th>Equations</th>
<th>Rho8 algorithm 30 m DEM ( r^2 )</th>
<th>DEMON algorithm 30 m DEM ( r^2 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>TMSAT NDVI vs Drainage Area</td>
<td>Linear</td>
<td>0.06</td>
<td>0.13</td>
</tr>
<tr>
<td></td>
<td>Quadratic</td>
<td>0.58</td>
<td>0.21</td>
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<td></td>
<td>Cubic</td>
<td>0.58</td>
<td>0.64</td>
</tr>
<tr>
<td></td>
<td>Exponential</td>
<td>0.07</td>
<td>0.14</td>
</tr>
<tr>
<td>Biomass vs Drainage Area</td>
<td>Linear</td>
<td>0.05</td>
<td>0.016</td>
</tr>
<tr>
<td></td>
<td>Quadratic</td>
<td>0.05</td>
<td>0.051</td>
</tr>
<tr>
<td></td>
<td>Cubic</td>
<td>0.07</td>
<td>0.065</td>
</tr>
<tr>
<td></td>
<td>Exponential</td>
<td>0.06</td>
<td>0.004</td>
</tr>
<tr>
<td>TMSAT Red vs Drainage Area</td>
<td>Linear</td>
<td>0.01</td>
<td>0.051</td>
</tr>
<tr>
<td></td>
<td>Quadratic</td>
<td>0.02</td>
<td>0.054</td>
</tr>
<tr>
<td></td>
<td>Cubic</td>
<td>0.05</td>
<td>0.058</td>
</tr>
<tr>
<td></td>
<td>Exponential</td>
<td>0.01</td>
<td>0.043</td>
</tr>
<tr>
<td>TMSAT NIR vs Drainage Area</td>
<td>Linear</td>
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<td>0.006</td>
</tr>
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<td></td>
<td>Quadratic</td>
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<td>0.091</td>
</tr>
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<td></td>
<td>Cubic</td>
<td>0.32</td>
<td>0.330</td>
</tr>
<tr>
<td></td>
<td>Exponential</td>
<td>0.02</td>
<td>0.009</td>
</tr>
</tbody>
</table>

5.2.5.2 Sensitivity Test between the Rho8 with a 30 m DEM and the DEMON algorithm with a 25 m DEM

Section 5.25b is a sensitivity study between the Rho8 algorithm with 30 m DEM and the DEMON algorithm with 25 m DEM. The inputs for TAPES-G have been changed to a 25 m DEM and DEMON algorithm. Other specifications include the depressionless DEM containing \( x, y \) and \( z \) values, drainage direction calculated by DEMON and the output slopes calculated using finite difference algorithms.

Drainage area for site J6 and B11 displays the greatest variation between the two methods. This could be due to the random flow pattern in the Rho8 algorithm producing different flow networks. The greater density of flow connections produced by the Rho8 distorts the drainage area particularly in flat or low patches in the landscape. Site J6 is located at the base (south direction) of a north – south slope. The DEMON algorithm has allowed the flow to converge into a stream tube down this gradient where each pixel downstream of the source pixel has been added to the flow accumulation producing high drainage area.
Comparisons between figure 5.14 and 5.6 show the differences in the two different algorithms and two DEM resolutions. There are also other small variations in some of terrain attributes such as slope and aspect between the 25 m and 30 m DEM outputs. These variations could be caused by the superior interpolation techniques in ANUDEM (version 4.6a) and the small resolution change in the DEM resolution from 30 m to 25 m. DEMON algorithm are shown below.

5.2.6 Modelled results from March 1993 using the DEMON algorithm and a 25 m DEM

Figure 5.16 shows a selection of the specifications used in the next modelling results to determine the correlation between vegetation (biomass and satellite observations) and five terrain attributes.

Figure 5.16 Specifications selected for further exploratory plots

Selected specifications:

- 25 m DEM version 4.6a of ANUDEM
- TAPES-G using the DEMON algorithm
- TMSAT NDVI calculated using the raw satellite data (without rescaling)
- The correlation coefficient ($r^2$) with constant included

March 1993

Figure 5.17 NDVI vs Drainage Area

Figure 5.17 shows a general trend of increasing drainage area and increasing TMSAT NDVI for March 1993.
Figures 5.18a and 5.18b compare the TMSAT NDVI vs the slope at ground sites. The left graph includes two open woodland sites and the graph on the right side excludes the open woodland sites.

Figure 5.19a  Satellite data (TMSAT red) vs Tangential Curvature

Figure 5.19b Statistics for TMSAT red vs Tangential Curvature

Linear $r^2 = 0.63$ Significant F = 0.001
Quadratic $r^2 = 0.66$ Significant F = 0.003
Exponential $r^2 = 0.62$ Significant F = 0.001
Cubic $r^2 = 0.67$ Significant F = 0.009

Figure 5.19 represents sites such as J6 better under the finer resolution DEM (25 m) than Figure 5.10a with the 30 m DEM. Sites J6 and J3 are convergent sites as shown above. Figures 5.19 and 5.10a show similar trends, even though 5.10a used the Rho8 algorithm and a 30m DEM and 5.19 used the DEMON algorithm and a 25m DEM.
March 1993

Correlating Biomass vs Aspect

![Figure 5.20a](image) ![Figure 5.20b](image)

Table 5.20c  Statistics from Biomass vs Aspect Correlations

<table>
<thead>
<tr>
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<th></th>
<th></th>
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<tbody>
<tr>
<td>Linear</td>
<td>L = 0.48</td>
<td>L = 0.48</td>
</tr>
<tr>
<td>Quadratic</td>
<td>Q = 0.54</td>
<td>Q = 0.49</td>
</tr>
<tr>
<td>Cubic</td>
<td>C = 0.58</td>
<td>C = 0.69</td>
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<tr>
<td>Exponential</td>
<td>E = 0.47</td>
<td>E = 0.56</td>
</tr>
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</table>

<table>
<thead>
<tr>
<th>r²</th>
<th>d.f.</th>
<th>sig. F</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.48</td>
<td>10</td>
<td>0.012</td>
</tr>
<tr>
<td>0.54</td>
<td>9</td>
<td>0.029</td>
</tr>
<tr>
<td>0.58</td>
<td>8</td>
<td>0.060</td>
</tr>
<tr>
<td>0.47</td>
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<td>0.014</td>
</tr>
<tr>
<td>0.49</td>
<td>9</td>
<td>0.049</td>
</tr>
<tr>
<td>0.69</td>
<td>8</td>
<td>0.019</td>
</tr>
<tr>
<td>0.56</td>
<td>10</td>
<td>0.005</td>
</tr>
</tbody>
</table>

March 1993

Correlating Biomass vs Slope

![Figure 5.21a](image)
Figure 21b    Statistics from Biomass vs Slope

<table>
<thead>
<tr>
<th>Equation</th>
<th>$r^2$</th>
<th>d.f.</th>
<th>sig. F</th>
</tr>
</thead>
<tbody>
<tr>
<td>Linear</td>
<td>L = 0.215</td>
<td>14</td>
<td>0.070</td>
</tr>
<tr>
<td>Quadratic</td>
<td>Q = 0.221</td>
<td>13</td>
<td>0.198</td>
</tr>
<tr>
<td>Cubic</td>
<td>C = 0.221</td>
<td>12</td>
<td>0.375</td>
</tr>
<tr>
<td>Exponential</td>
<td>E = 0.373</td>
<td>14</td>
<td>0.012</td>
</tr>
</tbody>
</table>

Therefore, although the correlations of biomass and remotely sensed data against modelled terrain attributes can be lower using the DEMON algorithm and 25m DEM they are considered more accurate.

5.2.7 Summary (March 1993)
Summary: Correlations between vegetation (biomass and satellite data) and modelled terrain attributes using the DEMON algorithm and a 25 m DEM in TAPES-G model

Drainage Area
The natural log of drainage area shows increasing drainage area and increasing NDVI or greenness (5.17). Under dry conditions this makes physical sense where soil moisture is high under large drainage areas allowing photosynthesis to produce green biomass assuming there is sufficient radiation.

Aspect
As shown in the summary charts (figure 5.19b, 5.20c and 5.21b) correlations exist between vegetation (biomass and satellite data) and modelled terrain attributes. Biomass and aspect display a strong relationship with an $r^2 = 0.69$ for a cubic fit from $0$ to $360^\circ$ and $r^2 = 0.58$ for a cubic fit from $0$ to $180^\circ$. The impact of the western slope at approximately $270^\circ$ is shown on Figure 5.20b where sites A9, B8 have a relatively high biomass due to the radiation load. Sites A12 and A2 are close to north and this correlates well with their comparatively high biomass. Further investigation between aspect and biomass is discussed in chapter 7.

Slope
Biomass and slope resulted in an exponential fit with a $r^2 = 0.37$. Increasing slope showed a decrease in biomass with could be attributed to less soil moisture at sites with greater inclinations however, sites such as A12 and A9 are close to north and therefore possibly have a higher moisture requirement. Sites J10 and J11 move into open woodland and the same trend
of decreasing biomass with increasing slope exists again however this could be due to canopy shading reducing the photosynthetic capacity of the biomass. The 0.58 correlation coefficient between NDVI and slope is interesting. It shows increased greenness of the biomass with increasing slope. This is unusual and in conflict with the result of decreasing biomass with increasing slope (Figure 5.18). Therefore there must be sufficient moisture in the soils of the upper slopes to allow greenness to increase with slope but gravity driven drainage could reduce the density of the growth.

Tangential Curvature

Tangential curvature (Figure 5.19) identifies convergent and divergent flows and has produced some interesting results in this low relief catchment. Divergent flow sites produced less photosynthetically active (browner) biomass and this type of spatially specific detail could aid catchment management especially in dry seasons. Identifying areas prone to drying-out allows the reduction in erosion by less grazing pressure applied to such areas.

5.3 Terrain Attributes: September 1993

5.3.1 Results (September/October 1993)

Figures 5.22 to 5.26 show results of correlations between vegetation data (biomass and satellite observations) and four modelled terrain attributes during the September October period. The four terrain attributes are drainage area, slope, aspect and tangential curvature. Drainage area was calculated using the DEMON algorithm and a 25 m DEM. Aspect was examined from 0 to 360° and from 0 to 180°. Tangential curvature were examined at all sites (figure 5.26) and also at nine sites, that were common to the March 1993 data set (figure 5.27). Figure 5.27 correlates TMSAT band 3 with tangential curvature as there was a statistical significant correlation between these two variables during March 1993. However, the satellite reflectance data from band 5 (chapter 3, figures 3.23 –3.25) showed that during the September October period the surface was moist and water flow represented by tangential curvature may not effect biomass levels at this time of the year.

Given the low biomass levels indicated by the plant growth modelling (chapter 4) during this time of the year, little correlation between vegetation and terrain attributes are anticipated. Figure 4.1 showed that there were lower biomass levels and catchment biomass was less variable during the September period as opposed to the March periods and this could reduce vegetation and terrain relationships.
Biomass and Satellite Data Vs Drainage Area

Figures 5.22a

Figure 5.22b: Correlation of Drainage Area to Biomass and Satellite Data

<table>
<thead>
<tr>
<th>Biomass</th>
<th>TMSAT NDVI</th>
<th>TMSAT Band 3</th>
<th>TMSAT Band 4</th>
<th>TMSAT Band 5</th>
<th>TMSAT Band 7</th>
</tr>
</thead>
<tbody>
<tr>
<td>( r^2 )</td>
<td>( L = 0.056 )</td>
<td>( L = 0.035 )</td>
<td>( L = 0.018 )</td>
<td>( L = 0.063 )</td>
<td>( L = 0.146 )</td>
</tr>
<tr>
<td></td>
<td>( Q = 0.361 )</td>
<td>( Q = 0.186 )</td>
<td>( Q = 0.092 )</td>
<td>( Q = 0.161 )</td>
<td>( Q = 0.150 )</td>
</tr>
<tr>
<td></td>
<td>( C = 0.347 )</td>
<td>( C = 0.186 )</td>
<td>( C = 0.084 )</td>
<td>( C = 0.161 )</td>
<td>( C = 0.150 )</td>
</tr>
<tr>
<td></td>
<td>( E = 0.039 )</td>
<td>( E = 0.048 )</td>
<td>( E = 0.028 )</td>
<td>( E = 0.075 )</td>
<td>( E = 0.133 )</td>
</tr>
</tbody>
</table>

L = Linear, Q = Quadratic, C = Cubic, E = Exponential
September October 1993

Biomass and Satellite Data Vs Slope

Figures 5.23 a

- **Biomass vs Slope**
- **TMSAT NDVI vs Slope**
- **TMSAT Band 3 vs Slope**
- **TMSAT Band 4 vs Slope**
- **TMSAT Band 5 vs Slope**
- **TMSAT Band 7 vs Slope**

Figure 5.23b: Correlation of Slope to Biomass and Satellite Data

<table>
<thead>
<tr>
<th></th>
<th>Biomass</th>
<th>TMSAT NDVI</th>
<th>TMSAT Band 3</th>
<th>TMSAT Band 4</th>
<th>TMSAT Band 5</th>
<th>TMSAT Band 7</th>
</tr>
</thead>
<tbody>
<tr>
<td>$r^2$</td>
<td>L = 0.013</td>
<td>L = 0.014</td>
<td>L = 0.159</td>
<td>L = 0.108</td>
<td>L = 0.039</td>
<td>L = 0.000</td>
</tr>
<tr>
<td></td>
<td>Q = 0.040</td>
<td>Q = 0.024</td>
<td>Q = 0.252</td>
<td>Q = 0.111</td>
<td>Q = 0.040</td>
<td>Q = 0.003</td>
</tr>
<tr>
<td></td>
<td>C = 0.041</td>
<td>C = 0.142</td>
<td>C = 0.262</td>
<td>C = 0.185</td>
<td>C = 0.098</td>
<td>C = 0.004</td>
</tr>
<tr>
<td></td>
<td>E = 0.022</td>
<td>E = 0.012</td>
<td>E = 0.154</td>
<td>E = 0.115</td>
<td>E = 0.041</td>
<td>E = 0.001</td>
</tr>
</tbody>
</table>

L = Linear, Q = Quadratic, C = Cubic, E = Exponential
Biomass and Satellite Data Vs Aspect (0 360°)

Figures 5.24 a

Biomass vs Aspect

TMSAT NDVI vs Aspect

TMSAT Band 3 vs Aspect

TMSAT Band 4 vs Aspect

TMSAT Band 5 vs Aspect

TMSAT Band 7 vs Aspect

Figure 5.24b: Correlation of Aspect (0-360)° to Biomass and Satellite Data

<table>
<thead>
<tr>
<th>Biomass</th>
<th>TMSAT NDVI</th>
<th>TMSAT Band 3</th>
<th>TMSAT Band 4</th>
<th>TMSAT Band 5</th>
<th>TMSAT Band 7</th>
</tr>
</thead>
<tbody>
<tr>
<td>$r^2$</td>
<td>$r^2$</td>
<td>$r^2$</td>
<td>$r^2$</td>
<td>$r^2$</td>
<td>$r^2$</td>
</tr>
<tr>
<td>L = 0.000</td>
<td>L = 0.003</td>
<td>L = 0.024</td>
<td>L = 0.004</td>
<td>L = 0.047</td>
<td>L = 0.057</td>
</tr>
<tr>
<td>Q = 0.067</td>
<td>Q = 0.066</td>
<td>Q = 0.099</td>
<td>Q = 0.123</td>
<td>Q = 0.399</td>
<td>Q = 0.202</td>
</tr>
<tr>
<td>C = 0.480</td>
<td>C = 0.157</td>
<td>C = 0.125</td>
<td>C = 0.151</td>
<td>C = 0.401</td>
<td>C = 0.222</td>
</tr>
<tr>
<td>E = 0.003</td>
<td>E = 0.007</td>
<td>E = 0.019</td>
<td>E = 0.001</td>
<td>E = 0.041</td>
<td>E = 0.048</td>
</tr>
</tbody>
</table>

L = Linear, Q = Quadratic, C = Cubic, E = Exponential
Chapter 5. Terrain Analysis and Vegetation Data
Spatio-temporal Modelling of Biomass

September October 1993

Biomass and Satellite Data Vs Aspect (0 – 180°)

Figure 5.25a

![Figure 5.25a: Biomass vs Aspect (0-180) degrees](image)

![Figure 5.25a: TMSAT NDVI vs Aspect (0-180) degrees](image)

![Figure 5.25a: TMSAT Band 3 vs Aspect (0-180) degrees](image)

![Figure 5.25a: TMSAT Band 4 vs Aspect (0-180) degrees](image)

![Figure 5.25a: TMSAT Band 5 vs Aspect (0-180) degrees](image)

![Figure 5.25a: TMSAT Band 7 vs Aspect (0-180) degrees](image)

Figure 5.25b: Correlation of Aspect (0-180)° to Biomass and Satellite Data

<table>
<thead>
<tr>
<th>Biomass</th>
<th>TMSAT NDVI</th>
<th>TMSAT Band 3</th>
<th>TMSAT Band 4</th>
<th>TMSAT Band 5</th>
<th>TMSAT Band 7</th>
</tr>
</thead>
<tbody>
<tr>
<td>L = 0.048</td>
<td>L = 0.118</td>
<td>L = 0.109</td>
<td>L = 0.234</td>
<td>L = 0.476</td>
<td>L = 0.203</td>
</tr>
<tr>
<td>Q = 0.064</td>
<td>Q = 0.290</td>
<td>Q = 0.110</td>
<td>Q = 0.444</td>
<td>Q = 0.494</td>
<td>Q = 0.203</td>
</tr>
<tr>
<td>C = 0.182</td>
<td>C = 0.290</td>
<td>C = 0.127</td>
<td>C = 0.444</td>
<td>C = 0.503</td>
<td>C = 0.213</td>
</tr>
<tr>
<td>E = 0.037</td>
<td>E = 0.139</td>
<td>E = 0.120</td>
<td>E = 0.292</td>
<td>E = 0.468</td>
<td>E = 0.201</td>
</tr>
</tbody>
</table>

L = Linear, Q = Quadratic, C = Cubic, E = Exponential
Chapter 5. Terrain Analysis and Vegetation Data
Spatio-temporal Modelling of Biomass

September October 1993

Biomass and Satellite Data Vs Tangential Curvature

Figures 5.26a

Biomass vs Tangential Curvature
TMSAT NDVI vs Tangential Curvature

TMSAT Band 3 vs Tangential Curvature
TMSAT Band 4 vs Tangential Curvature

TMSAT Band 5 vs Tangential Curvature
TMSAT Band 7 vs Tangential Curvature

Figure 5.26b: Correlation of Tangential Curvature to Biomass and Satellite Data

<table>
<thead>
<tr>
<th>Biomass</th>
<th>TMSAT NDVI</th>
<th>TMSAT Band 3</th>
<th>TMSAT Band 4</th>
<th>TMSAT Band 5</th>
<th>TMSAT Band 7</th>
</tr>
</thead>
<tbody>
<tr>
<td>r²</td>
<td>r²</td>
<td>r²</td>
<td>r²</td>
<td>r²</td>
<td>r²</td>
</tr>
<tr>
<td>L = 0.030</td>
<td>L = 0.001</td>
<td>L = 0.000</td>
<td>L = 0.001</td>
<td>L = 0.005</td>
<td>L = 0.043</td>
</tr>
<tr>
<td>Q = 0.101</td>
<td>Q = 0.039</td>
<td>Q = 0.014</td>
<td>Q = 0.208</td>
<td>Q = 0.022</td>
<td>Q = 0.046</td>
</tr>
<tr>
<td>C = 0.180</td>
<td>C = 0.169</td>
<td>C = 0.123</td>
<td>C = 0.208</td>
<td>C = 0.080</td>
<td>C = 0.121</td>
</tr>
<tr>
<td>E = 0.039</td>
<td>E = 0.000</td>
<td>E = 0.000</td>
<td>E = 0.002</td>
<td>E = 0.009</td>
<td>E = 0.050</td>
</tr>
</tbody>
</table>

L = Linear, Q = Quadratic, C = Cubic, E = Exponential
### September October 1993

Figure 5.27 Statistics from TMSAT Band 3 red versus Tangential Curvature at nine sites that are common with the March 1993 data set.

<table>
<thead>
<tr>
<th>Correlation</th>
<th>Equation</th>
<th>$r^2$</th>
<th>Degrees of freedom</th>
<th>Sign. F</th>
</tr>
</thead>
<tbody>
<tr>
<td>TMSAT Red vs Tangent Curvature</td>
<td>Linear</td>
<td>0.013</td>
<td>11</td>
<td>0.707</td>
</tr>
<tr>
<td></td>
<td>Quadratic</td>
<td>0.137</td>
<td>10</td>
<td>0.478</td>
</tr>
<tr>
<td></td>
<td>Cubic</td>
<td>0.693</td>
<td>9</td>
<td>0.011</td>
</tr>
<tr>
<td></td>
<td>Exponential</td>
<td>0.014</td>
<td>11</td>
<td>0.696</td>
</tr>
</tbody>
</table>

Although the high correlation of 0.69 between TMSAT red band 3 and tangential curvature indicates a trend of increasing divergent flow and increasing brown biomass, the cubic fit is too heavily based on the two extreme values (sites J6 and A9). Slight changes in surface shape do effect the amount of water available for shallow rooted plants and this influences the biomass and specifically the amount of brown biomass at that patch or region. The satellite data (TMSAT red) however, does not statistically show support a cubic fit with the given ground sites. Site J6 indicates an area of high surface moisture (it is at the base of slope), where the available radiation cannot convert this water to green material. Site A9 appears to be an outlier where biomass is high for such a divergent site. This confirms that other terrain attributes such as aspect are having a compound effect at this site. The general trend (excluding sites J6 and A9) show increasing brown biomass at divergent sites and decreasing brown biomass at convergent sites.

#### 5.3.2 Summary: September 1993

### Summary of September-October 1993 biomass and satellite versus the terrain data sets

All sites for this sampling period consist of site averaged biomass values. Six new sites were also examined. Site J12 appears as an outlier in many graphs and this is located in open woodland and near the top of a ridge.

#### Drainage Area

Biomass and drainage area had a cubic fit $r^2 = 36$. Two points are influencing this cubic fit. One is site J12 that has a high biomass and a low drainage area. Possibly the surrounding trees are supplying/holding the surface moisture with less evaporation and the open
pasture/grassland. Site A11 on the other hand has a high drainage area and a correspondingly high biomass. Site A11 not only has a high drainage area but it also is slightly lower in elevation (similar to a depression) than the sites on either side of it along the transect. Therefore there may be some possible water storage capacity or some ability for this particular site (A11) to not only have a high drainage area but also to maintain its soil moisture capacity relative to its nearest neighbouring sites A12 and A10.

**Aspect**

Biomass related to both aspects 0-360° and 0 to 180°. Biomass versus aspect 0 to 360° showed a cubic fit of $r^2 = 0.48$ and biomass had a cubic fit of $r^2 = 0.40$ with TMSAT band 5. Biomass versus TMSAT also produced a similar curve fit. Biomass versus aspect 0-180° correlated to TMSAT 4 and 5 with $r^2$ values equaling 0.44 and 0.50 respectively. TMSAT NDVI showed an increase in greenness at approximately 270° (western slope) location, although the cubic fit was not statistically significant. TMSAT NDVI correlated with aspect (0-180°) with increasing departure from south showing an increasing in the greenness index.

**Tangential Curvature**

Biomass had a very weak cubic relationship with tangential curvature during this September October, where increasing tangential curvature or divergent flow increased biomass and close to zero tangential curvature biomass showed quite a bit of scatter. This weak correlation would suggest that during September there were high moisture levels and at some sites divergent flow increased biomass. However, site A11 that has negative tangential curvature (convergent flow) and the second highest biomass in figure 5.26 (biomass vs tangential curvature). By removing this outlier (site A11) and examining nine grass/pasture sites (Figure 5.27) the cubic result of biomass versus TMSAT band 3 produced $r^2$ equal to 0.69. TMSAT 4 and tangential curvature have a quadratic fit ($r^2 = 0.21$), where negative tangential curvature reduces TMSAT band 4 and as tangential curvature increases to 0.1 TMSAT 4 also begins to decrease suggesting there could be a critical value for this season or amount of rainfall and the landcover.

**Slope**

There were no statistically significant correlations between vegetation and slope during this September/October period.

### 5.4 Terrain Attributes and March 1994 Vegetation Data

Figures 5.28 to 5.32 show the correlations and statistical significance between vegetation (biomass and satellite data) and the four modelled terrain attributes.
5.4.1 Results (March 1994)

As stated earlier these results were based on a 25 m DEM resolution (figure 5.16). March 1994

Biomass and Satellite Data Vs Drainage Area

Figures 5.28a

Biomass vs Ln Drainage Area

TMSAT NDVI vs Ln Drainage Area

TMSAT Band 3 (red) vs Ln Drainage Area

TMSAT Band 4 vs Ln Drainage Area

TMSAT Band 5 vs Ln Drainage Area

TMSAT Band 7 vs Ln Drainage Area

Figure 5.28b: Correlation of Biomass and Satellite Data to Drainage Area

<table>
<thead>
<tr>
<th>Biomass</th>
<th>TMSAT NDVI</th>
<th>TMSAT Band 3</th>
<th>TMSAT Band 4</th>
<th>TMSAT Band 5</th>
<th>TMSAT Band 7</th>
</tr>
</thead>
<tbody>
<tr>
<td>$r^2$</td>
<td>$r^2$</td>
<td>$r^2$</td>
<td>$r^2$</td>
<td>$r^2$</td>
<td>$r^2$</td>
</tr>
<tr>
<td>L = 0.163</td>
<td>L = 0.017</td>
<td>L = 0.009</td>
<td>L = 0.045</td>
<td>L = 0.202</td>
<td>L = 0.103</td>
</tr>
<tr>
<td>Q = 0.167</td>
<td>Q = 0.025</td>
<td>Q = 0.012</td>
<td>Q = 0.060</td>
<td>Q = 0.209</td>
<td>Q = 0.128</td>
</tr>
<tr>
<td>C = 0.167</td>
<td>C = 0.025</td>
<td>C = 0.012</td>
<td>C = 0.060</td>
<td>C = 0.209</td>
<td>C = 0.127</td>
</tr>
<tr>
<td>E = 0.099</td>
<td>E = 0.019</td>
<td>E = 0.013</td>
<td>E = 0.046</td>
<td>E = 0.178</td>
<td>E = 0.096</td>
</tr>
</tbody>
</table>

L = Linear, Q = Quadratic, C = Cubic, E = Exponential
March 1994

Biomass and Satellite Data Vs Slope %

Figures 5.29 a

Figures 5.29 b: Correlation of Biomass and Satellite Data to Slope

<table>
<thead>
<tr>
<th>Biomass</th>
<th>TMSAT NDVI $r^2$</th>
<th>TMSAT Band 3 $r^2$</th>
<th>TMSAT Band 4 $r^2$</th>
<th>TMSAT Band 5 $r^2$</th>
<th>TMSAT Band 7 $r^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>L = 0.199</td>
<td>L = 0.035</td>
<td>L = 0.414</td>
<td>L = 0.114</td>
<td>L = 0.316</td>
<td>L = 0.160</td>
</tr>
<tr>
<td>Q = 0.299</td>
<td>Q = 0.103</td>
<td>Q = 0.428</td>
<td>Q = 0.194</td>
<td>Q = 0.459</td>
<td>Q = 0.182</td>
</tr>
<tr>
<td>C = 0.424</td>
<td>C = 0.165</td>
<td>C = 0.448</td>
<td>C = 0.257</td>
<td>C = 0.460</td>
<td>C = 0.234</td>
</tr>
<tr>
<td>E = 0.208</td>
<td>E = 0.063</td>
<td>E = 0.467</td>
<td>E = 0.125</td>
<td>E = 0.364</td>
<td>E = 0.192</td>
</tr>
</tbody>
</table>

_L = Linear, Q = Quadratic, C = Cubic, E = Exponential_
March 1994

**Biomass and Satellite Data Vs Aspect (0 - 360°)**

Figures 5.30 a

![Graphs showing biomass vs aspect](image)

**Figure 5.30b: Correlation of Biomass and Satellite Data to Aspect (0-360°)**

<table>
<thead>
<tr>
<th>Biomass</th>
<th>TMSAT NDVI</th>
<th>TMSAT Band 3</th>
<th>TMSAT Band 4</th>
<th>TMSAT Band 5</th>
<th>TMSAT Band 7</th>
</tr>
</thead>
<tbody>
<tr>
<td>r²</td>
<td>r²</td>
<td>r²</td>
<td>r²</td>
<td>r²</td>
<td>r²</td>
</tr>
<tr>
<td>L = 0.200</td>
<td>L = 0.124</td>
<td>L = 0.014</td>
<td>L = 0.004</td>
<td>L = 0.008</td>
<td>L = 0.111</td>
</tr>
<tr>
<td>Q = 0.223</td>
<td>Q = 0.246</td>
<td>Q = 0.085</td>
<td>Q = 0.004</td>
<td>Q = 0.243</td>
<td>Q = 0.242</td>
</tr>
<tr>
<td>C = 0.244</td>
<td>C = 0.268</td>
<td>C = 0.094</td>
<td>C = 0.083</td>
<td>C = 0.350</td>
<td>C = 0.253</td>
</tr>
<tr>
<td>E = 0.223</td>
<td>E = 0.078</td>
<td>E = 0.007</td>
<td>E = 0.008</td>
<td>E = 0.002</td>
<td>E = 0.082</td>
</tr>
</tbody>
</table>

_L = Linear, Q = Quadratic, 04C = Cubic, E = Exponential_
Biomass and Satellite Data Vs Aspect (0-180°)

Figures 5.31a

Biomass vs Aspect (0-180) degrees
TMSAT NDVI vs Aspect (0-180) degrees
TMSAT Band 3 (red) vs Aspect (0-180) degrees
TMSAT Band 4 vs Aspect (0-180) degrees
TMSAT Band 5 vs Aspect (0-180) degrees
TMSAT Band 7 vs Aspect (0-180) degrees

Figure 5.31b: Correlation of Biomass and Satellite Data to Aspect (180°)

<table>
<thead>
<tr>
<th>Biomass</th>
<th>TMSAT NDVI</th>
<th>TMSAT Band 3</th>
<th>TMSAT Band 4</th>
<th>TMSAT Band 5</th>
<th>TMSAT Band 7</th>
</tr>
</thead>
<tbody>
<tr>
<td>r²</td>
<td>r²</td>
<td>r²</td>
<td>r²</td>
<td>r²</td>
<td>r²</td>
</tr>
<tr>
<td>L = 0.136</td>
<td>L = 0.251</td>
<td>L = 0.000</td>
<td>L = 0.317</td>
<td>L = 0.222</td>
<td>L = 0.053</td>
</tr>
<tr>
<td>Q = 0.180</td>
<td>Q = 0.320</td>
<td>Q = 0.000</td>
<td>Q = 0.396</td>
<td>Q = 0.222</td>
<td>Q = 0.082</td>
</tr>
<tr>
<td>C = 0.506</td>
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<td>C = 0.042</td>
<td>C = 0.459</td>
<td>C = 0.222</td>
<td>C = 0.100</td>
</tr>
<tr>
<td>E = 0.092</td>
<td>E = 0.245</td>
<td>E = 0.000</td>
<td>E = 0.359</td>
<td>E = 0.225</td>
<td>E = 0.057</td>
</tr>
</tbody>
</table>

L = Linear, Q = Quadratic, C = Cubic, E = Exponential


Chapter 5. Terrain Analysis and Vegetation Data
Spatio-temporal Modelling of Biomass

March 1994

Biomass and Satellite Data Vs Tangential Curvature

Figures 5.32 a

Biomass vs Tangential Curvature

TMSAT NDVI vs Tangential Curvature

TMSAT Band 3 (red) vs Ln Drainage Area

TMSAT Band 4 vs Tangential Curvature

TMSAT Band 5 vs Tangential Curvature

TMSAT Band 7 vs Tangential Curvature

Figure 5.32b: Correlation of Biomass and Satellite Data to Tangential Curvature

<table>
<thead>
<tr>
<th>Biomass</th>
<th>TMSAT NDVI</th>
<th>TMSAT Band 3</th>
<th>TMSAT Band 4</th>
<th>TMSAT Band 5</th>
<th>TMSAT Band 7</th>
</tr>
</thead>
<tbody>
<tr>
<td>r²</td>
<td>r²</td>
<td>r²</td>
<td>r²</td>
<td>r²</td>
<td>r²</td>
</tr>
<tr>
<td>L = 0.023</td>
<td>L = 0.004</td>
<td>L = 0.012</td>
<td>L = 0.008</td>
<td>L = 0.040</td>
<td>L = 0.036</td>
</tr>
<tr>
<td>Q = 0.063</td>
<td>Q = 0.005</td>
<td>Q = 0.208</td>
<td>Q = 0.195</td>
<td>Q = 0.190</td>
<td>Q = 0.091</td>
</tr>
<tr>
<td>C = 0.089</td>
<td>C = 0.314</td>
<td>C = 0.277</td>
<td>C = 0.568</td>
<td>C = 0.322</td>
<td>C = 0.229</td>
</tr>
<tr>
<td>E = 0.030</td>
<td>E = 0.004</td>
<td>E = 0.021</td>
<td>E = 0.003</td>
<td>E = 0.055</td>
<td>E = 0.051</td>
</tr>
</tbody>
</table>

L = Linear, Q = Quadratic, C = Cubic, E = Exponential
5.4.2 Summary (March 1994)

Summary of March 1994 biomass, satellite and terrain data sets
As stated earlier these results were calculated using the 25 m DEM and the DEMON algorithm.

Aspect
Biomass did relate to aspect (180° and 360°) $r^2$ values up to 0.51 and aspect correlated to TMSAT bands 4, 5 7 and TMSAT NDVI. NDVI increased with departure from south as shown in the aspect graph from 0 to 180°.

Drainage Area
Biomass appeared to decrease with increasing drainage area however this was not statistically significant, with one high drainage value creating this trend. TMSAT 5 and 7 increased with increasing drainage area. Wetness index studies following will help to understand this process.

Slope
Slope had a weak cubic fit with biomass ($r^2 = 0.42$), with increasing slope decreasing biomass. This relationship may be describing the subtle hydrologic process where water is flowing away from the surface (either infiltration, overland flow, near subsurface flow) where small increases in slope reduce the soil moisture levels. Slope had no such relationship in September October with increasing slope increasing biomass suggesting sufficient water was available. March 1993 was similar to March 1994 where increasing slope decreased biomass. However for both March 1993 and 1994 NDVI increased with slope suggesting the causative effect may not be slope but vegetation type, aspect, or a combination of a terrain shape and hydrologic processes determining water availability.

Tangential curvature
Biomass did not statistically correlate with tangential curvature during March 1994 as it did in March 1993. This lack of correlation in March 1994 could be due the preceding climatic conditions. That is, the five months preceding March 1994 had lower moisture levels and this decreased catchment biomass levels. Correlations between biomass and modelled terrain attributes are easier to discriminate with higher biomass levels as in March 1993. Tangential curvature correlates weakly to TMSAT bands 3, 4, 5 and 7 and TMSAT NDVI during March 1994. The weak correlation between satellite data and modelled terrain attributes was possible as the satellite data captured the vegetation to moisture correlation at the time of the overpass. Biomass reflects hydrologic principles by showing that preceding rainfall, terrain shape and water flow directly effect biomass even in this low relief catchment.
5.5 Summary and Conclusions

5.5.1 Summary charts of biomass, satellite and terrain correlations

Following are summary charts showing the correlations between biomass and satellite data against terrain attributes over three time periods. Figure 5.33 has the correlation coefficient set where $r^2$ as $\geq 0.20$, Figure 5.34 $r^2$ as $\geq 0.40$ and figure 5.35 have $r^2$ as $\geq 0.50$. All these results were calculated using the 25 m DEM resolution and the DEMON algorithm in TAPES-G.

Table 5.33 Statistical summary

<table>
<thead>
<tr>
<th>March 1993</th>
<th>October 1993</th>
<th>March 1994</th>
</tr>
</thead>
<tbody>
<tr>
<td>Biomass vs Aspect (180°)</td>
<td>Biomass vs TMSAT 7</td>
<td>Biomass vs Aspect (360°)</td>
</tr>
<tr>
<td>Biomass vs Aspect (360°)</td>
<td>Biomass vs Drainage Area</td>
<td>Biomass vs Drainage Area</td>
</tr>
<tr>
<td>Biomass vs Slope</td>
<td>Biomass vs Aspect</td>
<td>Biomass vs Slope</td>
</tr>
<tr>
<td>Biomass vs Tangential C.</td>
<td>TMSAT 3 vs Tangential C.</td>
<td>NDVI, 4, 5.7 vs Tangential C.</td>
</tr>
<tr>
<td>TMSAT 3 vs Tangential C.</td>
<td>TMSAT 4 vs Tangential C.</td>
<td>NDVI, TMSAT 5,7 vs Aspect (360°)</td>
</tr>
<tr>
<td>NDVI vs Drainage Area</td>
<td>TMSAT 5 vs Aspect (360°)</td>
<td>NDVI TMSAT 4,5 vs Aspect (180°)</td>
</tr>
<tr>
<td>NDVI vs Slope</td>
<td>TMSAT 4,5,7 vs Aspect (180°)</td>
<td>TMSAT 3,4,5,7 vs Slope</td>
</tr>
<tr>
<td>TMSAT 3 vs Slope</td>
<td>TMSAT 3 vs Slope</td>
<td>TMSAT 5 vs Drainage Area</td>
</tr>
</tbody>
</table>

Table 5.34 Statistical Summary

where the correlation coefficient has an $r^2 \geq 0.40$, NDVI * represents grass sites only

<table>
<thead>
<tr>
<th>March 1993</th>
<th>October 1993</th>
<th>March 1994</th>
</tr>
</thead>
<tbody>
<tr>
<td>Biomass vs Aspect (180°)</td>
<td>Biomass vs Aspect (360°)</td>
<td>Biomass vs Aspect (180°)</td>
</tr>
<tr>
<td>Biomass vs Aspect (360°)</td>
<td>Biomass vs TMSAT 5</td>
<td>Biomass vs Slope</td>
</tr>
<tr>
<td>TMSAT 3 vs Tangential C.</td>
<td>TMSAT 3 vs Tangential C.</td>
<td>TMSAT 4 vs Tangential C.</td>
</tr>
<tr>
<td>NDVI * vs Slope</td>
<td>TMSAT 4 vs Aspect (180°)</td>
<td>TMSAT 4 vs Aspect (180°)</td>
</tr>
<tr>
<td>TMSAT 5 vs Aspect (180°)</td>
<td>TMSAT 5 vs Slope</td>
<td>TMSAT 3 vs Slope</td>
</tr>
<tr>
<td>TMSAT 3 vs Slope</td>
<td>TMSAT 5 vs Drainage Area</td>
<td>TMSAT 5 vs Slope</td>
</tr>
</tbody>
</table>
Table 5.35 Statistical Summary

where the correlation coefficient has an $r^2 \geq 0.50$, NDVI * represents grass sites only

<table>
<thead>
<tr>
<th>March 1993</th>
<th>October 1993</th>
<th>March 1994</th>
</tr>
</thead>
<tbody>
<tr>
<td>Biomass vs Aspect (180°)</td>
<td>TMSAT 3 vs Tangential C.</td>
<td>Biomass vs Aspect (180°)</td>
</tr>
<tr>
<td>Biomass vs Aspect (360°)</td>
<td>TMSAT 5 vs Aspect (180°)</td>
<td>TMSAT 4 vs Tangential C.</td>
</tr>
<tr>
<td>TMSAT 3 vs Tangential C.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>NDVI * vs Slope</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Figure 5.36 shows the correlations which were common between any two time periods and when the correlation coefficient had $r^2$ exceeding 0.20.

Figure 5.36 Statistical Summary

<table>
<thead>
<tr>
<th>Correlations common to March '93 &amp; Sept '93</th>
<th>Correlations common to Sept '93 and March '94</th>
<th>Correlations common to March '93 &amp; March '94</th>
</tr>
</thead>
<tbody>
<tr>
<td>Biomass vs Aspect</td>
<td>Biomass vs Aspect</td>
<td>Biomass vs Aspect</td>
</tr>
<tr>
<td>TMSAT 3 vs Tangential C.</td>
<td>Biomass vs Drainage Area</td>
<td>Biomass vs Slope</td>
</tr>
<tr>
<td></td>
<td>TMSAT 3, 4 vs Tangential C.</td>
<td>TMSAT 3 vs Tangential C.</td>
</tr>
<tr>
<td></td>
<td>TMSAT 5 vs Aspect (360°)</td>
<td>NDVI, 4, 5 vs Aspect (180°)</td>
</tr>
<tr>
<td></td>
<td>NDVI, 4, 5 vs Aspect (180°)</td>
<td>TMSAT 3 vs Slope</td>
</tr>
<tr>
<td></td>
<td>TMSAT 3 vs Slope</td>
<td>NDVI vs Tangential C.</td>
</tr>
</tbody>
</table>

The correlations common to all 3 time periods using $r^2$ as $\geq 0.20$ were:

- Biomass vs Aspect (180° and 360°)
- TMSAT 3 vs Tangential Curvature

The correlations common to all 3 time periods using $r^2$ as $\geq 0.40$ were:

- Biomass vs Aspect (180° or 360°)
- TMSAT 3 or TMSAT 4 vs Tangential Curvature

The correlation common to all 3 time periods using $r^2$ as $\geq 0.50$ were:

- TMSAT 3 or TMSAT 4 vs Tangential Curvature
5.5.2 Conclusions from correlations between biomass, satellite data and terrain attributes.

- March 1993 had the best correlations with primary terrain attributes. The selected primary terrain attributes such as tangential curvature; drainage area and aspect are more critical under wet conditions. These correlations between biomass and terrain attributes occurred over the six month growth accumulation period prior to March 1993.
- Moisture levels were higher during March 1993 and September 1993 than the March 1994 growth period (Chapter 3, figures 3.23, 3.28, Chapter 4., figure 4.3). Therefore the high moisture and biomass levels in March 1993 produced better correlations between biomass and terrain attributes.
- Tangential curvature matches with TMSAT 3 for brown material with the highest correlation, while tangential curvature also correlates for September 1993 and March 1994 but with a lower correlation coefficient.
- Correlations between tangential curvature and TMSAT 4 and NIR in September 1993 suggests the surface cover is greener.
- Optimal conditions for maximum density of grass and pasture does not appear to have been achieved at any of the three time periods in this study.
- Biomass relates very weakly to aspect in September 1993 due to zero growth (results from GROWEST model Chapter 4) during this period.
- Slope as a single parameter is not sufficient to determine TMSAT NDVI (greenness) or photosynthetic information about biomass.
- During the September/October 1993 period there was no relationship between the satellite and biomass data, due to the dormancy of the grass and pasture land where growth had little variation
- The most accurate correlations between biomass, satellite data and the modelled terrain drainage analysis were produced using a 25m DEM resolution and the DEMON algorithm in TAPES-G (see Chapter 5., figure 5.16).
- DEM at the 25 m resolution was selected as the most appropriate resolution for comparisons between vegetation (biomass and satellite data) and modelled terrain attributes in this small catchment. The 25 m DEM matched the satellite data, as both were griddded to the same resolution.
Chapter 6.

Wetness Index
CHAPTER 6. WETNESS INDEX

6.1 Introduction
   6.1.1 Introduction
   6.1.2 Questions raised

6.2 March 1993
   6.2.1 Results – March 1993
   6.2.2 Summary – March 1993

6.3 September 1993
   6.3.1 Results – September 1993
   6.3.2 Summary – September 1993

6.4 March 1994
   6.4.1 Results – March 1994
   6.4.2 Summary – March 1994

6.5 Summary
   6.5.1 Summary
   6.5.2 Climatic conditions March 1993
   6.5.3 Discussion of questions explored in this chapter
   6.5.4 Chapter summary for chapters 5 and 6
Chapter 6. Wetness Index
Spatio-temporal Modelling of Biomass

6.1 Introduction

6.1.1 Introduction

This chapter is based primarily on the research initiated by the late Professor Moore (Moore et al 1986, 1988, and 1991). The wetness index concept arose out of the research of Sivapalan et al (1987) which was based on the theory of Beven and Kirkby (1979). Wetness indices essentially predict organized spatial fields of soil moisture (Western et al 1999). The association between runoff and spatial variation in soil moisture and topographic convergence has also been examined (Anderson and Burt 1987a, O'Loughlin 1981, and Barling 1994).

Baring et al (1994) has stated that in catchments with low relief and shallow slopes (< 6°) the effect of elevation is reduced and the soil water matrix potential becomes important. It has been suggested that the distribution of the soil water potential and simple partial area indices may not be applicable in some low relief topographic catchments (Anderson and Kneale 1982). Therefore, the spatial distribution of soil water content may not correlate to the wetness index in the Lockyersleigh catchment. Care must be taken when using a static wetness index to determine dynamic processes over time (Burt and Butcher 1986). However, the wetness index has been investigated in this thesis because soil moisture is critical to biomass and measured soil moisture data were not available.

Other contributions to this subject include Western et al (1998) who examined the geostatistical analysis of field data, Grayson and Western (1998) who compared field sampling regimes for reliable spatial estimates of soil moisture and Crave and Gascuel-Odoux (1997) who investigated the spatio-temporal influence of topography on surface soil moisture. Bloschl et al (1995) concluded that in the Cowetta catchment (17 km²) large scale variability of a representative elementary (REA) is due to precipitation, whereas small scale variability is related to soil characteristics and topography. More recently Western et al (1999) examined the spatial organisation of soil moisture in relation to terran indices during dry and non-dry periods.

Research into understanding soil moisture has also involved the use of remotely sensed data. One limiting factor in remotely sensed data is biomass saturation limits. This is where the backscatter no longer scales with the biomass (Imhoff 1993). Other studies by Lin et al (1994) found that catchment averaged soil moisture estimated by microwave sensors were in good agreement with ground measurements. The experimental catchment is 7.4 km². The microwave sensors (Push Broom Microwave Radiometer and Synthetic Aperture Radar) reflected the temporal variation in
soil moisture. They also concluded that hydrologic model results initialised by streamflow records yielded wetter estimates than ground observations. All soil moisture estimates were registered to 30m x 30m DEM for comparative studies. Predictions from the hydrologic model and the SAR signals correlated with the soil moisture patterns along the transects. However, the apparent soil moisture variations between the near stream, pasture and corn areas were not detected by either technique (Lin et al 1994). In this case study, biomass and satellite data (Thematic Mapper Satellite with a 25 m resolution) were correlated to the static wetness index calculated using a 25m DEM in TAPES-G (chapters 5 and 6).

One of the steady state assumptions is that the upslope area is an appropriate surrogate for the subsurface flow rate (Baring et al 1994). This may not be critical when assessing biomass or grasses and pastures as the soil depth or soil moisture level utilised is small with shallow rooted plants (approximately less than one metre) and the slope of the surface is not steep. Therefore the rate of flow may be small but still determined by rainfall events. Given that the calculation of the wetness index is based on the assumption that the topographic surface is the similar to the subsurface layers then the wetness index is an indicator of soil moisture suitable in low relief catchments.

The second assumption is that the hydraulic conductivity at any point declines exponentially with depth. This assumption is used on a wide range of soils however, transmissivity is not the same at depositional sites or where water flows along an unconformity and therefore must be carefully considered at such locations. Keeping this parameter spatially invariant assumes that the effects of ridges and flats on soil water processes are the same. It also ignores geomorphic processes/structures such as piping. Within the Lockyersleigh catchment depositional sites may be able to be identified by the negative tangential curvature (chapter 5).

The third assumption is that steady state conditions apply and there is uniform recharge to the groundwater. Such steady state conditions are more often found under humid conditions. The average depth to water table over the catchment equation can be arranged as:

\[ f(Z_{avg} - Z_t) = \{ln(a/s) - \lambda_1\} - \{lnT_o - lnT_e\} \]  

where:
- \( Z_{avg} \) is the average depth to water table
- \( Z_t \) is the topographic component
- \( a/s \) is the soil component
- \( \lambda_1 \) is the topographic component
- \( T_o \) is the soil component
- \( T_e \) is the topographic component

\( f \) is a function of the depth to water table and topographic conditions.
Chapter 6. Wetness Index
Spatio-temporal Modelling of Biomass

where:

\[ f = \text{function of the difference between the local and catchment average wetness index and} \]
\[ \text{the local and catchment average transmissivity} \]
\[ Z_{\text{avg}} = \text{average water table} \]
\[ Z_i = \text{water table point at} \]
\[ \lambda = \text{the catchment average } \ln (a/s) \]
\[ T_e = \text{the catchment average log profile transmissivity } \ln T_e = \int_0^a \ln(a/s) \, da \]

(Moore and Wilson 1992, Spatial and temporal variability in catchment hydrology, course notes 1998)

This equation calculates the difference between the average water table depth and the depth at point \( Z_i \), as a function of the difference between the local and catchment average wetness index and the local and catchment average transmissivity. It is common to assume that the spatial variation of \( T \) is unimportant relative to the spatial variation of the topographic wetness index. The index can then be interpreted as a measure of relative depth to the water table, with large values representing shallower water table according to equation 6.1 (Water Resource Foundation of Australia, short course notes 1998).

Wetness Index as defined by Bevan and Kirkby (1979) and used by Li Zhang et al (1996) is defined as:

\[ W = \ln (A_s \tan \beta) \]  
\[ (6.2) \]

where

\[ A_s = \text{specific catchment area (} m^2 m^{-1} \) \]
\[ \beta = \text{is the slope angle} \]

This wetness index has been used to detect soil erosion Li Zhang et al (1996). Moore et al (1986) used two and three dimensional models based on this equation to estimate sediment transport capacity at all points within a 3D catchment. The aim was to predict zones and potential zones of erosion using a mass-balance of the material in and out of successive contour elements. Zhang et al 1996 stated that the wetness index was a useful predictor as it combines contextual and site information via the upslope catchment area and slope. The limitations with the wetness index approach are that it has only has been validated at fine scales. The catchment scales range from 0.63 ha (Nyberg 1996) to 27 km\(^2\) (Grayson and Western 1998) using a 20 m x 10 m grid. The wetness index was calculated in this thesis using
Chapter 6. Wetness Index
Spatio-temporal Modelling of Biomass

\[ W = \ln \left( \frac{A}{\text{flow width} \times \text{cell size} \times \text{slope}} \right) \]  \hspace{1cm} (6.3)

where \( A \) = specific catchment area (calculated by TAPES-G) using the DEMON algorithm (chapter 5)

\( \text{flow width} \) = calculated by TAPES-G

\( \text{slope} \) = calculated by TAPES-G

One of the critical hydrologic processes in this catchment is the effect that catchment 'drying-out' has on biomass. Water stress affects all types of vegetation however, different biomass have different response curves. Wetness index can identify dry areas in a catchment. The following hypotheses are explored in this chapter to help understand hydrologic processes and their influence on biomass.

### 6.1.2 Questions explored using the Wetness Index

1. Does biomass increase with increasing wetness index?
2. Does the wetness index at Site C have less spatial variation than the other sites and therefore reflects lower soil moisture variability in more humid environment.
3. Is rainfall significant in determining whether the wetness index is related to biomass?
4. Can a range of critical wetness index values be identified where biomass decreases with an increasing wetness index?

### 6.2 March 1993

#### 6.2.1 Results - March 1993

Section 6.2.1 shows the correlation and statistical significance of relationships between vegetation (biomass and satellite data) and wetness indices. Figure 6.1a show plots of vegetation measures versus the wetness index at 12 sites for March 1993. The curve of best fit shown in each plot is indicated by the curve with the highest \( r^2 \) in figure 6.1b. No curve is plotted if \( r^2 \) exceed 0.08. Figure 6.2a and 6.2b show the same analysis for 63 sites, for which biomass was not generally available.
Chapter 6. Wetness Index
Spatio-temporal Modelling of Biomass

Biomass and Satellite Data vs Wetness Index: March 1993, 12 sites

Figures 6.1 a

Figures 6.1 b: Correlation of Biomass and Satellite Data to Wetness Indices

<table>
<thead>
<tr>
<th>Biomass</th>
<th>TMSAT NDVI</th>
<th>TMSAT Band 3</th>
<th>TMSAT Band 4</th>
<th>TMSAT Band 5</th>
<th>TMSAT Band 7</th>
</tr>
</thead>
<tbody>
<tr>
<td>r²</td>
<td>r²</td>
<td>r²</td>
<td>r²</td>
<td>r²</td>
<td>r²</td>
</tr>
<tr>
<td>L = 0.051</td>
<td>L = 0.006</td>
<td>L = 0.000</td>
<td>L = 0.005</td>
<td>L = 0.072</td>
<td>L = 0.097</td>
</tr>
<tr>
<td>Q = 0.188</td>
<td>Q = 0.013</td>
<td>Q = 0.071</td>
<td>Q = 0.019</td>
<td>Q = 0.210</td>
<td>Q = 0.240</td>
</tr>
<tr>
<td>C = 0.191</td>
<td>C = 0.013</td>
<td>C = 0.086</td>
<td>C = 0.019</td>
<td>C = 0.220</td>
<td>C = 0.254</td>
</tr>
<tr>
<td>E = 0.118</td>
<td>E = 0.008</td>
<td>E = 0.000</td>
<td>E = 0.008</td>
<td>E = 0.072</td>
<td>E = 0.092</td>
</tr>
</tbody>
</table>
March 1993

Wetness Index March 1993: 63 Sites in catchment.

**Biomass and Satellite Data vs Wetness Index**

**Figures 6.2 a**

- **NDVI vs Wetness Index (63 sites)**
- **TMSAT Band 3 vs Wetness Index**
- **TMSAT Band 4 vs Wetness Index**
- **TMSAT Band 5 vs Wetness Index**
- **TMSAT Band 7 vs Wetness Index**

**Figure 6.2b: Correlation of Satellite Data to Wetness Indices: March 1993**

<table>
<thead>
<tr>
<th>TMSAT NDVI R²</th>
<th>TMSAT Band 3 R²</th>
<th>TMSAT Band 4 R²</th>
<th>TMSAT Band 5 R²</th>
<th>TMSAT Band 7 R²</th>
</tr>
</thead>
<tbody>
<tr>
<td>L = 0.003</td>
<td>L = 0.003</td>
<td>L = 0.000</td>
<td>L = 0.008</td>
<td>L = 0.004</td>
</tr>
<tr>
<td>Q = 0.017</td>
<td>Q = 0.037</td>
<td>Q = 0.006</td>
<td>Q = 0.040</td>
<td>Q = 0.035</td>
</tr>
<tr>
<td>C = 0.033</td>
<td>C = 0.041</td>
<td>C = 0.013</td>
<td>C = 0.041</td>
<td>C = 0.037</td>
</tr>
<tr>
<td>E = 0.002</td>
<td>E = 0.003</td>
<td>E = 0.000</td>
<td>E = 0.007</td>
<td>E = 0.004</td>
</tr>
</tbody>
</table>

L = Linear, Q = Quadratic, C = Cubic, E = Exponential
Chapter 6. Wetness Index
Spatio-temporal Modelling of Biomass

6.2.2 Summary – March 1993

Biomass and Satellite Data versus Wetness Indices: March 1993

Site J6 showed reduced biomass under high wetness index values. The DEMON algorithm and a 25 m DEM were used in TAPES-G to calculate the specific catchment area (equation 6.3). Hydrologically, the specific catchment area $A_c$ is a measure of surface or shallow subsurface runoff at a given point on the landscape, and it integrates the effects of upslope contributing area and catchment convergence and divergence and runoff (Moore et al 1991). The DEMON algorithm produced a high drainage area index at site J6 (chapter 5, figure 5.17) and this makes physical sense, as it is located in valley (convergent site, with negative tangential curvature). The alternative Rho8 algorithm showed site J6 with a much lower drainage area (chapter 5, figure 5.6) which is not consistent with its topographic location. The trend between wetness index and biomass is best shown with the 12 sites where biomass increases then decreases with increased wetness values.

TMSAT bands 5 and 7 also show a similar trends where the reflection increases up to approximately 9 (wetness index value) then decreases. This trend suggests that the biomass cannot utilise the water/soil moisture to increase its productivity under these environmental conditions once the wetness index exceeds the value of 9.

Using 63 sites within the catchment the statistical significance levels are considerably lower. This is due to increased variability between sites. Site A10 (1.10) appears as an outlier and although its drainage area (993.84) is comparatively low when compared to site A11 (1.11), it has a northwesterly aspect (approximately 252°) and divergent flow (+0.049). Site A11 (1.11) has a southerly aspect (45°), same divergent flow (+0.049) but a large drainage area (785176.25). However, both A10 and A11 have similar biomass with large variations in wetness index. The large difference in satellite reflectance values could be that at the time of the satellite overpass, site A10 was drying out, while site A11 was wet or an inaccurate measurement.

6.3 September 1993

Section 6.3.1 shows the correlation and statistical significance of relationships between vegetation (biomass and satellite data) and wetness indices. Figure 6.3a show plots of vegetation measures versus the wetness index during September 1993. The curve of best fit shown in each plot is indicated by the curve with the highest $r^2$ in figure 6.3b. No curve is plotted if $r^2$ is less than 0.08.
6.3.1 Results – September 1993

Biomass and Satellite Data versus Wetness Index

Figures 6.3a

- Biomass vs Wetness Index
- TMSAT NDVI vs Wetness Index
- TMSAT Band 3 vs Wetness Index
- TMSAT Band 4 vs Wetness Index
- TMSAT Band 5 vs Wetness Index
- TMSAT Band 7 vs Wetness Index

Figure 6.3b: Statistical summary of the correlation of biomass and satellite data with Wetness Index

<table>
<thead>
<tr>
<th>Biomass</th>
<th>TMSAT NDVI</th>
<th>TMSAT Band 3</th>
<th>TMSAT Band 4</th>
<th>TMSAT Band 5</th>
<th>TMSAT Band 7</th>
</tr>
</thead>
<tbody>
<tr>
<td>$r^2$</td>
<td>$r^2$</td>
<td>$r^2$</td>
<td>$r^2$</td>
<td>$r^2$</td>
<td>$r^2$</td>
</tr>
<tr>
<td>L = 0.027</td>
<td>L = 0.045</td>
<td>L = 0.013</td>
<td>L = 0.086</td>
<td>L = 0.035</td>
<td>L = 0.002</td>
</tr>
<tr>
<td>Q = 0.378</td>
<td>Q = 0.071</td>
<td>Q = 0.120</td>
<td>Q = 0.089</td>
<td>Q = 0.110</td>
<td>Q = 0.107</td>
</tr>
<tr>
<td>C = 0.364</td>
<td>C = 0.094</td>
<td>C = 0.131</td>
<td>C = 0.144</td>
<td>C = 0.196</td>
<td>C = 0.116</td>
</tr>
<tr>
<td>E = 0.020</td>
<td>E = 0.049</td>
<td>E = 0.017</td>
<td>E = 0.088</td>
<td>E = 0.035</td>
<td>E = 0.002</td>
</tr>
</tbody>
</table>
6.3.2 Summary September 1993

Biomass and Satellite Data versus Wetness Index

September and October for this region are classified as part of the 'growing season' however they are preceded by winter and therefore growth at Lockyersleigh is still at low levels. The wetness index values for this season ranged between 1 and 16 with most values falling between 6 and 12. Biomass and wetness index produced $r^2 = 0.38$ with a quadratic fit where increasing wetness index and increased biomass. Site A11 (1.11) is strongly influencing by this relationship, where this site advantageously use the its large drainage area and wetness index with temperature and solar radiation allowing growth in this period/season. However, this site could also be considered an outlier, as radiation and temperature levels are low at this time of the year (chapter 4, figures 4.9 and 4.23).

The greenness index does not reflect this same trend and in this case with values greater than 14 the greenness index is reduced. Site A10 again affecting the correlations while site C has the greatest site variability in wetness index. Transect Cx is in the lowest part of the catchment and appears to have high wetness indices. This makes sense where elevation would act as a hydraulic gradient for the whole catchment. Crave and Gascuel-Odoux (l997) state that the increase in the wetness at the bottom of the catchment may express and increasing probability of the occurrence of saturation towards the stream, shown by the high variability of wetness in this part of the catchment. Their study catchment was 1.3 km$^2$. Overall for this time period biomass and TMSAT bands 3, 4, 5, and 7 appear to be increasing in value with increasing wetness index, but the relationships are not statistically significant.

At Lockyersleigh, the month of September is often wet with high moisture values (chapter 3, figure 3.24) and biomass levels are low (chapter 4, figure 4.1) therefore, correlations between vegetation and wetness indices are not easy to discriminate in this season.

6.4 March 1994

Section 6.4.1 shows the correlation and statistical significance of relationships between vegetation (biomass and satellite data) and wetness indices. Figure 6.4a show plots of vegetation measures versus the wetness index for March 1994. The curve of best fit shown in each plot is indicated by the curve with the highest $r^2$ in figure 6.4b.
Chapter 6. Wetness Index
Spatio-temporal Modelling of Biomass

6.4.1 Results – March 1994

Biomass and Satellite Data vs Wetness Index

Figures 6.4 a

**Figure 6.4b: Correlation of Biomass and Satellite with Wetness Index: March 1994**

<table>
<thead>
<tr>
<th>Biomass</th>
<th>TMSAT NDVI</th>
<th>TMSAT Band 3</th>
<th>TMSAT Band 4</th>
<th>TMSAT Band 5</th>
<th>TMSAT Band 7</th>
</tr>
</thead>
<tbody>
<tr>
<td>$r^2$</td>
<td>$r^2$</td>
<td>$r^2$</td>
<td>$r^2$</td>
<td>$r^2$</td>
<td>$r^2$</td>
</tr>
<tr>
<td>L = 0.048</td>
<td>L = 0.011</td>
<td>L = 0.020</td>
<td>L = 0.089</td>
<td>L = 0.014</td>
<td>L = 0.007</td>
</tr>
<tr>
<td>Q = 0.086</td>
<td>Q = 0.040</td>
<td>Q = 0.091</td>
<td>Q = 0.143</td>
<td>Q = 0.041</td>
<td></td>
</tr>
<tr>
<td>C = 0.250</td>
<td>C = 0.040</td>
<td>C = 0.380</td>
<td>C = 0.620</td>
<td>C = 0.325</td>
<td></td>
</tr>
<tr>
<td>E = 0.101</td>
<td>E = 0.003</td>
<td>E = 0.024</td>
<td>E = 0.087</td>
<td>E = 0.017</td>
<td></td>
</tr>
</tbody>
</table>

L = Linear, Q = Quadratic, C = Cubic, E = Exponential
### 6.4.2 Summary – March 1994

**Biomass and Satellite Data versus the Wetness Index**

Biomass were reduced when the wetness index value was greater than ten. The cubic correlation between biomass and wetness index produced a nonsensical result and was rejected in favour of the linear trend (figure 6.4b). Site A10 is affected by other processes as previously discussed. Site A2 is in a north-northeast aspect (45° from north), positive tangential curvature (+0.01), drainage area of (1317 x 100m) and therefore has high biomass with a wetness index of approximately 8.6. This wetness index value of approximately nine appears quite significant given the climatic conditions of March 1994 where biomass decreases with increasing wetness values. All the satellite data tended to increase slightly up to approximately wetness value of 14 and then level out or decrease but again the relationships are not really statistically significant. This wetness value of greater than 14 could show a different response to an increase in the wetness value. Wetness values less than 14 and greater than 6 show an increase in reflectance with increasing wetness values. These charts suggest that March 1994 had the highest wetness index given the reduction in the TMSAT reflectance (digital number) with wetness index numbers greater than 12.

### 6.5 Summary

**Figure 6.5** Summary chart of correlations between biomass and satellite data with Wetness Index

#### Correlations with $r^2 \geq 0.20$

<table>
<thead>
<tr>
<th>March 1993</th>
<th>October 1993</th>
<th>March 1994</th>
</tr>
</thead>
<tbody>
<tr>
<td>Biomass vs Wetness index ($r^2=0.19$)</td>
<td>Biomass vs Wetness Index</td>
<td>Biomass vs Wetness Index</td>
</tr>
<tr>
<td>Wetness index vs NDVI</td>
<td>Wetness Index vs TMSAT 5</td>
<td>Wetness Index vs TMSAT 3,4,5,7</td>
</tr>
<tr>
<td>Wetness index vs TMSAT 5, 7</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

The correlations common to all three time periods were:

- Biomass vs Wetness (with varying levels of significance)
- TMSAT Band 5 vs Wetness index
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Figure 6.6 Common correlations between vegetation and wetness indices

<table>
<thead>
<tr>
<th>Correlations common to March '93 &amp; Sept '93</th>
<th>Correlations common to Sept '93 and March '94</th>
<th>Correlations common to March '93 &amp; March '94</th>
</tr>
</thead>
<tbody>
<tr>
<td>Biomass vs wetness index</td>
<td>Biomass vs wetness index</td>
<td>Biomass vs wetness index</td>
</tr>
<tr>
<td>TMSAT 5 vs wetness index</td>
<td>TMSAT 5 vs wetness index</td>
<td>TMSAT 5.7 vs wetness index</td>
</tr>
</tbody>
</table>

6.5.2 Climatic conditions March 1993

Climatic conditions of the time of data acquisition.

The meteorological data from 1 to 22 February (satellite overpass) and 1 to 21 March (biomass samples collected) 1993 were examined to determine the type and significance of their correlations. See also chapter 2, figures 2.4a, b, c. Figure 6.7 shows a weather data summary for the days of the biomass sampling (21 March 1993) and the satellite overpass (22 February 1993). The difference in the satellite overpass and biomass collection dates occurred because 22 February 1993 was the closest day with clear sky conditions to the biomass sampling date: cloud free conditions are important for determination of reflectance data.

As described in Chapter 2 the climate data were collected from ground-based meteorological stations. The daily climatic data on data acquisition dates are shown in figure 6.7. Biomass is determined by a 26 week growth accumulation period, whereas satellite data is more influenced by recent climatic events.

Figure 6.7 Climate data for acquisition of biomass data and the satellite data overpass.

<table>
<thead>
<tr>
<th>Climatic Variable</th>
<th>22 Feb 1993</th>
<th>21 March 1993</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean air temp. °C</td>
<td>10.9</td>
<td>13.4</td>
</tr>
<tr>
<td>Max surface temp. °C</td>
<td>NA</td>
<td>23.0</td>
</tr>
<tr>
<td>Min surface temp. °C</td>
<td>NA</td>
<td>6.8</td>
</tr>
<tr>
<td>Vapour pressure mb</td>
<td>6.72</td>
<td>11.98</td>
</tr>
<tr>
<td>Solar radn MJ/m²</td>
<td>24.01</td>
<td>17.65</td>
</tr>
<tr>
<td>Mean wind speed kph</td>
<td>21.38</td>
<td>9.17</td>
</tr>
<tr>
<td>Rainfall mm</td>
<td>0.6</td>
<td>0.4</td>
</tr>
<tr>
<td>Runoff mm</td>
<td>0.01</td>
<td>0.01</td>
</tr>
</tbody>
</table>
Figure 6.8 below shows the cumulative differences between 1 - 22 Feb 1993 and 1 - 21 March 1993 for solar radiation and rainfall. Three time scales are examined prior to data collections, cumulative monthly, the previous week and the previous 48 hours. The latter hoping to estimate the antecedent soil moisture conditions.

### Figure 6.8 48 hourly, weekly and cumulative monthly solar radiation and rainfall differences

<table>
<thead>
<tr>
<th>Data collection dates: Feb - satellite data March - ground data</th>
<th>Monthly cumulative solar radn. &amp; rainfall MJ/m² and mm</th>
<th>The previous cumulative weekly solar radn. &amp; rainfall MJ/m² and mm</th>
<th>The previous 48 hours cumulative solar radn. &amp; rainfall MJ/m² and mm</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 - 22 February 1993</td>
<td>422.06 MJ/m², 42.6 mm</td>
<td>137.22 MJ/m², 13.2 mm</td>
<td>30.29 MJ/m², 7.8 mm</td>
</tr>
<tr>
<td>1 - 21 March 1993</td>
<td>384.11 MJ/m², 59.2 mm</td>
<td>126.48 MJ/m², 11.0 mm</td>
<td>36.51 MJ/m², 3.6 mm</td>
</tr>
</tbody>
</table>

Climatic conditions can have an impact on the correlation between biomass and primary terrain attributes. Although this experimental catchment is small (approx. 27 km²) the variability of the climate within the boundary layer is important as it affects the reflectance data and biomass productivity.

Rainfall had a larger variation at the monthly and 48 hour time period varying from February to March respectively 42.6 mm to 59.2 mm (monthly) and 7.8 mm to 3.6 mm in 48 hours. The weekly rainfall had less variation from 13.2 mm February and 11.0 mm March. The 48 hour antecedent rainfall shows the biomass collection date was drier than the reflectance data. However, figure 6.8 indicates this impact was not large. Figure 6.7. also confirms that rainfall on the actual day of data collection only varied 0.2 mm which is negligible.

Solar radiation showed less variation over the cumulative, previous week and previous 48 hours with February being slightly higher at all time steps except for the 48 time period. Monthly solar radiation differences for February and March were 37.95 MJ/m² (where February includes an extra day i.e., up to the 22 Feb and only 21 March). The weekly solar radiation difference was just 2.2 MJ/m² and the 48-hour difference was 4.2 MJ/m² higher in March. On the ‘day’ of data collection however, the solar radiation was 6.36 MJ/m² higher for February. Therefore the biomass collection
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data had less solar radiation than the satellite data except for the previous 48 hours. However, as discussed in Chapter 7 section 7.7.2 solar radiation does not greatly affect biomass and growth over one week. Monthly solar radiation values are most suitable for assessing biomass growth rates in this catchment.

These climatic factors suggest that the decrease in rainfall during March was partially offset by the increase in solar radiation during February. Under these climatic conditions it would be expected that evapotranspiration rates would be slightly less in March and therefore, the reduced rainfall did not affect the correlation of biomass to satellite data in February and March for this study. Both biomass and satellite vegetative information can be correlated to primary terrain attributes for the purposes of this study. It would be interesting to examine climatic impacts on the correlation between vegetation and the primary terrain attributes under different climatic conditions or a winter/summer pattern. In addition, data acquisition from February and March 1993 did not adversely affect biomass, as the growth accumulated over the 26 weeks before the biomass was collected.

6.5.3 Discussion of the questions explored using the Wetness Index

1. There were no statistically significant correlations between wetness index and biomass. This is not unusual in a low relief catchment, since the hydrologic processes are subtle and difficult to represent under dry conditions.

2. Sites at transect Cx were represented by remotely sensed data only. The variability in the wetness index at this transect was difficult to explain. However, site C15 is the lowest point in the catchment and it had the highest wetness index. Site A11 was concluded to be an erroneous data point.

3. Rainfall does relate to a dynamic wetness index, however, in this application the wetness index calculation is a static terrain attribute as shown in equation 6.3. In this equation the wetness is a function of the specific catchment area, DEM resolution and slope. This is appropriate for examining biomass as it accumulates over at least a three month period. The dynamic wetness index requires much more input data over the same temporal period.

4. A range of critical wetness index values (where increased wetness index, decreased biomass) could not be determined in this study.
Biomass does relate to static terrain attributes over time as demonstrated in Chapter 5. For management purposes a DEM containing such information would be valuable. The spatial location of these simple attributes could be incorporated into catchment plans for managing grazing, revegetation programs, soil conservation and other purposes. Process-driven properties are also extremely useful to determine the biomass with a catchment. The wetness index, drainage area and tangential curvature give an insight into hydrologic processes and how they can affect biomass. Climate, seasons and geographic location also affect these results.

Wetness Index was weakly correlated to biomass for all three time periods with the September October 1993 ($r^2 = 0.38$) having the highest correlation and March 1993 the lowest ($r^2 = 0.19$). Therefore, when moisture is limited March 1993 biomass did not correlate as well with the wetness index. In the wetter September October there was some correlation but still $r^2 < 0.4$ which is not statistically significant.

TMSAT NDVI on the other hand correlated significantly during the March 1993 period for grasses/pastures ($r^2 = 0.60$) but had no correlation in September October 1993 or March 1994. The highest wetness index correlation was between TMSAT band 5 during the March 1994 period ($r^2 = 0.62$) which requires further investigation. Radiation influences on sloping surface may give some insight into to this satellite to wetness index correlation.

The wetness index variability is difficult to explain as it appears to be sensitive to both the size of the catchment and the topographic gradient of the catchment. Crave and Gascuel-Odoux suggests that surface water content is dependent on micro-topography, probably due to the level of the water table and the soil physical properties.

The dependence of biomass on the preceding three to six months is a partial explanation for its weak correlation with wetness index. The satellite data, which are instantaneous measures of vegetative cover, appear to be more strongly related to wetness index. However, overall the impact of wetness index on vegetation, and vegetation measures is not large in this low relief seasonally wet/dry catchment. It has also been suggested by Crave and Gascuel-Odoux (1997) that the downslope topographic conditions may control the spatial distribution of the surface wetness of a catchment. They conclude that the spatial distribution of surface water content must be interpreted according to the topography and the spatial distribution of soils.
Chapter 7.

Spatio-temporal Modelling of Biomass

TOPO-CLIMATE MODELS

TIME
- 26 weeks
- 13 weeks
- Weekly

SPACE
- Aspect
- Tangential Curvature
- Drainage Area

Biomass Growth Stages:
- Initiate growth
- Senesce
- Accumulation

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CHAPTER 7. SPATIO-TEMPORAL MODELLING OF BIOMASS

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   7.1.2 Spatial resolution
   7.1.3 Temporal resolution
   7.1.4 Limits on data sets

7.2 Three Approaches to Spatio-temporal Biomass Modeling
   7.2.1 Sub-catchment model
   7.2.2 Satellite model
   7.2.3 Topo-climate model

7.3 Using topo-climate data to Spatially Disaggregate Biomass Models
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   7.3.2 Disaggregation using rainfall data?
     7.3.2.1 Conclusions to sub-catchment rainfall analysis
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   7.5.2 GCV outputs of the ten models
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   7.6.2 Residual outputs from subcatchment model
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7.7 Discussion and conclusions
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   7.7.2 Climatic controls on biomass distribution in a low relief catchment
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   7.7.4 Satellite data for model development
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7.1  Spatio-temporal Effects on Biomass Variability

7.1.1  Introduction

Spatio-temporal biomass data are important for catchment monitoring, management and environmental modelling of biological, atmospheric and hydrological processes (see Chapter 1). Biomass is affected by many variables within a catchment including climate, terrain, engineering and structural changes and anthropogenic factors (such as grazing and fertilizer application). The questions addressed by this chapter are what biomass related data are available, how accurate are the data and what data sets or combination of parameters (e.g. climate, terrain, or satellite data) can best represent spatially distributed biomass through time. Statistical analysis provides a method of distinguishing between models.

Model development in this chapter incorporates the temporal component developed in chapter 4 and the spatial models developed in chapters 4 and 5. This chapter examines three approaches to spatial temporal analysis of catchment biomass. The models are referred to as the sub-catchment, satellite and topo-climate models.

- **The sub-catchment models.** The first approach is a sub-catchment model, which calibrates the GROWEST model discussed in chapter 4 to biomass averaged separately over three sub-catchments.

- **The satellite model.** The second approach simply calibrates biomass data with observed satellite data (chapter 3).

- **The topo-climate models.** The third approach develops full spatio-temporal models, which simultaneously include terrain (the spatial component) and climate (the temporal component) effects on biomass distribution as investigated separately in chapters 4 and 5. The topo-climate models are fitted using thin plate smoothing splines (Hutchinson 1999).

7.1.2  Spatial Resolution

Different spatial resolutions are required to describe different variables affecting vegetation and accumulated biomass. Rainfall varies at a broad scale, with a grid resolution coarser than 2 km (Hutchinson and Gallant 1999). Rainfall can be correlated with elevation. However, the impact of
elevation is minimal in a low relief terrain such as in this study catchment. The catchment also has limited spatial extent in relation to the stated spatial resolution of rainfall variability. Solar radiation (total solar radiation) is also a broad scale variable and can be represented on a horizontal surface at a grid resolution of 2 km. However, radiation can also be calculated using different equations (Guerra 1995). The solar radiation model (SRAD) (Moore et al 1993) incorporates topographic effects and can estimate radiation on a sloping surface. SRAD, which utilises an accurate DEM, can increase the ground resolution as described in Chapter 5. Temperature can be examined at a finer scale of approximately 100-200 m resolution assuming data are available. It is closely linked to elevation as defined by the environmental lapse rate (approximately 6° per 1000 m) (Hutchinson and Gallant 1999). At finer scales temperature can vary with small changes in slope and aspect of the terrain and with the proximity to large water bodies (Hutchinson 1991). Humes et al (1997) stated that at a high spatial resolution surface temperature values appear strongly correlated with aspect and at more coarse spatial resolution, the surface temperature varies with background soil moisture variations caused by highly localised precipitation events. Humes et al (1997) aggregated surface temperature to 400 m spatial resolution for the purpose of computing spatially distributed sensible heat fluxes over the watershed. At a coarse resolution of 400 m it can be argued that elevation is the dominant control.

7.1.3 Temporal Resolution

Temporal data (like spatial data) at high resolution are difficult to collect (both on the ground and airborne) without incurring large costs. Therefore, modelled data are often used as a surrogate for actual temporal data. Climate data form a commonly used temporal component in determining plant growth or examining hydrological fluxes. Hydrologic models that incorporate plant growth require temporal climate data as inputs. Monthly mean climate data can be used by stochastic weather models to generate climate inputs at a daily scale. These daily data can then be incorporated into hydrological and ecological models. Rainfall is the most complex climatic variable, with large variations in both time and space.

7.1.4 Limits on data sets

The primary aim of this thesis is to obtain spatially and temporally varying estimates of biomass. Direct measurements of spatio-temporal biomass data are limited and therefore modelling of biomass in terms of more readily measured variables is essential, but also problematic. Some variables associated with biomass vary temporally, others vary spatially, and many have limited
data points (figure 7.1). Terrain data vary spatially, climate data vary spatially and temporally while satellite data vary both spatially and temporally but are limited to orbital dates. Accurate analysis requires accurate data sets, which are well distributed throughout the study site and available over time. There has been a lack of irradiance data throughout Australia (Forgan 1979). Even some spatially available data requires temporally consistent databases to be useful to vegetation analysis. For example, a fundamental problem with instantaneous radiation values is that biomass accumulates over months. In this thesis the measured biomass data has gaps due to field conditions and therefore the aim is to make spatial predictions where there is no monitored site data. Hutchinson (1987, 1995a) discusses ways to deal with insufficient climate data (evaporation, radiation, rainfall etc) by spatially interpolating monthly mean statistics using thin plate (or Laplacian) smoothing splines to support statistical simulation of a number of weather parameters. The aircraft data for this experiment were available for only one time period (Chapter 3). Therefore the aircraft data were not suitable for spatio-temporal modelling.

**Figure 7.1 Spatial, temporal and scale components of different variables**

<table>
<thead>
<tr>
<th>Variables</th>
<th>Spatial Component</th>
<th>Temporal Component</th>
<th>Resolution, Frequency, Availability</th>
</tr>
</thead>
<tbody>
<tr>
<td>Terrain</td>
<td>Varies over space</td>
<td>No temporal variation.</td>
<td>Resolution determined by DEM grid resolution. 25 m grid. Data available.</td>
</tr>
<tr>
<td>Modelled Growth Index GI 26 wk</td>
<td>No spatial variance. Catchment averaged.</td>
<td>Varies over time.</td>
<td>Frequency: 26 week integration over two years. Calculated weekly from available climate data.</td>
</tr>
<tr>
<td>Satellite data</td>
<td>Varies over space.</td>
<td>Varies over time.</td>
<td>Resolution determined by type of satellite. 25 m DEM grid selected.</td>
</tr>
<tr>
<td>Climate</td>
<td>Some spatial variance. Catchment averaged values selected.</td>
<td>Varies over time.</td>
<td>Frequency: Monthly and weekly mean data over 10 yrs. Input for hydrological model and GI output.</td>
</tr>
<tr>
<td>Measured biomass data</td>
<td>Spatially varying at fixed points in the catchment. Dependent parameter.</td>
<td>Varies over time.</td>
<td>Frequency: Determined by number of sites and number of data collection times. ~ 60 sites x 3 times.</td>
</tr>
</tbody>
</table>
7.2 Three Approaches to Spatio-temporal Biomass Modelling

The three types of models are developed in this chapter; a Sub-catchment model, a Satellite model and Topo-climate models. The sub-catchment model is simple and direct. It correlates sub-catchment averaged biomass and temperature to modelled growth indices. The sub-catchment model is temporally representative but spatially limited. Its calibration is limited by the biomass data collection at the sub-catchments. The Satellite model has excellent spatial coverage however, it needs to be atmospherically corrected and calibrated with ground data. The relationship between biomass and reflectance data is spatially extensive but indirect. The Topo-climate models have a direct physical link to catchment responses to rainfall and radiation. Terrain influences on climate have a major impact on spatial biological processes. Temporal biological responses of biomass to climatic variables are also investigated.

7.2.1 Sub-catchment model

This approach executed the GROWEST model at three sub-catchments to estimate biomass at the sub-catchment scale. Catchment-averaged rainfall were selected as input while interpolated monthly mean temperature varied at each sub-catchment. Biomass also varied over each sub-catchment. Two integration periods were examined (13 and 26 weekly intervals) to determine the best temporal representation of biomass growth by the GROWEST model in this catchment.

7.2.2 Satellite model

This model uses Thematic Mapper Satellite data to investigate spatial patterns in biomass across the catchment. This method required ground truthing, atmospheric and geometric corrections to the data source. The satellite data were then correlated to the surface biomass via linear regression analysis (chapter 3). Thematic Mapper Satellite band three was then normalised (to a selected reference scene) over three time periods (figure 7.30) so statistical comparisons between the satellite and topo-climate models could be determined across all three sample times.
7.2.3 Topo-climate Models

All the Topo-climate Models include the temporal climate component via the GROWEST model as described in chapter 4. There are ten topo-climate models developed in this chapter. Five 2D models and five 3D models. They rely on an accurate DEM (chapter 2) to determine the terrain attributes (chapters 5 and 6) and radiation surfaces (chapter 4). Linear regression modelling was used in chapter 5 to determine which terrain and radiation attributes were most suited for the spatial extension of biomass. Standard hypothesis testing was then used to assess the efficiency of these attributes in the various topo-climate models. The most statistically significant results, using terrain attribute and radiation correlations with biomass, led to five separate 2D topo-climate models (models #1 - 5). The three terrain attributes selected were: aspect, tangential curvature and drainage area. The selected radiation surface was solar radiation on a sloping surface (chapter 4).

Further model development produced a further five topo-climate models (models #6-10). Topo-climate models 6 to 10 were 3D models that combined two terrain attributes with the temporal growth index. Figure 7.11 list the 2D topo-climate models #1-5 and figure 7.16 list the 3D models # 6-10. The 3D models combined radiation and hydrological parameters with temporal climate data.

7.3 Using Topo-climate Data to Spatially Disaggregate Biomass Models

7.3.1 Introduction to disaggregation methods

There is considerable debate as to whether it is best to interpolate the inputs or outputs of data used in hydrologic models. The answer varies with the variable under examination and depends on whether the models have linear or non-linear relationships. In hydrology, it has been suggested that it is more important to quantify the variance than the mean (Dooge 1992). In remote sensing it has been suggested that is important to interpolate the outputs and determine a covariate. Generally, if the results produce a linear function then each way will produce a similar result. It is often faster to interpolate the results. However, it can be less accurate than interpolating the inputs, depending on data availability.

Spatial representation of catchment heterogeneity is also an important consideration when determining the spatial significance of data distribution within a catchment. Humes (et al 1997)
Chapter 7 Spatio-temporal Modelling of Biomass

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predict that future scenarios will include continuous simulation of spatially distributed water and energy fluxes that will require the merging of remotely sensed data with more complicated physically based models. These composite models would provide as many constraints as possible on the problem (Taconet et al. 1986, Sellers et al 1986).

In this study the inputs to the GROWEST model could be spatially disaggregated (if data were available) or the outputs of the model could be interpolated according to empirically derived relationships from terrain attributes. Rainfall, temperature, solar radiation and potential evaporation are the principal climatic inputs for GROWEST. Therefore, GROWEST inputs could be spatially disaggregated at the three rainfall stations (within the catchment), and with sub-catchment biomass variation. Satellite and ground biomass data could be used as validation of the both techniques. Alternatively, the catchment could be divided and GROWEST could be executed at the sub-catchment scale using spatial variations in monthly mean temperature as inputs (chapter 4). The problem of what to disaggregate can occur at many levels within data analysis. Disaggregation methods can be spatial, temporal or spatio-temporal in nature.

The aim of this paper was to utilise biomass, modelled growth, terrain and radiation measurements to generate spatially disaggregated biomass within the catchment with minimal error. The Topo-climate models developed in this thesis depend on static terrain model correlations to biomass developed in chapter 5 and 6, and the temporal GROWEST model outputs in chapter 4.

7.3.2 Disaggregation using rainfall data

Precipitation is highly variable and non-linear in its spatial distribution, although there is some correlation between precipitation and elevation. The general trend is that at higher elevations there is usually higher rainfall. Within the study catchment there are three separate rainfall stations at known elevations. Selections of rainfall data were examined to represent the seasons and the months of biomass data collection. January, April, July and October were selected to represent the four seasons (summer, autumn, winter and spring) while March and September were biomass acquisition dates. Each selected rainfall station was regressed with elevation to determine any possible correlations within this catchment. Mean rainfall data were only calculated for the years where there were rainfall at all three stations. Figure 7.2 to 7.8 shows the monthly rainfall data regressed against its elevation for the years of available data. Where, _ symbol indicates that the data were not available and * indicates that some daily data within that month were missing.
Station A 1991, with data value of 0.4 mm appears unreliable and inconsistent with the other January precipitation data. When excluded from the data set the mean monthly data for station A, B and C are 68.67 mm, 83.73 mm and 70.29 mm. As stated these mean rainfall values are only calculated for the years where there were recorded rainfall at all three stations. During 1988 and 1989 the rainfall decline is consistent with the lower elevations at stations B and C. Years 1991 and 1993 however, show a negative correlation between rainfall and elevation suggesting with this limited data set and spasmodic rainfall in January, this simple correlation does not fully account for the spatial variability in rainfall.
Figure 7.4  Monthly Rainfall for **March**: 1987 – 1993

<table>
<thead>
<tr>
<th>Rainfall</th>
<th>Station A 665 m</th>
<th>Station B 628 m</th>
<th>Station C 608 m</th>
</tr>
</thead>
<tbody>
<tr>
<td>1987</td>
<td>–</td>
<td>77.8</td>
<td>58.4</td>
</tr>
<tr>
<td>1988</td>
<td>14.0</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>1989</td>
<td>205.2</td>
<td>208.0</td>
<td>132.8 *</td>
</tr>
<tr>
<td>1990</td>
<td>50.8</td>
<td>56.4</td>
<td>–</td>
</tr>
<tr>
<td>1991</td>
<td>7.8</td>
<td>8.4</td>
<td>10.0</td>
</tr>
<tr>
<td>1992</td>
<td>66.2</td>
<td>66.8</td>
<td>59.6</td>
</tr>
<tr>
<td>1993</td>
<td>106.2</td>
<td>88.0</td>
<td>92.6</td>
</tr>
<tr>
<td>mean</td>
<td>96.35</td>
<td>92.80</td>
<td>73.75</td>
</tr>
</tbody>
</table>

Figure 7.5  Monthly Rainfall for **April**: 1987 – 1993

<table>
<thead>
<tr>
<th>Rainfall</th>
<th>Station A 665 m</th>
<th>Station B 628 m</th>
<th>Station C 608 m</th>
</tr>
</thead>
<tbody>
<tr>
<td>1987</td>
<td>–</td>
<td>31.8</td>
<td>25.8</td>
</tr>
<tr>
<td>1988</td>
<td>223.2</td>
<td>228.4</td>
<td>–</td>
</tr>
<tr>
<td>1989</td>
<td>144.0</td>
<td>163.4</td>
<td>–</td>
</tr>
<tr>
<td>1990</td>
<td>129.0</td>
<td>131.4</td>
<td>–</td>
</tr>
<tr>
<td>1991</td>
<td>47.4</td>
<td>52.0</td>
<td>38.0</td>
</tr>
<tr>
<td>1992</td>
<td>40.4</td>
<td>32.2</td>
<td>–</td>
</tr>
<tr>
<td>1993</td>
<td>5.2</td>
<td>3.4</td>
<td>2.0</td>
</tr>
<tr>
<td>mean</td>
<td>26.3</td>
<td>27.7</td>
<td>20.0</td>
</tr>
</tbody>
</table>
Figure 7.6  Monthly Rainfall for **July:** 1987 – 1993

<table>
<thead>
<tr>
<th>Rainfall</th>
<th>Station A 665 m</th>
<th>Station B 628 m</th>
<th>Station C 608 m</th>
</tr>
</thead>
<tbody>
<tr>
<td>1986</td>
<td>0.75</td>
<td>NA</td>
<td>1.01</td>
</tr>
<tr>
<td>1987</td>
<td>2.16</td>
<td>1.43</td>
<td>1.61</td>
</tr>
<tr>
<td>1988</td>
<td>1.99</td>
<td>NA</td>
<td>1.57</td>
</tr>
<tr>
<td>1989</td>
<td>1.46</td>
<td>1.42</td>
<td>0.94</td>
</tr>
<tr>
<td>1990</td>
<td>2.52</td>
<td>2.46</td>
<td>NA</td>
</tr>
<tr>
<td>1991</td>
<td>3.38</td>
<td>3.30</td>
<td>2.57</td>
</tr>
<tr>
<td>1992</td>
<td>0.44</td>
<td>0.44</td>
<td>NA</td>
</tr>
<tr>
<td>mean</td>
<td>1.81</td>
<td>1.81</td>
<td>1.54</td>
</tr>
</tbody>
</table>

Figure 7.7  Monthly Rainfall for **September:** 1986 – 1992

<table>
<thead>
<tr>
<th>Rainfall</th>
<th>Station A 665 m</th>
<th>Station B 628 m</th>
<th>Station C 608 m</th>
</tr>
</thead>
<tbody>
<tr>
<td>1986</td>
<td>32.6</td>
<td>18.2</td>
<td>28.4</td>
</tr>
<tr>
<td>1987</td>
<td>20.0</td>
<td>74.4</td>
<td>19.8</td>
</tr>
<tr>
<td>1988</td>
<td>70.6</td>
<td>11.6</td>
<td>68.8</td>
</tr>
<tr>
<td>1989</td>
<td>13.2</td>
<td>70.8 *</td>
<td>_</td>
</tr>
<tr>
<td>1990</td>
<td>70.5</td>
<td>70.8 *</td>
<td>_</td>
</tr>
<tr>
<td>1991</td>
<td>36.2</td>
<td>43.0</td>
<td>38.2</td>
</tr>
<tr>
<td>1992</td>
<td>37.6</td>
<td>38.0</td>
<td>_</td>
</tr>
<tr>
<td>mean</td>
<td>28.1</td>
<td>30.6</td>
<td>29.0</td>
</tr>
</tbody>
</table>

Figure 7.8  Monthly Rainfall for **October:** 1986 – 1992

<table>
<thead>
<tr>
<th>Rainfall</th>
<th>Station A 665 m</th>
<th>Station B 628 m</th>
<th>Station C 608 m</th>
</tr>
</thead>
<tbody>
<tr>
<td>1986</td>
<td>54.6</td>
<td></td>
<td>55.6</td>
</tr>
<tr>
<td>1987</td>
<td>108.2</td>
<td>107.0 *</td>
<td>93.8</td>
</tr>
<tr>
<td>1988</td>
<td>11.6</td>
<td>12.4</td>
<td>10.8</td>
</tr>
<tr>
<td>1989</td>
<td>25.2</td>
<td>28.8</td>
<td>_</td>
</tr>
<tr>
<td>1990</td>
<td>33.2</td>
<td>35.2</td>
<td>_</td>
</tr>
<tr>
<td>1991</td>
<td>29.2</td>
<td>28.8</td>
<td>15.0</td>
</tr>
<tr>
<td>1992</td>
<td>55.0</td>
<td>60.8</td>
<td>_</td>
</tr>
<tr>
<td>mean</td>
<td>49.67</td>
<td>49.40</td>
<td>39.87</td>
</tr>
</tbody>
</table>
Results of rainfall correlations with elevations

Figures 7.2 to 7.8 show that monthly rainfall is highly variable and therefore long-term (at least greater than 10 years rainfall data) are required to detect trends in monthly mean rainfall patterns.

January had four complete years of data at all three rainfall stations. 1991 had a high correlation between rainfall and elevation. However, with limited rainfall data, 1993 data produced negative trends between rainfall and height. February had high correlation in 1987 and 1988 but negative correlations in 1989 and 1991 and therefore there was no correlation for the monthly mean rainfall with respect to elevation in February. 1989 had only 3.2 mm difference in all 3 rainfall stations therefore its correlation is not significant. These summer patterns confirm that convective rainfall in summer has limited dependence on elevation especially in this low relief catchment.

March had consistently high correlations with the exclusion of 1991, which displayed a negative trend. April had only two years of complete data for all three stations. Therefore the autumn season showed some correlation between rainfall and elevation at station A and C during March. July recorded a typical low rainfall winter pattern but it demonstrated a weak correlation between rainfall and elevation. This correlation is small and therefore could also be considered as static where rainfall was consistent at the three elevations within the catchment.

Both September and October had only three complete years of data. September showed no correlation between rainfall and elevation and October was highly variable. Therefore, during the spring season there was not a correlation in September but there was in October. Even though the rainfall in October was highly variable and limited there still was a distinct correlation between rainfall and elevation. Therefore, from all these limited rainfall data sets and the small range the elevations (only 57 m difference in height) there appears to be no consistent correlation between rainfall and elevation except for the months of March and October which have limited data sets.

Summary of rainfall analysis

- Limited data, only three rainfall gauges, with irregular recordings restricted the data analysis
- Low range in elevation increased the difficulty of statistically validating trends
- Limited spatial extent of the data also limited the determination of reliable trends on elevation
- Summer months are driven by connective rainfall, and therefore elevation dependence is less obvious
Therefore, given the high degree of spatial variability in biomass and the lack of consistent correlation between rainfall and elevation it would be unwise to spatially disaggregate rainfall within this small catchment on the basis of elevation dependence. The sub-catchment rainfall examination would produce only small differences in the growth index (GI). The sensitivity of GI is not sufficient to spatially discriminate the GI with such similarity in the sub-catchment rainfall. Therefore, the questions of scale and catchment heterogeneity are raised. Within this small experimental study site (27 km$^2$) terrain features need to be examined. However, surfaces derived from a larger sample area may provide more stable results.

### 7.3.2.1 Conclusions to sub-catchment rainfall analysis

- Spatial variation in rainfall did not discriminate GI for biomass, therefore topographic attributes and radiation need to be examined.
- Spatio-temporal rainfall analysis gives temporal but not useful spatial discrimination in this catchment (refer also to chapter 4).
- Therefore, modelling biomass via GROWEST at sub-catchments using disaggregated rainfall would be not necessarily increase the accuracy of the outputs due to the spatial insensitivity of the rainfall data. However, the sub-catchment modelling did provide useful calibrations between biomass and GI (chapter 4).

Kogan (1990) noted that it was important to stress the diversity of rainfall regime over his study period. He found biomass in Sudan was low during the extremely dry period in 1984 and high during the fairly wet period in 1985. He also noted that NDVI values did not show agreement with the precipitation dynamics. Rainfall and biomass were examined in chapter 4, where averaged biomass increased with increased rainfall in 1993 but this was also a function of radiation and spatial location.

### 7.3.3 Disaggregation: using the Light Index within the growth model.

To examine the sensitivity of biomass to the light index in GROWEST. Five values of slope-based radiation data (chapter 4) covering the total range in radiation during March and September were related to the light index. Chapter 4 figures 4.8 to 4.10 show the approximate range of radiation from 16 MJ m$^{-2}$ to 22 MJ m$^{-2}$. Figure 7.9 (below) shows the radiation range and the light index range.
The light index as calculated in GROWEST can be expressed as:

Relative radiation \( (R) = \frac{\text{total solar radiation}}{31.401} \)

Light index \( = 1.03 - \exp(-3.5 \times R) \)

### Figure 7.9 Comparisons between slope-based radiation and the light index.

<table>
<thead>
<tr>
<th>Slope-based Radiation MJ m(^{-2})</th>
<th>Relative Radiation (R)</th>
<th>( \exp(-3.5 \times R) )</th>
<th>Light Index (1.03 - \exp(-3.5 \times R))</th>
</tr>
</thead>
<tbody>
<tr>
<td>16</td>
<td>0.51</td>
<td>0.169</td>
<td>0.86</td>
</tr>
<tr>
<td>17</td>
<td>0.54</td>
<td>0.151</td>
<td>0.88</td>
</tr>
<tr>
<td>19</td>
<td>0.60</td>
<td>0.122</td>
<td>0.91</td>
</tr>
<tr>
<td>21</td>
<td>0.67</td>
<td>0.096</td>
<td>0.93</td>
</tr>
<tr>
<td>22</td>
<td>0.70</td>
<td>0.086</td>
<td>0.94</td>
</tr>
</tbody>
</table>

Therefore,

\[ \nabla LI / \Delta R = 0.013 \]

Therefore, the application of the GROWEST light index (refer to Chapter 4) shows light can only account for approximately 6% of the biomass variation during September. The total effect of the light index also does not correlate with biomass changes within the catchment as light was a non-limiting factor.

### 7.3.4 Summary of the disaggregation methods

Figures 4.23 - 4.41 with outputs from the 13 week integrated GROWEST values (at weekly timesteps), clearly show the decline of moisture in the March periods and the decrease of temperature during September. GROWEST was also executed using a 26 week accumulation period. For this accumulation period, biomass was well represented (chapter 4). Therefore the optimal accumulation period for biomass during 1993 and 1994 was a six month growing period. Biomass at all sub-catchments was influenced by climate. Sub-catchment \( A_x \) was also influenced by aspect where the northerly sites yielded a high site-averaged biomass. For sub-catchment \( B_x \) the relatively flat topography had a small influence and the lower temperatures and higher moisture reduced biomass. Denser grazing could also have influenced site \( B_x \). Biomass at sub-catchment \( J_x \) (the steepest in the catchment) could be influenced by terrain variations. Sub-catchment \( J_x \) in the September period however, did not indicate radiative terrain influences as shown in figure 4.9 but
did show correlation with slope-based radiation during the March. Chapters 5 also indicated terrain influences, including aspect, were correlated to biomass at sites, which included $J_x$.

7.3.5 Conclusions from the disaggregation methods

- Modelled rainfall varied temporally but was relatively constant spatially at a sub-catchment scale due to the low relief and limited spatial extent of the catchment (Chapters 4 and 7).
- Biomass response to the spatial variance of temperature will be investigated in section 7.4.
- Radiation varied spatially but less so temporally (Chapter 4).
- The effect of elevation alone on biomass in this low gradient terrain was not significant. Elevation is constant temporally (Chapter 2).
- The low range of variation in solar irradiance in space and time across the study area minimised differences in the light index (Chapter 7, section 7.3.3).

7.4 Spatial Disaggregation using the Temporal Biomass Signal

7.4.1 Introduction

Linear models have been used since at least the nineteenth century (Stigler 1986). This technique estimates the parameters for a straight line by minimising the squared sum of residuals. The relationship is linear as stated and the residuals are usually assumed to be independent and normally distributed with constant variance. The assessment of the fit is evaluated by a reduction in variance and analysis of model residuals. Linear regression modelling was applied in Chapters 3, 4 and 5 and the results and statistical outputs were used to access the accuracy or level of significance. These linear regression results produced a wide range of exploratory plots from which a selection of terrain attributes were determined. These selected terrain attributes were then utilised in developing spatio-temporal models. The linear modelling alone does not have a temporal component and is only relevant at individual time periods. Therefore, linear modelling was not used for the spatio-temporal models in this chapter.

Multi-variate regressions are a statistical technique that use variables to explain as much of the variation in the observed response as possible (Battaglin and Goolsby 1997). These regressions could include a temporal component. One of the assumptions of multiple regression is that independent variables are not correlated. Highly correlated multi-collinearity of the independent variables creates instability in the coefficients. Therefore, it is usually assumed that the independent variables are not strongly correlated. Aspect is not directly related to tangential curvature and
drainage area. Drainage area and tangential curvature are calculated at different scales. Tangential curvature is constricted by the cell size of the DEM used in its calculation while drainage area is defined by the upslope area (no. of cells) contributing to the site where drainage area is calculated. Thus, drainage area and tangential curvature are also not directly related. Therefore, if multi-variate modelling were applied to attain biomass the equation could be as follows:

\[ Y_i = \beta_0 + GI + \beta_1 X_{pi} + \beta_2 X_{2i} \ldots + \beta_p X_{pi} + e_i \]  

(7.1)

\[ Y = \text{biomass} \]

\[ GI = \text{growth index} \]

\[ \beta_0 = \text{constant} \]

\[ \beta_1 = \text{coefficient of drainage area} \]

\[ \beta_2 = \text{coefficient of aspect} \]

\[ \beta_p = \text{coefficient of the independent variable} \]

\[ X_{pi} = \text{drainage area at site } i \]

\[ X_{2i} = \text{aspect at site } i \]

The notation \( X_{pi} \) indicates the value of the \( p \)th independent variable for case \( i \). The \( \beta \) terms are unknown parameters and the \( e_i \) terms are independent random variables that are normally distributed with mean 0 and constant variance \( \sigma^2 \). The model assumes that there is a normal distribution of the dependent variable for every combination of the values of the independent variables in the model. Other variables that could be used in this equation include minimum air temperature (assuming the data were available).

Standard multi-variate linear models are not well suited to modelling more complex dependencies on the independent variables. On the other hand multivariate thin plate splines are well suited to this task and the ANUSPLIN package of Hutchinson (1999) permits ready conversion of fitted spline models to regular two dimensional grids for mapping purposes. The thin plate splines discussed in section 7.5.3 can be viewed as a generalisation of the standard multi-variate linear regression with the parametric model replaced by a suitably smooth non-parametric function (Hutchinson 1999). The degree of smoothness or complexity of the fitted function is determined from the data by minimising a measure of predictive error of the fitted surface given by the generalised cross validation (GCV) (Hutchinson 1999). The theoretical justification of the GCV on simulated data is described in Craven and Wahba (1979).
7.4.2 Spline analysis for interpolating the spatio-temporal biomass data

The aim of this chapter is to incorporate a temporal component into the spatial analysis of biomass. Spatial temporal analysis allows the extension from point data, to spatial catchment scale coverage, to modelling the spatial temporal changes in biomass. The method for incorporating spatial and temporal data into one model was addressed by using multivariate thin plate spline functions. This is highly relevant for the many Australian catchments that are physically similar to the experimental catchment in this study and for which the biomass variability within catchments are relatively unknown. Quantification of the spatio-temporal biomass variations aid management strategies, environmental modelling and catchment conservation.

Spatial interpolation analysis using ANUSPLIN version 4.1 (Hutchinson 1991a, 1999) for the application of the thin plate smoothing spline method was used for spatial coverage of biomass. Within the ANUSPLIN program there are two types of spline fitting programs (SPLINA and SPLINB) which fit multi-variate noisy data (Hutchinson 1999). SPLINA is designed for small data sets and uses relatively large computational time and disk space. SPLINB was selected as it can be used on larger data sets and in particular permits coincident data points by using one “knot” point for each unique data position (figure 7.0).

To use the SPLINB program a knot index file (SELNOT) is required. The SELNOT program selects a specified number of data positions as knots by equi-sampling the independent spline variable space. The number of knots required varies with the spatial complexity of the data set. In this study SELNOT was used to obtain unique positions from coincident data points.

The two main aims of using thin plate spline interpolation methods were to:

1. generate a time series from spline outputs using terrain attributes as the controlling spatial variable and growth index (GI) as the temporal component.
2. identify which terrain attribute/s replicated the spatial biomass patterns with greatest accuracy.

**Spline Components**

In simple terms ANUSPLIN uses thin plate smoothing splines to interpolate biomass as a function \( f \) of terrain attributes and a growth index (GI) using all the given data \( Z_i \) at each site and time for
Chapter 7 Spatio-temporal Disaggregation of Biomass

Spatio-temporal Disaggregation of Biomass

It includes a spatially discontinuous error component \((E_i)\) and it is non-parametric and therefore relatively insensitive to the distribution of the parent populations. The data for the 2D spline model is given by

\[
Z_i = f(Y_i, G_i) + E_i \quad (i = 1, ..., n) \quad \text{(7.2)}
\]

Where,

- \(Z_i\) = biomass measured at site \(i\)
- \(Y_i\) = terrain parameter at site \(i\)
- \(G_i\) = growth index
- \(E_i\) = error term

The \(f\) is an unknown smooth function and \(E_i\) are the independent random errors with zero mean and variance \((\sigma^2)\). The variance \((\sigma^2)\) is usually unknown. The function \(f\) is determined by minimising

\[
\sum_{i=1}^{n} \left[ z_i - f(Y_i, G_i) \right]^2 + p J_m (f) \quad \text{(7.3)}
\]

where \(J_m (f)\) is a measure of the complexity of \(f\). This 'roughness penalty' is defined in terms of an integral of \(m\)th order partial derivatives of \(f\). Here \(m = 2\). The \(p\) is a positive number called the smoothing parameter. As \(p\) approaches zero, the fitted function approaches an exact interpolant, and as \(p\) approaches infinity the function approaches a least squares polynomial. The value of the smoothing parameter is normally determined by minimising a measure of predictive error of the fitted surface given by the generalised cross validation (GCV) (Hutchinson 1999). The GCV is calculated by implicitly removing each data point in turn and summing, with appropriate weighting, the squared difference of each omitted data value from a spline fitted to all other data points (Hutchinson and Gessler 1994). The solution may be expressed as:
where \( \phi_j \) are a set of \( M \) low order monomials and \( \sigma \) is a scalar function of the euclidean distance \( r_i \) between \( Y, G \) and \( Y_i, G_i \). Both \( M \) and the function \( \sigma \) depend on the number of independent spline variables and the order of derivative \( m \) (Wahba and Wendelberger, 1980). The coefficients \( b_i \) are restricted to satisfy the boundary conditions (Hutchinson and Gessler 1994) given by:

\[
\sum_{i=1}^{n} b_i \phi_j(Y_i, G_i) = 0 \quad (j = 1, \ldots, M) \quad (7.5)
\]

Thin plate spline analysis defines an influence matrix \( A \) (i.e. an \( n \times n \) matrix) which expresses the fitted values \( f(Y_i, G_i) \), given in equation 7.3, as a linear function of the data values \( z_i \). The trace \( \text{tr} (I - A) \), where \( I \) is the identity matrix, may be interpreted as the degrees of freedom of the residual sum of squares, or the noise in equation 7.2 (Hutchinson and Gessler 1994). An estimate of the error variance can be calculated by:

\[
\sigma^2 = \frac{(z - Az)^T (z - Az)}{\text{tr} (I - A)} \quad (7.6)
\]

Here \( z \) denotes the \( n \) dimensional vector of observation \( z_i \). The variance \( \langle \sigma^2 \rangle \) can then be used to estimate the smoothing parameter by minimising the true mean square error \( \text{TMSE} \) of the fitted surface over all data points (Hutchinson and de Hoog 1985). However, even when an estimate of \( \sigma^2 \) is available, it is generally preferable to determine the smoothing parameter and the order of derivative by minimising the GCV, which does not depend on an estimate of \( \sigma^2 \) (Hutchinson and Gessler 1994). Minimising the GCV is equivalent to an approximation of minimising \( \text{MSE} \), the true mean square error, since it can be shown (Craven and Wahba 1979) that asymptotically, as the density of the data points increases,

\[
\text{GCV} = \text{MSE} + \sigma^2. \quad (7.7)
\]
The spline outputs include a “signal” which is the effective number of parameters in the model or the level of complexity. The simplest model, a multi-linear function, would have a signal of 3.0, which would correspond to a linear model with a fitted constant and the coefficients of the two independent variables. The GCV can vary considerably depending on the model specifications. The RTGCV is the root mean square of the GCV and it can be considered a conservative estimate of model error, which includes measurement errors. RTVAR is the standard error of noise \( (e_i) \).

The noise in this model consists of two components: measurement error and deficiencies in the model. Biomass measurement error was highlighted by two extraneous data points in initial spline analyses. These points were deleted.

### 2D Spline Analysis

#### 7.4.3 Spline analysis using two independent parameters (2D model)

The SPLINB program was selected to fit the noisy biomass data to two independent variables to interpolate spatial catchment coverage of biomass. Each possible terrain independent variable is listed in Figure 7.11. The other independent variable was the 26 week integrated Growth Index (GI). Two methods were tested; one data set including the zero values of biomass for values for GI; the other data set contains only site collected biomass samples. The larger data set including the zero values approximately constrained the fitted function to have zero biomass for zero GI. This was reviewed in Chapter 4.
Figure 7.0  Spatio-temporal Modelling of Biomass


Terrain attribute data (Y). Chapters 4, 5, 6

Temporal growth indices (G). Chapter 4.

SPLINB: Fit spline surface
Biomass = f(Y, G)

LAPGRD: Generate gridded outputs

Gridded terrain surfaces. Chapter 5.

Spline surfaces.

GIS: ARCINFO
Map production.

Spatio-temporal model.
Topo-climate models of biomass

It was clear from the box plots in chapter 4 (figure 4.1) that there was a wide range in the biomass distribution within data collection time periods and between the different seasons. Therefore, a square root transformation was applied to the dependent variable to reduce the differentiation of the more extreme values. Cressie (1991) states that the square root transformation leads to a more resistant variogram estimator and it is easier to determine whether a large value is the result of the skewness or of an atypical observation.

Model # 1 (without zeros in figure 7.11) produced a signal of 3.0, which indicates that \( p \) in equation 7.5 is approaching infinity and the function \( f \) has reduced to a least squares plane. Aspect 360° yielded the lowest RTGCV for the 2D models, with and without added zero points.
Figure 7.12 Surface Statistical Outputs for the 2D Model with zeros.

<table>
<thead>
<tr>
<th>2D Model # (1-5)</th>
<th>RTGCV</th>
<th>RTMSR</th>
<th>MSR</th>
<th>Signal</th>
<th>Error d.f.</th>
<th>Var. $\sigma^2$</th>
<th>N (K)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tangential Curvature Growth Index 1</td>
<td>1.72</td>
<td>1.53</td>
<td>2.33</td>
<td>6.9</td>
<td>54.1</td>
<td>2.62</td>
<td>61 (52)</td>
</tr>
<tr>
<td>Aspect 360° Growth Index 2</td>
<td>1.63</td>
<td>1.32</td>
<td>1.75</td>
<td>11.4</td>
<td>49.6</td>
<td>2.16</td>
<td>61 (58)</td>
</tr>
<tr>
<td>Aspect 180° Growth Index 3</td>
<td>1.68</td>
<td>1.47</td>
<td>2.18</td>
<td>7.3</td>
<td>53.7</td>
<td>2.47</td>
<td>61 (58)</td>
</tr>
<tr>
<td>Drainage Area Growth Index 4</td>
<td>1.65</td>
<td>1.52</td>
<td>2.31</td>
<td>4.8</td>
<td>56.2</td>
<td>2.51</td>
<td>61 (58)</td>
</tr>
<tr>
<td>Radiation slope-based Growth Index 5</td>
<td>1.76</td>
<td>1.59</td>
<td>1.59</td>
<td>4.8</td>
<td>43.2</td>
<td>2.79</td>
<td>48 (44)</td>
</tr>
</tbody>
</table>

7.4.3.1 2D Spline Interpolations without using the Square Root Transformation

The data set with zeros was also modelled using untransformed data to review the signal difference, which was transformed by taking the square root. As expected the signal is slightly lower and the residuals from the data were slightly larger than the residuals in Figures 7.30 and 7.31.

Figure 7.13 Surface Statistical Outputs for the 2D Model untransformed data with zeros.

<table>
<thead>
<tr>
<th>2D Model # (1-5)</th>
<th>RTGCV</th>
<th>GCV</th>
<th>RTMSR</th>
<th>MSR</th>
<th>Signal</th>
<th>Error d.f.</th>
<th>Var. $\sigma^2$</th>
<th>N (K)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tangential Curvature Growth Index 1</td>
<td>31.1</td>
<td>969</td>
<td>28.7</td>
<td>821</td>
<td>4.9</td>
<td>56.1</td>
<td>892</td>
<td>61 (52)</td>
</tr>
<tr>
<td>Aspect 360° Growth Index 2</td>
<td>30.4</td>
<td>924</td>
<td>25.2</td>
<td>633</td>
<td>10.5</td>
<td>50.5</td>
<td>765</td>
<td>61 (58)</td>
</tr>
<tr>
<td>Aspect 180° Growth Index 3</td>
<td>30.7</td>
<td>943</td>
<td>27.9</td>
<td>777</td>
<td>5.6</td>
<td>55.4</td>
<td>856</td>
<td>61 (58)</td>
</tr>
<tr>
<td>Drainage Area Growth Index 4</td>
<td>30.7</td>
<td>940</td>
<td>28.3</td>
<td>798</td>
<td>4.8</td>
<td>56.2</td>
<td>866</td>
<td>61 (58)</td>
</tr>
<tr>
<td>Radiation slope-based Growth Index 5</td>
<td>33.3</td>
<td>1110</td>
<td>30.0</td>
<td>900</td>
<td>4.7</td>
<td>43.3</td>
<td>999</td>
<td>48 (44)</td>
</tr>
</tbody>
</table>
Additional statistics on the transformed data, were calculated to explicitly determine the untransformed MSR and RTMRS for: accurate comparisons with the statistical outputs of the linear regressions (chapter 5); satellite statistical analysis comparisons; F-test calculations and for checks with the ANUSPLIN statistical outputs.

Figure 7.14  Statistical verification of the 2D Model outputs without zeros.

<table>
<thead>
<tr>
<th>2D Model Variables</th>
<th>Model # (1-5)</th>
<th>Signal</th>
<th>Root mean square residual</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tangential curvature Growth Index</td>
<td>1</td>
<td>3.0</td>
<td>31.9</td>
</tr>
<tr>
<td>Aspect 360° Growth Index</td>
<td>2</td>
<td>9.3</td>
<td>27.4</td>
</tr>
<tr>
<td>Aspect 180° Growth Index</td>
<td>3</td>
<td>3.6</td>
<td>32.0</td>
</tr>
<tr>
<td>Drainage Area Growth Index</td>
<td>4</td>
<td>3.6</td>
<td>31.8</td>
</tr>
<tr>
<td>Radiation slope-based Growth Index</td>
<td>5</td>
<td>5.2</td>
<td>30.8</td>
</tr>
</tbody>
</table>

Figure 7.15  Statistical verification of the 2D Model outputs with zeros.

<table>
<thead>
<tr>
<th>2D Model Variables</th>
<th>Model # (1-5)</th>
<th>Signal</th>
<th>Root mean square residual</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tangential curvature Growth Index</td>
<td>1</td>
<td>6.9</td>
<td>28.3</td>
</tr>
<tr>
<td>Aspect 360° Growth Index</td>
<td>2</td>
<td>11.4</td>
<td>25.0</td>
</tr>
<tr>
<td>Aspect 180° Growth Index</td>
<td>3</td>
<td>7.3</td>
<td>27.5</td>
</tr>
<tr>
<td>Drainage Area Growth Index</td>
<td>4</td>
<td>4.8</td>
<td>28.3</td>
</tr>
<tr>
<td>Radiation slope-based Growth Index</td>
<td>5</td>
<td>4.8</td>
<td>29.7</td>
</tr>
</tbody>
</table>
The data set with zeros produced the superior results with higher signals and lower GCVs. This matches the physical understanding that biomass would be zero if the GI were zero over a 6 month growth interval. Given these results, the larger data set was used for further 3D modelling.

The difference in aspect $360^\circ$ and aspect $180^\circ$ agree with the results of chapter 5 where the impact of the western slopes increases the statistical validity of aspect $360^\circ$. Model 2 (aspect $360^\circ$) produced the best 2D model. It had the least difference in performance between using and not using the zero biomass values, an indication of the robustness of this model. Model 4 (drainage area) was the second most statistically significant 2D model according to the GCV outputs. 2D Model 1 (tangential curvature and GI) produced a smooth spline with a linear sum of least squares function with only 3 variables in the equation within the spline function. This result is limited by lack of data, errors in the data, spatial differentiation between data points, and the inherent limits on distributing noisy data. Other spline models were run with a reduced tangential curvature data set (40 (35)N(K)) and the GCV was minimised to 2.29 with a signal of 3.3.

### 3D Spline Analysis

#### 7.4.4 Spline analysis using three independent variables (3D model)

Further model development involved the combination of hydrological driven parameters (tangential curvature or drainage area) and radiation-driven parameters (radiation on a sloping surface or aspect) into the spline analysis. Both these parameters are strongly influenced by the terrain but they indicate very different processes. The combination of these two distinct processes makes physical sense in the catchment as they represent the dominant processes that influence biomass variability, outside anthropogenic activities.

Models 6, 7, 9 and 10 = a radiative terrain parameter + hydrologically driven parameter/s
Model 8 = a slope based radiation + radiative terrain parameter (aspect).

The 3D spline model produced higher signals for all models but it also produced a higher GCV in all models expect for models 6 and 9. Refer to F-test section 7.5.1 for model validity.

Figure 7.16 shows the 3D topo-climate models that incorporate both radiative and hydrologically driven parameters.
Figure 7.16  Surface statistical outputs from the 3D Topo-climate Model

<table>
<thead>
<tr>
<th>3D Model # (6-10)</th>
<th>RTGCV</th>
<th>RTMSR</th>
<th>MSR</th>
<th>Signal</th>
<th>Error d.f.</th>
<th>Var. $\sigma^2$</th>
<th>N (K)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Radiation slope-based</td>
<td>0.67</td>
<td>0.05</td>
<td>0.00</td>
<td>51.4</td>
<td>4.6</td>
<td>0.04</td>
<td>56 (52)</td>
</tr>
<tr>
<td>Tangential Curvature Growth Index</td>
<td>6</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Radiation slope-based</td>
<td>1.72</td>
<td>1.18</td>
<td>1.40</td>
<td>15.1</td>
<td>32.9</td>
<td>2.04</td>
<td>48 (45)</td>
</tr>
<tr>
<td>Drainage Area Growth Index</td>
<td>7</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Radiation slope-based</td>
<td>1.82</td>
<td>1.18</td>
<td>1.38</td>
<td>17.0</td>
<td>31.0</td>
<td>2.14</td>
<td>48 (45)</td>
</tr>
<tr>
<td>Aspect 360 degrees Growth Index</td>
<td>8</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Tangential curvature</td>
<td>1.58</td>
<td>0.85</td>
<td>0.73</td>
<td>28.1</td>
<td>32.9</td>
<td>1.34</td>
<td>61 (58)</td>
</tr>
<tr>
<td>Aspect 360 degrees Growth Index</td>
<td>9</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Drainage Area</td>
<td>1.66</td>
<td>1.15</td>
<td>1.32</td>
<td>18.7</td>
<td>42.3</td>
<td>1.91</td>
<td>61 (58)</td>
</tr>
<tr>
<td>Aspect 360 degrees Growth Index</td>
<td>10</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Figure 7.17 Verification of the 3D model of interpolated biomass

<table>
<thead>
<tr>
<th>3D Model Variables</th>
<th>Model # (6-10)</th>
<th>Signal</th>
<th>Root mean square residual</th>
</tr>
</thead>
<tbody>
<tr>
<td>Radiation slope-based</td>
<td>6</td>
<td>51.4</td>
<td>0.85</td>
</tr>
<tr>
<td>Tangential Curvature Growth Index</td>
<td>6</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Radiation slope-based</td>
<td>7</td>
<td>15.1</td>
<td>22.2</td>
</tr>
<tr>
<td>Drainage Area Growth Index</td>
<td>7</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Radiation slope-based</td>
<td>8</td>
<td>17.0</td>
<td>22.3</td>
</tr>
<tr>
<td>Aspect 360 degrees Growth Index</td>
<td>8</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Tangential curvature</td>
<td>9</td>
<td>28.1</td>
<td>15.5</td>
</tr>
<tr>
<td>Aspect 360 degrees Growth Index</td>
<td>9</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Drainage Area</td>
<td>10</td>
<td>18.7</td>
<td>21.7</td>
</tr>
<tr>
<td>Aspect 360 degrees Growth Index</td>
<td>10</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
### 7.5 Statistical Significance and validation of the Disaggregation Models

#### 7.5.1 F-test for variance homogeneity between 2D and 3D models

The aspects of the data that need to be considered when statistically differentiating between models are:

- Sample size
- The presence or absence of correlation between data from the two data sets
- Homogeneity of the sample variances

It is known that in small data sets the loss of a degree of freedom can be critical. Model complexity (e.g. from a 2D to 3D model) also has a trade-off with data fidelity and degrees of freedom. The GCV incorporates a penalty on the increase in the number of parameters or model complexity. It is
vital to distinguish between statistical significance of the two error variances of the simple and more complex models in order to test the validity of the more complex model. Using the F-test (equation 7.10) can test the statistical significance of the more complex model. The null hypothesis is that the more complex model is not statistically significant. It is rejected if the F-value is greater than the F-value in the F-table for the chosen significance level. It is known from the output statistics in equation 7.6 and figure 7.8 that the signal degrees of freedom and the error degrees of freedom for each surface add up to N (the number of data points).

F-test for determining statistical significance of the variance homogeneity between the Topo-climate Models

\[ F = \frac{(\text{RSS} - \text{RSS}_i)}{(\text{Sig} - \text{Sig}_i)} / \frac{\text{RSS}_i}{\text{error}} \]

(7.8)

where,

\( \text{RSS} = \) residual sum of squares of the simple model
\( \text{RSS}_i = \) residual sum of squares of the more complex model being tested
\( \text{Sig} = \) signal of the simple model
\( \text{Sig}_i = \) signal of the more complex model

and,

\( \text{RSS}_i / \text{error} = \) estimate of the error variance of the more complex model being tested
\( \text{RSS}_i / \text{error} = \) estimate of the error variance of the more complex model being tested

F-test # 1. Model 10 versus Model 2

\[ F = \frac{(106.8 - 80.52)}{(49.6 - 42.3)} = 1.88 \]

\[ 1.91 \]

Using degrees of freedom of 7.3 and 42.3 the upper 5% critical point of the corresponding F-distribution was found to be (via F-tables)

\( F_{7.3,42.3} = 2.2 \)
Therefore the reduction in the residual sum of squares is not significant at the 5% level. Since the tested 3D model (#10) produced a lower F-value it is concluded from this statistical test that model #10 is not a significant improvement on model #2. That is, adding drainage to the model was not a statistically significant improvement.

**F-test #2. Model 9 verses Model 2**

\[ F = \frac{(106.8 - (0.725 \times 61)) / (49.6 - 32.9)}{1.34} = 2.80 \]

Using degree of freedom of 16.9 and 32.9 the F-tables were consulted

\[ F_{16.9, 32.9} = 1.97 \text{ at the } 5\% \text{ level, } 2.62 \text{ at the } 1\% \text{ level.} \]

Therefore the reduction in the residual sum of squares was significant at both the 5% and 1% level.

**Figure 7.19**

Summary table for the F-test on the 3D models verses the 2D model of aspect 360° and GI.

<table>
<thead>
<tr>
<th>3D model</th>
<th>Model # (6-10)</th>
<th>F-value</th>
<th>F-test 5% level</th>
<th>F-test 1% level</th>
</tr>
</thead>
<tbody>
<tr>
<td>Radiation slope-based Tangential Curvature Growth Index</td>
<td>6</td>
<td>∞</td>
<td>---</td>
<td>---</td>
</tr>
<tr>
<td>Radiation slope-based Drainage Area Growth Index</td>
<td>7</td>
<td>1.16</td>
<td>2.82</td>
<td>4.4</td>
</tr>
<tr>
<td>Radiation slope-based Aspect 360 degrees Growth Index</td>
<td>8</td>
<td>1.02</td>
<td>2.75</td>
<td>4.22</td>
</tr>
<tr>
<td>Tangential curvature Aspect 360 degrees Growth Index</td>
<td>9</td>
<td>2.80</td>
<td>1.97</td>
<td>2.62</td>
</tr>
<tr>
<td>Drainage Area Aspect 360 degrees Growth Index</td>
<td>10</td>
<td>1.89</td>
<td>2.2</td>
<td>3.1</td>
</tr>
</tbody>
</table>

--- F-test could not be calculated due to MSR value = 0

Model 6 was rejected as the GCV method failed to determine a sensible degree of data smoothing.
Thus, figure 7.36 shows that the only 3D model that was statistically more significant than the 2D model #2 was model #9 (i.e. aspect + tangential curvature + growth index).

7.5.2 GCV outputs of the 10 models

As stated the GCV is a statistical validation test for the accuracy of the model fit. The bar graph (Figure 7.20) shows that model #8 had the highest GCV and therefore the highest error and the least model fit. 3D Model #8 had two independent variables representing radiation (i.e. radiation on a sloping surface and aspect) and one independent variable as the growth index (GI). This model did not incorporate a hydrological variable and this combined with two radiation-driven variables proved to represent biomass distribution with the least accuracy. The GCV outputs demonstrate the need for both hydrological driven and radiation-driven parameters to disaggregate biomass in this catchment.

Figure 7.20 also confirms that models #9 (3D) and #2 (2D) with the lowest GCV's represented spatio-temporally disaggregated biomass with greatest accuracy. The F-test (equation 7.10) verified that model #9 was more statistically significant than model #2. The F-test also validates that the GCV outputs are reflecting the model fits with statistical significance. The F-test also proved that model #2 was more stable than model #10 and therefore more statistically significant than model #10.

Figure 7.20 Statistical Validation of the Topo-climate Models

GCV for 9 Topo-climate Models

2D models 1-5, 3D models 7-10
Chapter 7 Spatio-temporal Disaggregation of Biomass
Spatio-temporal Disaggregation of Biomass

From the spline analysis it is evident that the lowest GCV and therefore the best result was model #9 (3D: with tangential curvature, aspect $360^\circ$ and GI). This is encouraging as most of Australia is covered with low relief terrain and spline analysis could provide subtle insights into the spatial distribution of biomass by incorporating tangential curvature. In Chapter 5, the 30 m DEM had high correlation coefficients (0.78) using tangential curvature against satellite data (TMSAT 3). Further adjustments were made in tangential curvature 2D spline analysis. These included the removal of outliers. The results substantially reduced the GCV and improved the interpolation of tangential curvature with the growth index to produce spatial biomass. Spline analysis with 39 knots of transformed tangential curvature data produced a GCV of 2.45 and MSR of 2.13. Using 35 knots of transformed tangential curvature data the GCV was 2.29 and MSR 1.93. The linear regression analysis did not produce a statistically significant correlation between tangential curvature and biomass over all time periods. Aspect $360^\circ$ produced similar results in the spline analysis and the linear regression suggesting biomass is linked to aspect even in such a low relief catchment. In chapter 4, there was a correlation between biomass and radiation during the March periods of growth using regression analysis, however, in the spline analysis the RTGCV was large. Thus the regression analysis was only useful at single time periods, while the spline interpolation applied to all time periods.

7.5.3 Fine-scale investigation of the temporal fits with the original data points

Validation of modelling processes is not always a direct and easy task to accomplish. Therefore in addition to minimising the GCV (fig 7.20), a fine-scale examination of the temporal and spatial smoothing processes of the 2D and 3D models was examined. The following figures show the results from: model 2 and 1 (2D with zeros); and 3D model 9 (with zeros). The spline fit for model 2 (aspect 0-360$^\circ$) did reasonably well given the noisy biomass data points.

Figure 7.21 2D Model of aspect (0 – 360) degrees and the original biomass data points
Figure 7.21  2D Model of aspect (0 – 360°) degrees and the original biomass data points

Figure 7.22  2D Model of aspect (0 – 360°) and the original biomass data points: Sept. 1993
From the fine-scale examination of the spatio-temporal modelling it is clear that at the September time period there is not a correlation and the range of the biomass response is limited. This is in agreement with the individual linear modelling results in chapter 5. Figures 7.32 and 5.31 (chapter 5) are directly comparable showing the interpolation procedures. It is also evident that both the March time periods show the same trend where south (180°) indicated the lowest biomass and north (90°) the highest biomass while west (270°) shows a slight decrease in biomass compared to east, where the western slopes procure more afternoon radiation. The impact of the western slopes was discussed in chapter 5 with the individual linear regressions. It is encouraging to note that the spline analysis also detected the radiation impact on biomass at approximately 270°. Tangential curvature was also examined at the individual timesteps as the GCV was low in the 2D models even though the linear modelling in chapter 5 did not produce statistically significant results.
Figure 7.24  2D Model of Tan. Curvature and original biomass data points: March 1993

Figure 7.25  2D Model of Tan. Curvature and original biomass data points: Sept. 1993
It is clear from the individual analysis of the spatio-temporal spline fit that biomass had a small but consistent response to tangential curvature. Thus aspect produced the dominant terrain impact on biomass and tangential curvature indicated a more subtle hydrological response.
Figure 7.28  Spline Curve of 3D Model #9 during September 1993

Spline fit: Aspect + Tangential Curvature

3D Model September 1993

Figure 7.29  Spline Curve of 3D Model #9 during March 1994

Spline fit: Aspect + Tangential Curvature

3D Model March 1994
Figures 7.27 to 7.30 show the temporal components of the 3D model with tangential curvature set to zero. This model produced the most accurate spatial biomass patterns. Ideally figures 7.27 and 7.29 would be periodic and the $0^\circ$ and $360^\circ$ value would be equal. Further analysis could constrain the data to do this. Both figures however, demonstrate the radiative impact on biomass between $0^\circ$ to $90^\circ$ and the $270^\circ$ western slope effect with slightly less biomass than the northeastern slopes. During September the zero growth period the spline curve fit shows little response to biomass.

### 7.5.4 Conclusions of the two aims of the topo-climate model analysis

1. Spline interpolation methods proved very successful under the limited data sets and in this low relief catchment. This technique is valuable as data are often limited and subtle changes in the terrain surface are often difficult to detect.

2. Aspect ($0^\circ - 360^\circ$) was the dominant radiation related terrain parameter affecting biomass and tangential curvature was the dominant hydrological parameter.

### 7.6 Statistical Model Comparisons and Validation

One common problem is that ground data are limited to points (Chapter 1, figure 1.1) while spatio-temporal data are required to deal for complex catchment management problems. The next problem is what model/s or techniques provide the most statistically accurate spatio-temporal data. It is important to be able to statistically compare different models in order to determine the model accuracy and validation of the techniques used within various models. Other considerations include; data availability, model complexity, predictive capacity, retrospective examinations and costs involved.

#### 7.6.1 Residual outputs from the satellite data

The atmospherically corrected TMSAT band 3 data were normalised against the October 1993 data (figure 7.30). This normalised data produced a spatio-temporal model of reflectance over the three time periods (figure 7.30a). Residual outputs from the satellite model indicate the accuracy of the model fit (figures 7.31 and 7.32). Chapter 3 (figure 3.20) showed a similar trend to figure 7.30.

Figure 7.30b   Biomass verses the Satellite Model
Figure 7.30b  Biomass versus the Satellite Model

Atmospherically Corrected Satellite
Normalised TMSAT band 3

95% confidence limits shown

Figure 7.31  Statistical outputs from the linear regression Satellite model

<table>
<thead>
<tr>
<th>Analysis of variance</th>
<th>Degrees of freedom</th>
<th>Sum of squares</th>
<th>Mean square (RTMSR)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Regression</td>
<td>1</td>
<td>276661.77</td>
<td>276661.77</td>
</tr>
<tr>
<td>Residuals</td>
<td>44</td>
<td>64957.79</td>
<td>1476.31 (38.42)</td>
</tr>
</tbody>
</table>

Figure 7.32  Statistical outputs from the quadratic regression Satellite model

<table>
<thead>
<tr>
<th>Analysis of variance</th>
<th>Degrees of freedom</th>
<th>Sum of squares</th>
<th>Mean square (RTMSR)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Regression</td>
<td>2</td>
<td>276820.62</td>
<td>138410.31</td>
</tr>
<tr>
<td>Residuals</td>
<td>43</td>
<td>64798.95</td>
<td>1506.95 (38.82)</td>
</tr>
</tbody>
</table>
Chapter 7. Spatio-temporal Modelling of Biomass
Spatio-temporal Modelling of Biomass

Figure 7.30a The Satellite Model

- **Biomass Data.** Data collection time similar to satellite overpass date. Chpts 2, 3
- **Spatio-temporal Modelling of Biomass**
- **Correlations** between biomass and satellite data Chapters 5 and 6
- **TMSAT band selections** from correlations between biomass & satellite data. Empirical relationship.
- **Select reference scene. Normalise data over time.**
- **Regress biomass data over time. Empirical relationship.**
- **GIS: ARCINFO development Map production.**
- **The Satellite Model.**
- **Scaling issues.**
- **Spatio-temporal data. TMSAT Bands 3, 4, 5 and 7. Chapter 3 Gridded to 25 m DEM resolution.**
- **GIS development for Atmospheric corrections via invariant pixels calibrations. Chpt 3.**
Chapter 7 Spatio-temporal Disaggregation of Biomass
Spatio-temporal Disaggregation of Biomass

It is clear that the linear fit represents the satellite and biomass relationship with the lowest residuals. The data set could not support a cubic fit. Therefore using the linear fit, the residual model comparison was determined by dividing the sum of squares by the total number of data points (degrees of freedom). \( \frac{64957.79}{45} = 1443.51 \) and \( \sqrt{1443.51} = 37.99 \). This is different from the internal model validation where the root mean square residual was 38.42.

### 7.6.2 Residual outputs from sub-catchment analysis

The following figures show the statistical analysis of the sub-catchment and total catchment examination between biomass and GI at 26 weeks. Sub-catchments \( A_x \) and \( B_x \) show lower residuals than the total catchment response, which is not surprising given that they incorporate 6 parameters instead of 2 parameters for the total catchment response.

#### Figure 7.33 Sub-catchment \( A_x \)

<table>
<thead>
<tr>
<th>Analysis of variance</th>
<th>Degrees of freedom</th>
<th>Sum of squares</th>
<th>Mean square (RTMSR)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Regression</td>
<td>1</td>
<td>168369.11</td>
<td>168369.11</td>
</tr>
<tr>
<td>Residuals</td>
<td>19</td>
<td>10782.07</td>
<td>770.15 (27.75)</td>
</tr>
</tbody>
</table>

#### Figure 7.34 Sub-catchment \( B_x \)

<table>
<thead>
<tr>
<th>Analysis of variance</th>
<th>Degrees of freedom</th>
<th>Sum of squares</th>
<th>Mean square (RTMSR)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Regression</td>
<td>1</td>
<td>75745.23</td>
<td>75745.23</td>
</tr>
<tr>
<td>Residuals</td>
<td>17</td>
<td>18695.83</td>
<td>1099.76</td>
</tr>
</tbody>
</table>

#### Figure 7.35 Sub-catchment \( J_x \)

<table>
<thead>
<tr>
<th>Analysis of variance</th>
<th>Degrees of freedom</th>
<th>Sum of squares</th>
<th>Mean square (RTMSR)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Regression</td>
<td>1</td>
<td>49246.24</td>
<td>49246.24</td>
</tr>
<tr>
<td>Residuals</td>
<td>11</td>
<td>18780.16</td>
<td>1707.29 (41.32)</td>
</tr>
</tbody>
</table>
Figure 7.36 Total catchment response

<table>
<thead>
<tr>
<th>Analysis of variance</th>
<th>Degrees of freedom</th>
<th>Sum of squares</th>
<th>Mean square (RTMSR)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Regression</td>
<td>1</td>
<td>272381.67</td>
<td>272381.67</td>
</tr>
<tr>
<td>Residuals</td>
<td>44</td>
<td>69236.98</td>
<td>1573.57 (39.67)</td>
</tr>
</tbody>
</table>

Root mean square residual model comparison:

Sub-catchment residuals:

\[ \text{RSS } A_x + \text{RSS } B_x + \text{RSS } J_x = Y \]
\[ Y / 45 = Z \]
\[ \therefore Z = 48258.06/45 = 1072.40, \text{ sq root } = 32.75 \]

Total catchment residual:

\[ \text{RSS / 45 } = Z \]
\[ \therefore Z = 69236.98/45 = 1538.60, \text{ sq root } = 39.23 \]

Sub-catchment disaggregation of climate, terrain, biomass and growth indices data did not provide sufficient correlations to use for biomass disaggregation at the sub-catchment scale. Sub-catchment analysis did confirm the need for 26 week GROWEST accumulation period. In addition, the sub-catchment analysis indicated that in this low relief catchment the disaggregation of biomass requires the combination of modelled biomass, terrain and biomass data to produce spatio-temporal biomass models and maps.

7.6.3 Root mean square residual comparisons between models

Figure 7.37 provides a statistical comparison between the different models developed in this study. It is clear that the 3D model, which incorporated both radiative, hydrological and terrain specific parameters, as well as a modelled growth index provides the most accurate information and best captures biomass distribution within the catchment.
Residual analysis allows for model validation and statistical comparison between models. This validation process shows model complexity versus the statistical significance of the effective number of parameters. Although the 3D model is complex (i.e. requires 28 parameters), statistically these parameters are valid as the root mean square residual is low. Given there are not zero values in the validation data file, and the spline models complexity has minimised the GCV the model comparison is accurate across the different model types. Holding some variables constant (figures 7.23 - 7.26) also showed the effective impact of different parameters. From these results it was determined that aspect 0-360° was the dominant factor controlling the spatial distribution of biomass. In conclusion, it is evident that the 3D spatio-temporal model developed using spline analysis represented biomass disaggregation within this catchment with greatest accuracy.

### 7.6.4 GIS development: Maps for the 2D, 3D topo-climate models and satellite images

Spatio-temporal model development, validation and statistical comparison combined with GIS capabilities can produce robust models with tangible outputs such as maps. Using LAPPGRD (Hutchinson 1999) the interpolated spatio-temporal biomass data was imported into ARCINFO.
Figure 7.38
Spatially Distributed Biomass
2D Topo-climate Model
Lockyersleigh Catchment
March 1993

Biomass g/0.25 m\(^2\)

- 0 - 15
- 15 - 25
- 25 - 35
- 35 - 50
- 50 - 65
- 65 - 80
- 80 - 100
- 100 - 120
- 120 - 145
Chapter 7. Spatio-temporal Modelling of Biomass
Spatio-temporal Modelling of Biomass

Figure 7.39
Spatially Distributed Biomass
2D Topo-climate Model
Lockyersleigh Catchment
September 1993

1km

Biomass g/0.25 m-2

- 0 - 15
- 15 - 25
- 25 - 35
- 35 - 50
- 50 - 65
- 65 - 80
- 80 - 100
- 100 - 120
- 120 - 145

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Figure 7.40
Spatially Distributed Biomass
2D Topo-climate Model
Lockyersleigh Catchment
March 1994
Figure 7.41
Spatially Distributed Biomass
3D Topo-climate Model
Lockyersleigh Catchment
March 1993
Figure 7.42
Spatially Distributed Biomass
3D Topo-climate Model
Lockyersleigh Catchment
September 1993

Biomass g/0.25 m²

- 0 - 15
- 15 - 25
- 25 - 35
- 35 - 50
- 50 - 65
- 65 - 80
- 80 - 100
- 100 - 120
- 120 - 145

1km
Figure 7.43
Spatially Distributed Biomass
3D Topo-climate Model.
Lockyersleigh Catchment
March 1994

Biomass g/0.25 m²

- 0 - 15
- 15 - 25
- 25 - 35
- 35 - 50
- 50 - 65
- 65 - 80
- 80 - 100
- 100 - 120
- 120 - 145
Further GIS interrogation, involved grouping biomass levels to different shades, clipping the catchment boundary and producing sensible, easy-to-read, and useful maps. The lack of biomass variability (catchment homogeneity) during winter is clearly shown in September (3D model #9, figure 7.42). This is in agreement with; initial biomass variability checks (figure 4.1), the plant physiology of grass/pasture growth, and the climate for this region.

The 2D models incorporating aspect (0 – 360°) and GI produced statistically accurate results (figure 7.37) and the maps are easy to interpret (figure 7.38 – 7.40). Aspect is a radiation influenced terrain parameter that is relatively simple when compared with the radiation calculations in the SRAD model and even the adjustments in the aspect (0 – 180°) models. Aspect showed a correlation with biomass (chapter 5) and when combined with GI it accurately distributed biomass in this low relief catchment.

Figure 7.38 shows that aspect and GI are suitable indicators of biomass levels during March 1993. The left side of the catchment shows the northeastern slopes produced the highest biomass (65 – 80 g 0.25 m²). The terrain conditions here were warm but not too hot to dry out the surface, unlike the northwestern slopes where surface moisture was not able to be maintained due to the radiation load. Another north-eastern patch (near the eastern end of transect A₀) indicated high biomass for the same reasons. The north-western areas (right side of catchment, green areas) with biomass between 25 – 35 g 0.25 m², indicate soil moisture was not maintained, due to surface drying and biomass levels were reduced. The red areas are on high dry ridges where the biomass was low (15 – 25 g 0.25 m²), and the white areas are on the southern slopes where there was not enough radiation to support growth during March 1993.

September 1993 (Figure 7.39) shows less variation in biomass than March 1993. Reduction in catchment biomass levels is consistent with the original collected biomass data and chapter 4 (figure 4.1). The biomass range was 25 – 80 g 0.25 m² during September as opposed to March 1993 and 1994 (figures 7.38, 7.40) where the biomass range was 65 – 140 g 0.25 m². Generally, the north-eastern and north-western slopes produced lower biomass levels than the March periods and this is in agreement with the climatic conditions during winter, the plant physiology of grasses and pasture, and the growth indices of the modelled outputs. The modelled outputs for September for the 2D and 3D models indicate that there is not a strong trend between biomass, climate and terrain during September and modelling biomass at this season is difficult.

March 1994 2D model (figure 7.40) shows a similar biomass pattern to the March 1993 2D model, except higher levels of biomass due to the climatic conditions mainly due to higher antecedent
Spatio-temporal Disaggregation of Biomass

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rainfall. The catchment biomass is responding to both aspect and GI in a similar way to March 1993.

The 3D model (figure 7.41) shows a more complex pattern with higher statistical accuracy (figure 7.37). This 3D model incorporates climate (via GI) and two terrain parameters (aspect and tangential curvature). These model results are sensible as biomass does respond to both temperature and water availability. The increase in model complexity of the 3d model (#9) suggests significant interaction between aspect (0-360°) and tangential curvature in their effects on biomass. Again the northeastern slopes are producing the highest biomass (120 – 145 g 0.25 m²) during March 1993 and 1994. The temperature moisture balance is critical for plant growth. This is verified by the north-western slopes (biomass 80 – 100 g 0.25 m³) which indicate the next highest biomass where the radiation load of the western slopes is causing some surface drying out. The water flow patterns as indicated by tangential curvature, show regions where potential wetting and drying out can occur. This greater differentiation of biomass distribution provides more details about surface cover for management purposes. The southern slopes are producing less biomass but not as low as the 2D models (figures 7.38 - 7.40). The 3D March 1993 model agree with the trends of the 2D March 1993 but also indicate higher levels of biomass and finer scale patterns of biomass distribution. An example of the fine scale response of biomass is shown in the 3D September 1993 model where the biomass close to the streamlines suggests wet grasslands and low biomass levels. Also during March 1993 and 1994 these wet southerly regions produced less biomass than surrounding regions. Further examination of the 3D model (#9) also confirmed the effect of tangential curvature at transect Bx. Transect Bx is relatively flat in comparison to the other sites and therefore aspect had less effect on biomass and tangential curvature had an impact where convergent sites increased biomass. The 3D model represented the catchment with greater complexity through the interaction of two terrain variables as opposed to the 2D models with one terrain variable.

The satellite images represent the catchment in different ways to the topo-climate models and more analysis would be required to obtain the same explanation of spatio-temporal biomass data that is evident in the topo-climate models. The relationship between biomass and satellite data (TMSAT band 3) is based on figure 3.20 (chapter 3), March 1993. The quadratic fit with $r^2 = 0.72$ showed the vegetation just beginning to senesce (turn yellow/brown). These observations with high reflectance (yellow/brown tone) had high biomass at some sites in transect Ax, while other sites at transect Bx with lower elevation had less brown and more green tones (Cusack 1997). All three satellite images (figures 7.44 – 7.46) indicate the divisions between the trees and grass, as well as depicting roads, buildings and the railway track. However, depending on the temporal period (satellite overpass date/season) the reflectance of the different biomes can produce different colours.
Figure 7.44
Thematic Mapper Satellite
TMSAT Band 3
March 1993

Raw Reflectance Values.

- 0 - 15
- 15 - 20
- 20 - 25
- 25 - 30
- 30 - 35
- 35 - 40
- 40 - 45
- 45 - 50
- 50 - 65
- 65 - 108
Figure 7.45
Thematic Mapper Satellite
TMSAT Band 3
Lockyersleigh Catchment
September/October 1993
Figure 7.46
Thematic Mapper Satellite
TMSAT Band 3
Lockyersleigh Catchment
March 1994

Raw Reflectance Values.

- 0 - 15
- 15 - 20
- 20 - 25
- 25 - 30
- 30 - 35
- 35 - 40
- 40 - 45
- 45 - 50
- 50 - 65
- 65 - 108
For example, the trees are shown by green (20-25 reflectance value) during March 1993 and October 1993, while during March 1994 the trees are represented by the white colour (0-15 reflectance value).

During March 1993 the 2D and 3D topo-climate models and the satellite model show some similarity and this is particularly evident at positions \(X, Y\) and \(Z\) (figure 7.46), as well as at the north eastern edge of the catchment. Areas \(X, Y\) and \(Z\) indicate higher biomass than the surrounding regions due to aspect effects i.e., north to north eastern slopes. Area \(W\) could indicate variation due to both aspect and tangential curvature. The southerly slopes have low biomass and the ridges have slightly higher biomass. However, area \(W\) could also represent the dissecting effect of the railway track. The railway line (refer to chapter 2, figure 2.1a) could act as a fence where grazing is more intense on the northern side of the line. Alternatively the railway could be reducing subsurface flow, which is driven by the catchment gradient. The reduction in subsurface flow is less likely due to the low relief of the catchment and the shallow soil profile structure of the railway construction. The satellite image for this time period indicates a line of trees around area \(Y\) where a tree planting line is used as a windbreak.

As stated earlier during September 1993 there was too much cloud cover and therefore the closest orbital date, 4 October 1993, was used. There is little variation in the catchment at this time, which is physiologically valid for this catchment. The satellite image is representing the trees clearly and areas \(X, Y\) and \(Z\) do have higher reflectance values.

The March 1994 satellite image has a surprisingly low variability (figure 7.46). This could be due to the higher rainfall and growth and therefore the less browning of the grasses as compared to March 1993. The trees are very green in this image as shown by the reflectance values between 0 – 15 and the roads can be easily seen (refer to figure 2.1a).

### 7.6.5 Discussion of model comparison and validations

Clearly the 3D spline topo-climate model represents biomass distribution with the greatest statistical accuracy (residuals 17.7) and is justified in the usage of 28 effective parameters (figure 7.37). This proves that a) the interpolation method (ANUSPLIN, Hutchinson 1999) is effective and b) the combination of hydrological and radiation driven parameters are important for accurate spatio-temporal biomass distribution. The 2D topo-climate model using aspect and GI was also a suitable model proving that at this scale aspect is an important terrain variable in determining biomass.
distribution. Interestingly, the sub-catchment model was quite efficient using only three effective parameters to produce residuals similar to the 2D topo-climate model that incorporated tangential curvature and GI. This suggests that the 2D topo-climate model using seven effective parameters is not as efficient as the sub-catchment model. However, the 2D model is more statistically significant and did produce sensible maps (figures 7.38-7.40) which are well suited for both research and management purposes. Spatially sub-dividing biomass and temperature (the sub-catchment model) produced better results at a finer scale than spatially varying biomass, tangential curvature and GI (3D model #9, figures 7.41-7.43). Finally the total catchment model with catchment averaged biomass verses GI and the satellite model produced similar results and the highest residuals and therefore the worst model fit in this comparison. The total catchment model required monthly climate data while the satellite model incorporated calibrated reflectance data at the times of biomass sampling.

Other model comparisons can be visually assessed via the maps (section 7.6.4). Although the maps can be georeferenced and are accurate they are a 1D representation of interpolated and classified data. Gridded map comparisons are more accurate than individual maps and this is where the GIS development can produce model comparisons between the outputs of different models.

7.7 Discussion and conclusions

This chapter discussed the development of a sub-catchment, satellite and topo-climate models for spatio-temporal disaggregation of biomass. Each model has different inputs and outputs with varying levels of statistical significance. Effective biomass modelling requires an accurate interpolation method that can be validated, as well as satellite input terrain and climate data. At this scale (Lockyersleigh 27 km$^2$) biomass disaggregation can support a 3D topo-climate model for accurate representation of spatio-temporally varying biomass. The key terrain variables are aspect and tangential curvature. However, further investigation of the considerable extra detail shown by the 3D model is warranted. In the absence of additional data support and in view of the extra stability of the 2D model it is the preferred spatio-temporal model.

7.7.1 Summary of findings

This chapter has shown that the
Terrain shape and drainage are more important parameters than elevation in low relief catchments (chapter 4, 5). And the combination of terrain and hydrologic parameters produced an accurate spatio-temporal model.

Limitations of single-scene remotely sensed data sets e.g. single aircraft data set

Problems with temporal remotely sensed data and the need for atmospheric corrections

High temporal variance in rainfall over the catchment

There was no consistent dependence of rainfall on elevation at this scale and in this low relief catchment

Spatially disaggregated sub-catchment temperature data was appropriate in this catchment as supported by the sub-catchment modelling results

Modelled biomass averaged separately over three sub-catchments was possible

A range of GI accumulation periods for biomass from weekly to integrated weekly biomass over a 26 week growing season was tested. The 26 week GI accumulation period captured the most accurate biomass results during 1993 and 1994.

Biomass (growing over 26 weeks) did not directly relate to monthly radiation. This was particularly noted during September when growth was suppressed.

Aspect (0 – 360 °) provided the most effective terrain parameter

Tangential curvature produced the most suitable hydrological response. Negative tangential curvature (convergent flow) produced higher biomass at transect B_x.

The most accurate 3D model was the combination of aspect (0 – 360 °), tangential curvature and a 26 week accumulated growth indices

The second most statistically significant model was the 2D spline model with aspect 360 ° and 26 week accumulated GI.

7.7.2 Climatic controls on biomass distribution in this low relief catchment

Topographic and climatic parameters determine vegetation distribution along with species differentiation and competition, grazing, nutrient availability, insect and fungal predation and anthropogenic activities. Important climatic determinants include, light, moisture and temperature. The climatic variables work jointly to influence biomass distribution.

As discussed in chapter 4, light has two primary functions: to provide energy for photosynthesis hence, growth; and secondly to indicate day length hence, seasonal changes. These functions provide energy for growth and timing for efficient reproduction in vegetation. Plants are sensitive
to light four major ways: presence/absence; direction; daily duration and spectral composition. The presence/absence of light (topographic, canopy and diurnal effects) and daily duration (day length) were briefly discussed in chapter 4. The spectral composition were discussed in detail in chapters 3, 4 and direction reviewed in chapters 5 and 7. The spectral composition of light was examined using CASI and satellite data (chapter 3). Different wavelengths of light are absorbed by plant phytochromes and converted into energy for plant growth. Combinations of different wavelengths were also examined to determine the best correlations with biomass. NDVI is commonly used as a light differentiation tool to determine green growth or photosynthetically active material (chapter 3). Light was also examined in its total light spectrum i.e. solar incident radiation (chapter 4). The light index (chapter 4) transforms the non-linear response of plant biomass to incident solar radiation into a linear scale. The impact of light was expressed as aspect throughout this thesis (chapter 5, 7). Given the size of the experimental catchment latitudinal changes are not reviewed. Aspect was examined from 0 to 360° and from 0 to 180°. Aspect from 0 to 360° shows the periodic sinusoidal fit of radiation, whereas, aspect from 0 to 180° indicates the curve fit as departure from south (figure 5.20a, 5.20c). Aspect from 0 to 360° produced a stronger correlation with biomass over time and proved to be the most suitable terrain parameter to represent biomass (chapters 5, 7).

Moisture affects biomass distribution through rainfall, humidity, hydrology, and soil moisture. Rainfall was discussed in chapters 2, 4, 7, hydrology chapters 4, 5, 7, soil moisture chapter 6 while humidity and boundary layer conditions were not examined directly in this study. Direct rainfall and biomass correlations were examined and although the general trend showed increased March rainfall with increased biomass the correlation was not statistically significant (Figure 4.10 and chapter 4). The effect of rainfall routed over the catchment surface was modelled using an accurate DEM (Hutchinson 1989) and different algorithms in the TAPES-G model (chapters 2, 5) to produce hydrologic parameters such as drainage area and tangential curvature. These hydrologic terrain parameters were correlated directly with biomass and statistically significant results were utilized in the development spatio-climatic models of biomass distribution (chapter 7). Rainfall was also used as an input into the water balance plant growth model (GROWEST) to produce temporal growth indices (chapters 4, 7). Direct correlations between growth indices and biomass were evaluated in chapter 4. These temporal growth indices were also combined with the terrain attribute data allowing the development of spatio-climatic models for biomass distribution (chapter 7).

Temperature influences moisture availability and the rate at which chemical reactions occur (Weier et al 1982). Generally high temperatures at the Lockyersleigh catchment increased biomass.
However, high temperatures and a low vapour pressure (dry atmosphere) cause high evaporation rates and therefore without sufficient moisture availability even shallow rooted grasses and pastures will not reach optimal growth (chapter 4). It was evident that low winter temperatures at the Lockyersleigh catchment reduced growth during the winter months (chapters 4, 7). The senesced growth during winter confirmed the need for a 26 week GI accumulation period. The sub-catchment temperature analysis showed that biomass responses at the finer scale still required a 26 week accumulation period. Topography greatly influences soil and air temperature (Weier et al 1982). Even minor differences in aspect create micro-environments which can affect biomass (chapters 5, 7) (Cusack et al 1997). Temperature is an estimate of the heat energy available from solar radiation. Solar radiation is absorbed, scattered or reflected within the atmosphere and only about half the total radiation may reach the ground and heat it. Radiation combined with a slope-based calculation at a monthly timestep provided correlations with biomass (chapters 4, 7). In September however, there was not a correlation between slope-based radiation and biomass due to: a) reduced growth with low winter temperatures and b) monthly radiation values verses a 26 week GI accumulation period for biomass (chapters 4, 7). For plant growth long term average radiation is required although seasonal variations must also be considered (Gallant 1997).

It is not surprising that rainfall and temperature are the controls on biomass within this catchment, however, quantifying and identifying physical processes that represent these climatic variables is difficult in this low relief catchment. Rainfall is driving the hydrologic component and this is expressed via the limiting moisture index in summer and via tangential curvature across the catchment. Temperature is partially represented by the solar radiation described as aspect from 0 to 360 degrees. Aspect was the dominant of the two terrain variables (chapter 7). Aspect has two specific functions in this study; it identifies increases in solar intensity due to the proximity to north and west and in combination with slope it can provide more accurate spatial disaggregation of solar radiation (Cusack et al 1997). The 3D spatio-climatic model combining the hydrologic and radiative parameters with the temporal growth index was evidence of this by representing biomass disaggregation with the greatest accuracy. However, further investigation of the influence of tangential curvature would be worthwhile.

7.7.3 Scale and Disaggregation

Scale is an important consideration when examining environmental data and processes and for the development of environmental models. It is important to capture both the physical properties (e.g. terrain data) and the environmental processes (e.g. biological production) at an appropriate scale for
accurate representation of their interactions with other processes. Environmental modelling often incorporates dependencies on terrain and therefore appropriate scale matching is essential (chapter 1).

Although most terrain data is temporally static the resolution and interpolation of source data are essential for accurate spatial representation of surface shape. Accurate representations of surface shape and drainage structure are facilitated by the development of locally adaptive process-based DEM interpolation techniques (chapter 2). The scale of the source data is a guide for resolution selection and this needs to be matched to the environmental scales of terrain-dependent applications (Hutchinson and Gallant 1999).

Scale issues can be categorised into spatial and temporal scales. Generally, static terrain attributes can be assessed at the spatial scale and environmental processes at the temporal scale. However, this is not always the case as temporal and spatial scales are dependent on each other. Light for example could be examined at different temporal scales. Hyperspectral examination of different wavelengths of light can be studied at the intercellular level, where it takes only minutes for light to alter the movement of ions across membranes (chapter 3). Light can be assessed in terms of providing energy for growth and this can take months for biomass accumulation (chapter 7). Given this vegetative growth rate, climatic determinants can be examined at a monthly timescale (Cusack et al 1997). Light at an ecosystem scale and annual timestep may be viewed as a non-limiting climatic variable for plant growth and therefore it is only the timing of the season with the year that is significant. Light however, is limiting in much of the tropics. Other climatic variables like precipitation are known to be highly variable at both spatial and temporal scales.

Understanding scale is a key to determining which variables most accurately represents spatio-temporal patterns of biomass. In this study aspect and tangential curvature were found to be the key spatially varying determinants of biomass. DEM accuracy was essential for the assessment of scale-dependencies in terrain-dependent applications such as aspect. DEM accuracy is even more critical for the determination of tangential curvature, which detects minor changes in the surface shape (chapter 5). Even though tangential curvature is a static terrain variable, it describes the accumulation of surface water and therefore it is affected by spatial and temporal rainfall patterns in a dynamic context. Unlike aspect and tangential curvature, the wetness indices (chapter 6) are dependent on the shape of the surface some distance away from the reference location. In this study a 25 m DEM was selected as the resolution that matched the source topographic data and the associated calculated terrain data.
Environmental modelling and scale applications are described in figure 1.2 chapter 1. Steyaert (1996) suggested that DEM at fine scale resolutions are required to spatially distribute the outputs of broader-scale models. It has also been suggested that DEM scales between 5 to 50 metres could be used to make aspect-based corrections to remotely sensed data (Ekstrund 1996, Hinton 1996).

Essentially as DEM resolution becomes coarser, surface detail is lost, leading to reduced slopes and curvature, and an increasingly simplified drainage network (Hutchinson and Gallant 1999). Therefore, scale dependencies between terrain and environmental processes must be carefully matched to the original data source.

**Disaggregation**

There is also a distinction between spatial and temporal disaggregation. There is also a link between scaling and disaggregation procedures. Generally, at the fine scale disaggregation is temporal in nature and at coarser scales disaggregation methods move towards spatial interrogations. For example, point based biomass data needs to be examined over time via temporal growth indices, whereas, terrain attributes are static over time and therefore only require spatial disaggregation. However, some data can be both spatially and temporally disaggregated. An example of spatial and temporal disaggregation is shown in the fine-scale investigation of the 3D topo-climate model (figures 7.39, 7.41, chapter 7)

Spatial disaggregation from total catchment to sub-catchment scale shows subtle differences. Sub-catchment spatial disaggregation of biomass helped to illuminate the need for a longer growing period required over the winter for grasses and pastures. Temperature disaggregation indicated that the reduced temperatures during winter suppressed growth both at the sub-catchment and catchment scale. Slope-based radiation is another example of spatial disaggregation (chapters 4, 7). However, it would not be sensible to disaggregate radiation during September, as it was not correlated to biomass during the winter months.

In this thesis disaggregation refers to the techniques for the spatio-temporal estimates of biomass (at the catchment scale) obtained from modelling processes. The disaggregation method uses spatially distributed terrain attributes as an independent variable along with temporal disaggregated climatic data (modelled GI) as the other independent variable to produce a spatio-temporal model. By utilising the sophistication of ANUSPLIN the Topo-climate model provided better predictions of biomass than either the sub-catchment or satellite models. Strictly speaking the Topo-climate
models incorporates a semi-disaggregated method because it uses point-based biomass data from representative sites as input data.

Disaggregation can occur at different spatial and temporal levels of data analysis. Preliminary analysis can provide information as to which parameters to disaggregate and whether the disaggregation could be spatial, temporal or both. Based on such analysis a decision making process is required about what and how to disaggregate. In this thesis biomass was disaggregated throughout the catchment using spline interpolation methods which included spatially disaggregated aspect and tangential curvature and temporally disaggregated growth indices.

### 7.7.4 Satellite data for Model Development

The Satellite model has complete spatial coverage at a high resolution, however, it needs to be atmospherically corrected and calibrated with ground data (chapter 3). Although the relationship between biomass and reflectance data is indirect it supplies unique information which otherwise is not possible to collect. One advantage of the remotely sensed data is its potential to explain not only biomass but also the status of the biomass i.e. photosynthetically active material, nitrogen concentration in the biomass or potentially erodible surfaces. Chapter 3 (figures 3.23 to 3.28) show how different wavebands reflect different processes. For example, TMSAT band 5 is very moisture sensitive (figure 3.1). Limitations do apply to satellite data; these include orbital dates, spatial rectification, atmospheric corrections, biomass calibrations, purchasing costs and lack of synchrony with ground measurements.

The limitation of satellite data is that these are not a generic tool. Even with normalised and atmospherically corrected satellite data, these are only available on orbital dates and each new observation needs calibration. These factors limit the predictive capacity of satellite models. Future simulations would therefore require continuous updating. Therefore, the predictive ability of the topo-climate models (which require only monthly climate data and terrain data) makes them very attractive as opposed to obtaining additional temporal satellite data.

### 7.7.5 Sub-catchment Model Development

The sub-catchment modelling proved to be a useful tool and produced reasonable results (figure 7.37) at this small scale. Sub-catchment modelling confirmed the need for a 26 week growth period and allowed further temporal disaggregation of the biomass and temperature data. Sub-catchment
modelling did capture small scale biomass variability. Further development of the sub-catchment model would be worthwhile given the results of this simple disaggregation method (see chapter 8, section 8.3.4).

7.7.6 Spline Analysis for Model Development

Interpolating point and/or area data are essential for the spatial and temporal disaggregation of biomass. Model development would not be possible without some interpolation technique. Thin plate smoothing spline analysis (Hutchinson 1999) has proven to be successful in the spatio-temporal disaggregation of biomass in this experimental catchment. Thin plate smoothing spline analysis has combined terrain, climate and hydrological data to produced interpolated biomass data (chapter 7). Using thin plate splines the dependence of the estimated function on the fitted data was determined from the data themselves.

Spline smoothing analysis also supplied statistics on the data error and complexity of the underlying biomass data. The error estimation and GCV minimization are robust tools for examining individual model outputs as demonstrated in this chapter. The ratio of the signal to the number of data points also identifies model deficiencies. For example, 3D model number six produced a signal (51) that was too high for the number of data points (56), indicating that this model was unsuccessful. Fine scale examination of the spline interpolation method was also possible. Individual examination of spline fits at single time periods from the spatio-temporal models provided a rigorous investigation of the smoothing processes (Figures 7.21 – 7.26). In addition, root mean square residual outputs allowed statistical comparisons between a range of models, including comparisons between higher and lower dimensional models (Figure 7.37). Thus, as stated, validation methods have been applied throughout the spline analysis at various stages.

Spline analysis provided a unique method for predictive modelling the spatio-temporal distribution of biomass data. It supplies spatio-temporal coverage and has indicated areas for further research where more extensive data could be investigated. Without such an efficient and adaptable interpolation technique, spatio-temporal modelling of biomass would be difficult.

An advantage of the ANUSPLIN (Hutchinson 1999) interpolation technique is its compatibility with Geographic Information Systems (GIS). The LAPPGRD program in ANUSPLIN allows the production of gridded surfaces. These gridded surfaces are easily imported into GIS systems such as ARCINFO for the presentation of maps and gridded surfaces. Not only do these maps visualise
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Spatio-temporal Disaggregation of Biomass

spatial data sets but they also allow for gridded comparisons between variables and time periods (chapter 7). The spatio-temporal extension of data and the production of maps are very important for many resource management issues. Interpolated data sets and maps are also very important for scaling-up to larger scale catchments. In addition, simulations for predicting spatio-temporal biomass patterns using monthly climate data are possible.

7.7.7 Anthropogenic factors

Due to management changes at the Lockyersleigh catchment, this study covers a unique period where there were few anthropogenic influences within the catchment. Discussions with the catchment manager proved useful, as the study period 1993 and 1994 was a time of management transition. Due to a personal tragedy, external anthropogenic influences were kept to a minimum and grazing, fertilizer application, planting and fencing was constant throughout the catchment study during 1993 and 1994.

Chapter 1 lists some of the applications of spatio-temporal biomass models that can occur at a range of different scales (figure 1.2). At the catchment scale, management requires spatio-temporal biomass distribution patterns as they are essential for understanding plant population maintenance, distribution patterns and heterogeneity within the catchment. For example, vegetation retains soil during precipitation events (which vary temporally and spatially) and therefore accurate spatio-temporal biomass patterns are important for erosion management. Other uses for spatio-temporal biomass models at the catchment scale are for research purposes such as carbon accounting under elevated CO₂ conditions and quantifying the impact of land disturbance on future spatio-temporal biomass patterns. Spatio-temporal biomass patterns would also assist in the determination locations and number of tree plantings required in cleared catchments.

Sub-catchment scale anthropogenic factors influence numbers of grazing animals, time and amount of fertilizer application etc. These factors could be quantified at the paddock scale using spatio-temporal biomass information. Scaling-up from the catchment scale to larger areas is useful for hydrological and atmospheric modelling purposes for validation and sub-grid checks.
Chapter 8.

Discussions and Conclusions
CHAPTER 8. DISCUSSION AND CONCLUSIONS

8.1 Thesis Hypothesis and Objectives

8.1.1 Principle Hypothesis
8.1.2 Broad Objective 1.
8.1.3 Broad Objective 2.
8.1.4 Broad Objective 3.
8.1.5 Broad Objective 4.
8.1.6 Broad Objective 5.

8.2 Management Strategies for Catchment Biomass Improvement

8.2.1 Recommendation 1.
8.2.2 Recommendation 2.
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8.2.4 Recommendation 4.
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8.3 Modelling Directions and Further Research

8.3.1 Predictive spatio-temporal biomass models
8.3.2 Scaling-up and scaling-down
8.3.3 Technological combination models
8.3.4 Future modelling directions and further research
8.1 Thesis Hypothesis and Objectives

8.1.1 Principle Hypothesis

The principle hypothesis was that topographic and climatic attributes combined with modelled growth outputs could be used to model the spatio-temporal distribution of biomass in a low relief catchment. This hypothesis was proved to be valid with development of ten topo-climate models. Two of the topo-climate models represented the spatio-temporal dynamics of biomass with accuracy. The 2D topo-climate model which incorporated biomass, the terrain attribute aspect (from 0 to 360°) and modelled GI, reproduced observed biomass patterns (figures 7.38-7.40). These aspect effects varied spatially, seasonally and with rainfall distribution and amount over a 26 week period. The 3D topo-climate model that incorporated biomass, two terrain parameters (aspect and tangential curvature) and modelled GI reproduced spatio-temporal varying biomass with greater detail (figure 7.37, map figures 7.41-7.43). All topo-climate modelling required an accurate DEM to spatially disaggregate terrain attributes. The DEM resolution was determined from the original source data (chapter 2.). The temporal component in the topo-climate models was enhanced by modelled growth indices (chapter 4). Terrain attribute selection was based on exploratory plots in chapters 4, 5 and 6. Model development involved interpolating biomass, modelled growth indices and terrain attributes using ANUSPLIN (Hutchinson 1999). These models provide a framework for further research and management strategies.

8.1.2 Objective 1.

Objective one was to develop a Sub-catchment model of biomass distribution. The GROWEST model was successful in achieving biomass growth indices at the sub-catchment scale. These sub-catchment models correlated disaggregated biomass to GI. The models also identified the optimal accumulated growth interval for this region (26 weeks) and allowed further disaggregation of climate variables (temperature) which were used as inputs. Sub-catchment disaggregation was discussed in chapter 4. From statistical comparisons it is evident that sub-catchment biomass modelling increased the accuracy of biomass distribution (chapter 7, figure 7.37) and the linear fits of biomass to GI were closer than the catchment averaged biomass model (chapter 4, figures 4.22a, 4.22b). Further development of the sub-catchment model would be worthwhile, given these results (refer to section 8.3.4).
8.1.3 **Objective 2.**

Objective two was to develop a satellite model. Remotely sensed data, examined in chapter 3, supplies spatially dense data at regular intervals assuming there is limited cloud cover. The frequency of satellite data is increasing with more satellites in orbit and technological advances that allow researchers to launch their own sensors. However, methods of calibration, rectification and atmospheric corrections to satellite data are still being developed and there is a need for a standardised approach for direct comparisons between satellite data interpreters. Aircraft and satellite data require geometric and atmospheric corrections, before correlations of biomass and remotely sensed data are investigated. However, once calibrated, remotely sensed data provides a unique spatial image of the land surface and are particularly useful in discerning between grasslands and trees, or anthropogenic structures such as buildings or roads. Satellite data are also useful at the regional or coarser scale > 50m and for monitoring of structural change over time.

8.1.4 **Objective 3.**

Objective three was to develop topo-climate models. Ten topo-climate models were developed on explicit correlations between the biomass and the terrain shape and between biomass and climate and growth indices. This approach preserved the integrity of source data and ‘real’ catchment attributes. The topo-climate model therefore:

- provided a spatio-temporal model
- can be validated (figures 7.21 – 7.29)
- retains the capacity for re-analysis and improvement
- provides the GIS developmental capacity for map production through LAPGRD
- has predictive capacity

The transparency of the topo-climate models was evident and their outputs show a distinct seasonality in biomass production as well as discrete spatial patterns based on the terrain and climatic conditions. These patterns can also provide a general indication of the surface moisture regime and an estimate of the energy budget changes within the catchment. The north to northwesterly slopes within the catchment with the grass vegetation would be expected to have a greater moisture uptake than the northeastern slopes (grasslands) and the eastern boundary of the catchment.
with woodlands. These observations suggest that on the north and north-western slopes and the high ridges, the bare soil and transpiration components of evapotranspiration would contribute to higher latent heat fluxes (and therefore lower sensible heat fluxes) than those observed over the north-eastern and southerly slopes and the woodlands regions near the eastern boundary of the catchment.

8.1.5 Objective 4.

Objective four was to provide statistical comparisons between the different types of models. Model veracity can be determined via statistical analysis of the residuals and comparisons between the effective number of parameters used in the model (figure 7.37). This analysis suggests that, given the accuracy of the models, scaling up and down the space-time continuum may be feasible. Statistical confirmation makes management recommendations possible and provides a platform for further research. Statistical examinations can also highlight areas that do not match our understanding of the physical environment. These errors are due to data inaccuracy and model limitations, and they provide an opportunity for further investigation of these apparent mismatches. Validation procedures include checking extremely high and low biomass values in the 3D models. These values indicate instability in the model. Comparisons between the 3D model (#9), field data and the 2D topo-climate model would be worth further investigation.

8.1.6 Objective 5.

Objective five was to use GIS for mapping purposes and future model comparisons. Visualisation of model outputs is useful for management purposes and can also indicate the surface resolution required for specific outcomes. LAPGRD (Hutchinson 1999) provided gridded surface outputs that were compatible with ARCINFO, which provided GIS capabilities for map production.

8.2 Management Strategies for Catchment Biomass Improvement

8.2.1 Recommendation 1. Eastern to North-eastern slopes

The eastern to north-eastern slopes within this catchment had the highest biomass levels, (and) therefore these areas could support higher grazing numbers than the surrounding regions. Over-
growing is a common environmental problem in Australia, therefore conservative estimates of growing numbers should be applied. The north-eastern slopes could be grazed at high to medium growing levels for this region. Chapter 2 recorded the grazing numbers at Lockyersleigh at 4.5 dry sheep equivalent. These levels could be tested in the north-eastern regions of the catchment. In addition, grazing densities could be adjusted in accordance with climate data using the predictive capacity of the topo-climate models.

8.2.2 Recommendation 2. North-westerly slopes

The north-westerly slopes could support less grazing densities due to the lower biomass levels. These areas are on the eastern side of the streamline in the Lockyersleigh Catchment. Based on the biomass range during March 1993 (figure 7.41) a suggested level of grazing would be 3.1 dry sheep equivalent. These grazing densities would need to consider the climatic conditions. The planting of improved pastures and leguminous species, and grazing rotations for promotion of biomass growth and the reduction in soil compaction would also improve the land cover in these regions.

8.2.3 Recommendation 3. Southerly slopes

The southerly slopes produced low biomass levels. Grazing would only add pressure to these regions. Therefore, these regions would be well suited to the establishment of native vegetation into an arboretum. Low, dense, relatively fast growing species (such as acacia species) could be used as a natural fenceline to protect the more slow growing trees.

8.2.4 Recommendation 4. Fine-scale responses

Tangential Curvature is a terrain attribute that describes the potential surface movement of water over a point in the catchment. In this thesis tangential curvature has been referred to as a fine scale hydraulic response, which could be used to identify potential waterlogged areas and dry areas. These areas could be monitored for biomass levels and erosion potential sites. However, further investigation of the modelling of tangential curvature is necessary before this data could be applied directly.

8.2.5 Additional guidelines 5. (i, ii)

i) Streamline restoration and preservation of native vegetation
In order to manage the vegetation resources that support the grazing demands in a catchment, it is important to preserve the stream networks within the catchment to prevent erosion, sedimentation and eutrophication. Deterioration in water quality affects the vegetation and grazing animals that rely on it. Streamlines and the adjoining vegetation affect water quality and the erosion potential. Therefore, preserving native vegetation along streams or planting native vegetation along streams will create a physical barrier to the direct influx of pollutants and protect the soils from compaction of animals. Streams such as Lockyersleigh Creek are perennial and prone to many forms of erosion. Therefore, spatio-temporal biomass models can be used to identify streamlines, surface water flow patterns and biomass levels in order to determine accurate locations for the planting or maintenance of native vegetation. The DEM would be useful to determine the elevation gradients along streamlines. In Lockyersleigh a native vegetation strip (suggested minimum distance 50 m) along streamlines would be useful.

8.2.5 Additional guidelines 5 (i, ii)

ii) Native vegetation

The clearing at Lockyersleigh Catchment has occurred largely at the expense of eucalyptus and acacia woodlands. Salinisation is a major environmental problem in Australia that has been exacerbated by large scale clearing, erosion and irrigation. Part of the solution to salinisation is to plant trees. The maintenance and replanting of native vegetation can be aided by spatio-temporal biomass models, which are based on an accurate DEM for catchment shape and elevation. Spatio-temporal models of biomass levels help identify the most suitable areas for revegetation. Spatio-temporal biomass models also directly help the maintenance and productivity of agricultural based activities (sections 8.2.1-8.2.4). Strategic planting of native vegetation would be useful at the following locations: along streamlines (section 8.2.5), at elevation of 685 m and above (presently dense woodlands above 690 m), along southerly slopes (section 8.2.3), at erosion points, around dams near roads and tracks and close to the stream outlet at the Wollondilly River.
Predictive models can provide data/information that can become part of the solution to environmental problems (chapter 1). However, the models need to reflect the underlying physical properties of the catchment (chapter 2) in order for research and management strategies to address land management issues and climate variability. Predictive topo-climate models can be used to monitor landscape functions and identify areas with changes in physiological activity caused by climate variability.

### 8.3.2 Scaling-up and scaling-down

Landscape models can have reference scales from broad river basins, to local catchment attributes, to biomass levels and to plant cellular levels. These levels of stratification determine which methods (scaling techniques) can be applied to different environmental variables. Scaling issues also include input data suitability, predicting error margins and validation of methods.

Catchment management requires scaling-up from point and area biomass data to spatio-temporal catchment values of biomass. Modelling increases the accuracy of these biomass predictions outside measured values. However, spatio-temporal biomass estimations and the resolutions of maps produced from modelled data are still at the mercy of the source data availability and quality for their calibration, and also the inherent model limitations. Catchment management also requires the scaling-down for specific biomass values at certain locations. Spatio-temporal biomass models could provide methods for scaling up and down. That is, the sub-catchment model provides a scaling down procedure, while the simplicity of the 2D topo-climate models may be well suited to scaling up. In addition the predictive capacity of spatio-temporal models allow early planning of catchment management issues.

### 8.3.3 Technological combination models

Environmental modelling is an integral part of environmental management. Terrain, modelled plant growth models and satellite data provide valuable information on land cover. Spatial vegetation data are usually limited to a selection of representative points. Remotely sensed data are spatially dense and require calibration, terrain data provides useful catchment attributes and requires an accurate DEM, while modelled data supplies a temporal component and needs climate data as
inputs. Therefore, all the data sources have individual requirements but together they can potentially provide a detailed composite spatio-temporal description of vegetation dynamics.

Satellite data in concert with ground and terrain data as well as growth indices would be a worthwhile modelling pursuit. Combining these different data sets and technology could provide new insights into spatio-temporal biomass distribution patterns. Research in this area is presently being examined, however Ikeda et al (1999) noted that most of the estimations for grassland biomass have mainly been at the coarse spatial scale but high frequency satellite resolutions such as NOAA/AVHRR scale. They presented a methodology involving fine resolution by low frequency satellite data using Landsat TM data and they found an exponential equation for estimation of plant growth following satellite observations. Their plant growth modelling included plant growth as a function of daily mean air temperature. More research would be required to examine the effective cumulative temperature on plant growth rate in this model (Ikeda et al 1999). The direction of further research in this field is directed at the prediction of spatio-temporal biomass by incorporating biomass, a growth model and satellite data.

8.3.4 Future modelling directions and further research

Models that represent catchment processes such as biomass distribution in space and time will continue to dominate the future research of agricultural and native vegetation regions. Future research from the three approaches to the spatio-temporal biomass modelling developed in this thesis include

- **Scaling-down.** The sub-catchment model is simple and does not utilise terrain attributes. It utilises climate data and biomass data and therefore would be well suited for sub-catchment and even chamber vegetation analysis. This fine scale resolution produced accurate results in these small subcatchments. This analysis could be tested for different vegetation types. It would also be suitable for vegetation chamber analysis, where biomass or other plant physiological attributes such as leaf temperature could be coupled with modelled growth indices and represented in space and time.

- **Satellite data** represented the structural features of the landscape. There was also a correlation between biomass and TMSAT band 3 during March 1993. Further investigation of the satellite data would be worthwhile with the aim to incorporate satellite, terrain and modelled growth data into one model. Preliminary results from modelling that incorporated satellite data as an
independent variable with GI show promising results although rigorous analysis would be required to determine the statistical significance of this trend over time. Consideration needs to be given to the different spatial scales of the data inputs. The satellite data were gridded to a 25 m DEM resolution and the modelled growth index were at 26 week growth integration period. TMSAT band 3 and modelled GI were interpolated as independent variables with biomass as the dependent variable using ANUSPLIN. These results require more data, validation and the inclusion of a terrain attribute for further model development.

- Scaling up and further development of the topo-climate models. These models show a lot of promise as they are spatially and temporally dynamic, can be predictive, have statistical significance, are linked to physical attributes in the catchment and they reflect catchment processes such as biomass growth. These explicit space time models are highly suited for further environmental modelling. The 2D topo-climate models are linked to catchment attributes and would be suitable for scaling-up to larger scale catchments for further statistical testing. Their simplicity would allow scaling up given data and statistical validation would be possible. In the 2D topo-climate model the dominant terrain features can be incorporated explicitly into the modelling procedure. The 3D topo-climate models account for both the radiative and hydraulic influences on biomass. These models require further examination and refinement. They would be well suited for further research in particular, in relation to carbon accounting. Catchments could be disaggregated into biomass levels using 3D topo-climate models that could be used for heat flux exchange rates, carbon accounting and the impact of climate variability on biomass.

Finally, the topo-climate models developed in this thesis give spatially explicit biomass coverage for science-based environmental problem solving. The 3D and 2D numeric models are predictive and highly relevant to solving catchment management problems relating to biomass. Specifically, the 2D topo-climate model improves our understanding of biomass variability in low relief catchments and increases our predictive capacity of spatio-temporal biomass distribution. There are known limitations of these models and the effects of variations in fertilizer, grazing and other anthropogenic activities would also reduce the accuracy of the predictions. Catchment management decisions on biomass distribution patterns need to be balanced with science theory, appropriate data sources, accurate models and maps. Numeric biomass distributions could be directly linked to decisions made in relation to human initiated activities within low relief catchments. In addition, accurate spatio-temporal biomass models are essential for research into carbon accounting for CO₂ gas inventories.
In summary the spatio-temporal biomass models developed in this thesis reflect catchment processes, have varying levels of statistical significance and could be useful for different purposes. Generally: the 2D topo-climate model would be useful for management, research and scaling up tests; the sub-catchment model would be useful for scaling down and when only climate and biomass data were available; the satellite model would be useful for identifying structural differences in the landscape; and the 3D topo-climate model would be useful for research purposes, further interrogation and model refinement.

Therefore, predictive spatio-temporal biomass models with statistical validity provide useful tools for the scientific disciplines of both management and research.
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