Scale Issues in Developing Regional-Scale Soil Water Balance Surfaces

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ABSTRACT

Availability of water in the soil is a key environmental parameter for many models of physical systems from those dealing with plant ecology and biodiversity, crop production, and even soil erosion, ground water pollution and hydrological processes. Landcare Research has been developing a model for making spatial estimates of soil water balance based on best available soil and climate data. This paper reports on progress in developing this model. Our model takes a distributed “interpolate first - model later” approach. That is, climate and soil input parameters are estimated spatially, and water balance calculations carried out using these spatial layers. We discuss the methods used to develop the input data layers. Validating the model results has highlighted some key scale issues that affect the accuracy and precision of model output. One issue is how water balances modelled on a monthly time increment, relate to water balance measurements (temporal scaling). Another issue is variability of the temporal scale of climate processes. For example, the model provides good estimates of monthly water balance under extreme conditions of drought, but is less able to cope with the not so extreme seasons when wetting and drying events occur on shorter time scales.

Keywords and phrases**:** soil water balance, spatial modelling, GIS, scale, variability, uncertainty

1.0 INTRODUCTION

Availability of sufficient water for agriculture practices is a crucial issue in drought-prone areas of New Zealand. Water, solar energy (heat and light), and a suitable medium in which plants can grow are the primary environmental requirements for biomass production. Most soil limitations can be overcome with improved management practices, but water remains a major limiting factor to production. Because regional water resources are limited in many parts of New Zealand, so information about the moisture status of the soil is important for assessing drought impacts and allocating scarce water resources.

Soil moisture can be measured directly at specific locations using gravimetric sampling (Hillel, 1971), neutron probes (King, 1967), or time domain reflectometry (Davis & Annan, 1977). Soil moisture can be estimated using climatological data and simple water-balance models based on rainfall data and estimated evapotranspiration (e.g., Heine, 1984; Jensen *et al.*, 1990). Measurements of soil moisture content or point-based water balance models are very useful for providing detailed temporal patterns of moisture availability at a range of time scales. However, a considerable number of measurements or points are needed for this data to be useful in differentiating spatial patterns of moisture availability at the local or regional scale.

If spatial estimates of soil moisture condition are required, they can be derived by geostatistical analysis given a suitably distributed sample of soil moisture measurements across the area of interest (e.g., Stein *et al.*, 1991; Or & Hanks, 1992) or from remotely sensed imagery, most recently radar imagery (e.g., Mattikalli *et al.*, 1996; Wang *et al.*, 1989). However, generation of spatial estimates of soil moisture time-series from measured data, requires a prohibitive amount of data collection, and high-resolution remotely sensed data is difficult and expensive to collect regularly. These limitations mean that we tend to either know a great deal about the temporal variation of soil moisture at a point in space but little about its spatial variation, or a great deal about the spatial variation of soil moisture at a point in time but little about its temporal variation. While there must always be a trade-off between temporal and spatial knowledge, use of a simple deterministic model (e.g., a water balance) implemented in a GIS provides an environment in which we can attempt to explain as much as possible about both spatial and temporal variation in soil moisture content.

GIS-based water balance models range from lumped to semi-distributed to distributed models. Lumped models aggregate data either spatially, temporally, or both. Variability within the aggregated areas and/or time units is ignored. In the GIS modelling environment, lumped modelling frequently involves working in a vector polygon format with the study area divided into regions based on the distribution of key input parameters, which are assumed to be homogeneous within that region. Typically each region will contain at least one source of point data where key model parameters have been recorded. The model is run using the data recorded in each region, and the results assumed to apply to the whole region. While only gross spatial patterns between regions can be determined in this way, temporal patterns can be determined with moderate accuracy (e.g., Barringer *et al.*, 1995; Karnieli, 1991).

As the size of the regions decreases, the number of regions increase, and the model becomes progressively more distributed. Distributed models take into account the spatial distribution and variability of input parameters with much greater resolution. In the GIS-environment distributed models are usually implemented in a raster format, where the raster cell size is sufficiently small that the variation in input parameters can be considered to be continuous, and where only a small number of raster cells actually contain a measured point-source of data. Model input parameters are estimated for every raster cell, and the model run separately for every individual cell even though most have no measured data associated with them. Provided that sufficient measured point-data is available to drive the spatial interpolation of the raster input layers, distributed models can give reasonably accurate estimates of spatial variability. However, the trade-off is lesser knowledge of temporal variation. This trade-off is unavoidable given the nature of spatial variability of rainfall over short time periods, and the computational demands of interpolating rainfall and other input variables for the model at high spatial and temporal resolution (e.g., daily).

This paper reports on work in progress to improve upon previous semi-distributed soil moisture modelling (Barringer *et al.*, 1995), by bringing together techniques for spatial interpolation (Hutchinson, 1991), with improved soils data (Barringer *et al.*, 1998), and a distributed, raster-based, GIS water-balance model to model monthly water balances over substantial areas of flat or near flat terrain. We discuss the results of our analysis in light of the trade-off between temporal and spatial resolution of water balance calculations. This has important implications for determining the uncertainty of modelled surfaces, and developing methods for integrating this uncertainty into the modelling process.

2.0 WATER BALANCE MODELLING

In this study we use a distributed approach to modelling soil moisture content. Each mapped soil unit is assumed to contain a single homogeneous horizon, which is at least as deep as the rooting depth of the plants growing in it (Heine, 1984). A plant readily available water (PRAW) value for the soil is used to define the size of the soil water reservoir (the amount of moisture available to plants). When the soil pores are holding the maximum possible amount of water, the soil is said to be at field capacity (FC). When all the water that a plant can extract from the soil has been removed, the soil water reservoir is said to be at wilting point (WP). The difference between these two is the PRAW and is recorded as an equivalent depth of water in millimetres. When the soil moisture reservoir is between FC and WP, the amount of water required to fill up the reservoir to FC is called the soil moisture deficit (SMD), and the amount of water remaining in the reservoir is called the available water capacity (AWC).

The model runs a straightforward water- balance calculation where inputs of moisture come from rainfall, and losses are via drainage/runoff and evapotranspiration depending on the state of the soil water reservoir. We use a geostatistical analysis employing thin-plate smoothing splines (ANUSPLIN – Hutchinson, 1991) to estimate input rainfall spatially from standard climatological data from NIWA's CLIDB database (Penney, 1999). The output from this analysis is raster layers of monthly rainfall. It is assumed that there is no unsaturated drainage or runoff. We chose to calculate mean monthly potential evapotranspiration (PE) using the Priestley-Taylor method (Priestley & Taylor, 1972; Jensen *et al.*, 1990) which provides an acceptable compromise between input data requirements and overall model accuracy. The Priestley-Taylor method requires spatial inputs for air temperature and net radiation. Climate surfaces for maximum and minimum temperature are generated by ANUSPLIN using standard climatological data. There are insufficient data in CLIDB to generate a net radiation surface using ANUSPLIN. Instead, an "actual sunshine hours" surface is generated using ANUSPLIN and, combined with a latitudinally based "potential sunshine hour" surface (Sellers, 1972) and a direct-beam solar radiation model (Kumar *et al.*, 1997), which calculates solar radiation over a topographic surface derived from 20 m contours (LINZ licence no. TD098872), to estimate net radiation. Once a PE surface has been derived from these input surfaces using the Priestly-Taylor PE algorithm (Jensen *et al.*, 1990), actual evapotranspiration losses from the soil can be estimated by comparing the PE surface with the rainfall and soil PRAW data. Given rainfall, actual evapotranspiration, and soil moisture storage capacity in each grid cell, the water balance calculations become a straightforward accounting process where any excess of rainfall over storage and evapotranspiration loss is assumed to be runoff/drainage, which is lost from the system.

The model was implemented in Arc Macro Language (AML) using ARC/GRID (ARC/INFO 7.2.1) on an ULTRASPARC 100 workstation.

3.0 MODEL VALIDATION

Model validation has been carried out at several levels. Climate surfaces are assessed statistically and visually and the SMD surface is validated against recorded data of soil water content.

ANUSPLIN provides a global statistic describing the accuracy of surfaces fitted to climatological data — generalised cross validation (GCV). Where possible, the output of methods used to estimate intermediate surfaces (e.g., solar radiation, net radiation) were compared with CLIDB point measurements of radiation within the study areas to confirm that modelled input layers provide an acceptable match to measured data at specific locations. Figure 1 compares modelled and recorded data for mean monthly global radiation in the Canterbury area. These data indicate that, while the modelled seasonal variability of radiation is not a perfect match, the model estimates radiation loadings reasonably well during the critical summer months when evaporative processes are at their peak. In addition to the GCV statistic, climate surfaces generated from ANUSPLIN were also validated by plotting maps of the surfaces and visually checking that surface values (e.g., monthly rainfall) remain within or close to expected ranges.

Although the model is to be used extensively throughout New Zealand, there is limited data on soil moisture available for model validation. We have assessed model accuracy for Canterbury only, by comparing model results with volumetric data of soil water content collected using a neutron probe for seven sites on the Canterbury Plains between late 1983 and early 1987 (Gray & Hutchinson, unpublished data). This is the same dataset used to validate an earlier study for the mid-Canterbury area using a New Zealand Meteorological Service (NZMS) water balance model (Barringer *et al.*, 1995). Figure 2 shows the weekly soil-moisture data from the neutron probe (converted to soil moisture deficit) plotted against modelled monthly SMD for Lincoln. The fit, particularly in the early part of the period, is not good, but is very comparable with that achieved in the previous study using the NZMS model. Figure 3 compares the results from the two models. The poor fit between modelled and measured data may be due to a possible inconsistency identified in the early part of the neutron probe record (Barringer *et al.*, 1995). A statistical analysis of this correlation has not been attempted because the monthly output from the water balance model and the irregular recording dates of the neutron probe data are not paired.

Notwithstanding the differences between the widely accepted NZMS model and our GIS model, and the differences between parts of the neutron probe record and both models, this analysis indicates that within the temporal limitations imposed by a monthly time step, the two models are producing similar results. We conclude that our Priestly/Taylor implementation is providing an adequate first approximation of soil moisture conditions.

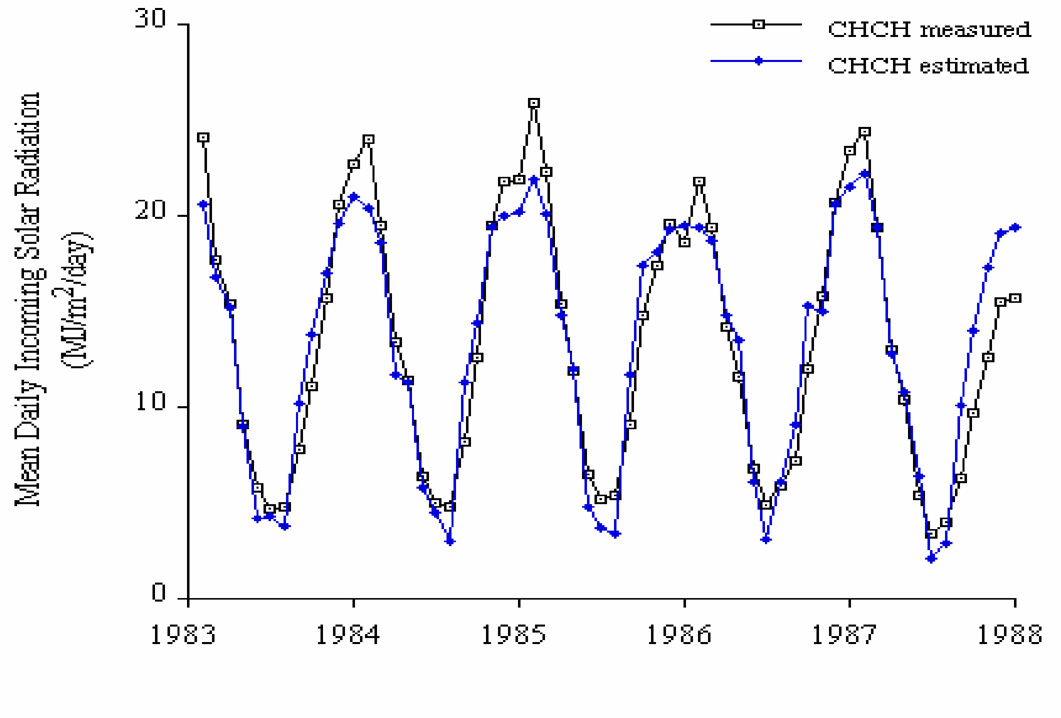

Figure 1: A plot of mean daily total incoming solar radiation compared with estimated daily total incoming solar radiation over the same period.

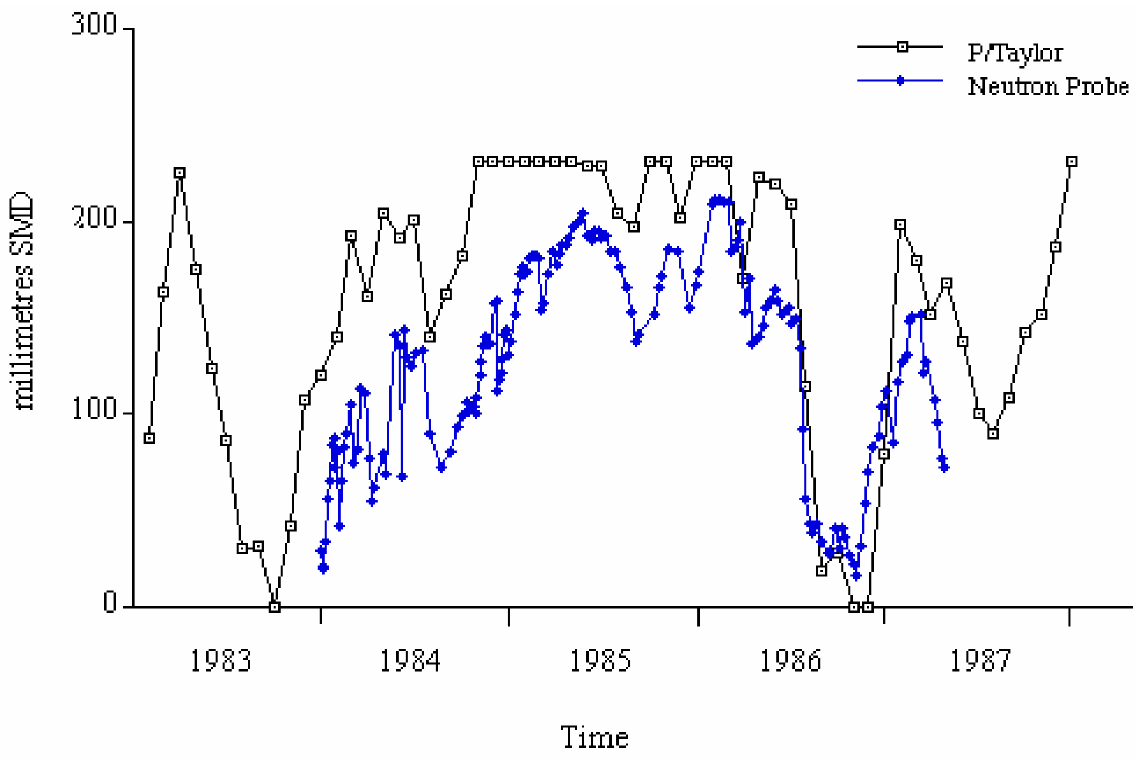

Figure 2: Neutron probe data plotted against the Priestly/Taylor model used in this study for the Lincoln climate station.

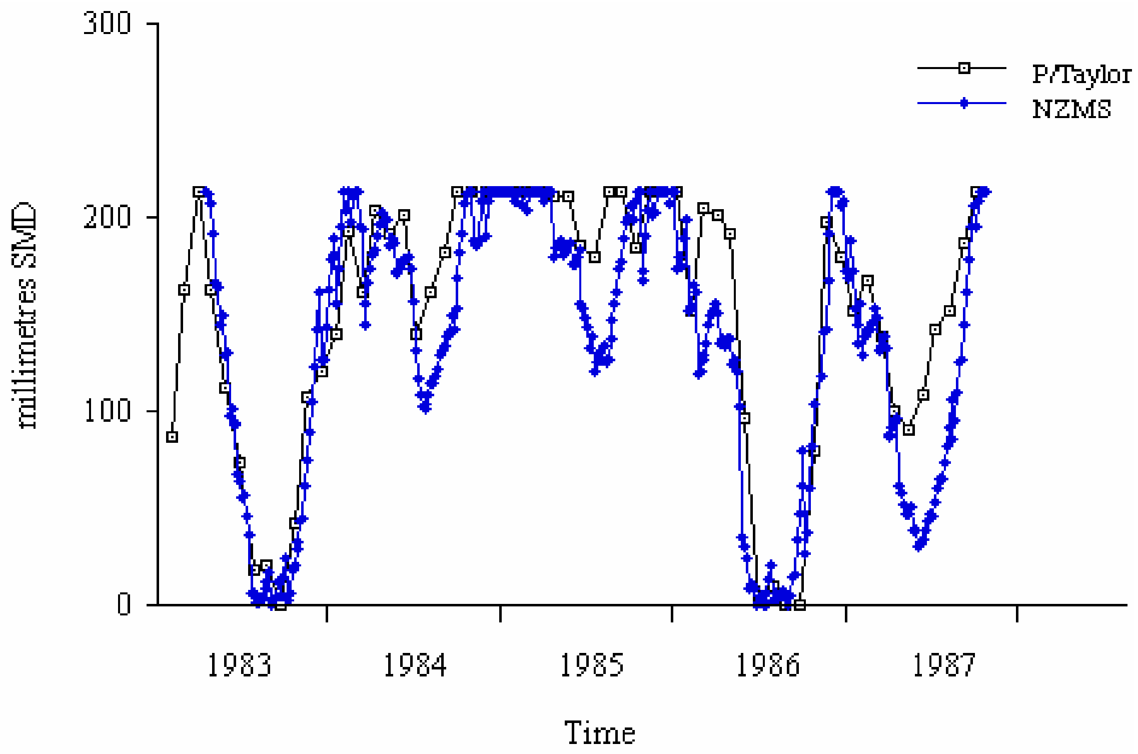

Figure 3: A plot of the NZ Meteorological Service Penman model against the Priestly/Taylor model used in this study for the Lincoln climate station.

4.0 RESULTS

Figure 4 illustrates typical results from the model. Spatial patterns of soil moisture show a combination of continuous variation where climate variability is the dominant factor, and more discrete variation where soil PRAW dominates. Early in the summer when most soils are above WP and SMD is generally low, even for those soils with a low PRAW, climate will dominate over soil PRAW in determining SMD patterns. As the season progresses and soils with low PRAW reach WP and can lose no more moisture, the pattern of SMD is increasingly dominated by the pattern of PRAW rather than climate. While these general patterns are similar to those observed in the previous study (Barringer *et al.*, 1995), the use of continuous climate surfaces and higher-resolution soils data better mimics the natural system being modelled.

5.0 SPATIAL AND TEMPORAL SCALE ISSUES

The validation process outlined above indicates that the model is producing a simulation that correctly identifies major temporal variations in SMD at the test location, particularly during the dry summers of 1983 and 1986, but also during 1984 and 1985, which were wetter years. However, minor temporal variations in SMD are not always correctly identified. This may be caused by a number of factors related to temporal scaling. The validation data and the model output are recorded over different time intervals. A discrete measurement taken once a week is not directly comparable with an estimate derived from total monthly rainfall and temperature from the 15th day of the month. However, measurements may match estimates when the temporal scale of rainfall variability equals or is greater than the temporal scale of modelling. Extended drought, or very wet periods, can endure over a period of months. Such events will be reflected in the monthly estimates, but shorter events will not. For example, 100 mm of rain may fall in a month. If it occurs in 10-mm events every three days, SMDs will remain low; if it occurs in two 50-mm events on the first and last days of the month, SMDs may become quite high during the intervening period. A monthly model does not distinguish between these two scenarios. The quite arbitrary boundary in time between months can have a significant effect on calculated water balances over a monthly time increment leading to quite different results when rainfall data are grouped over slightly different time periods.

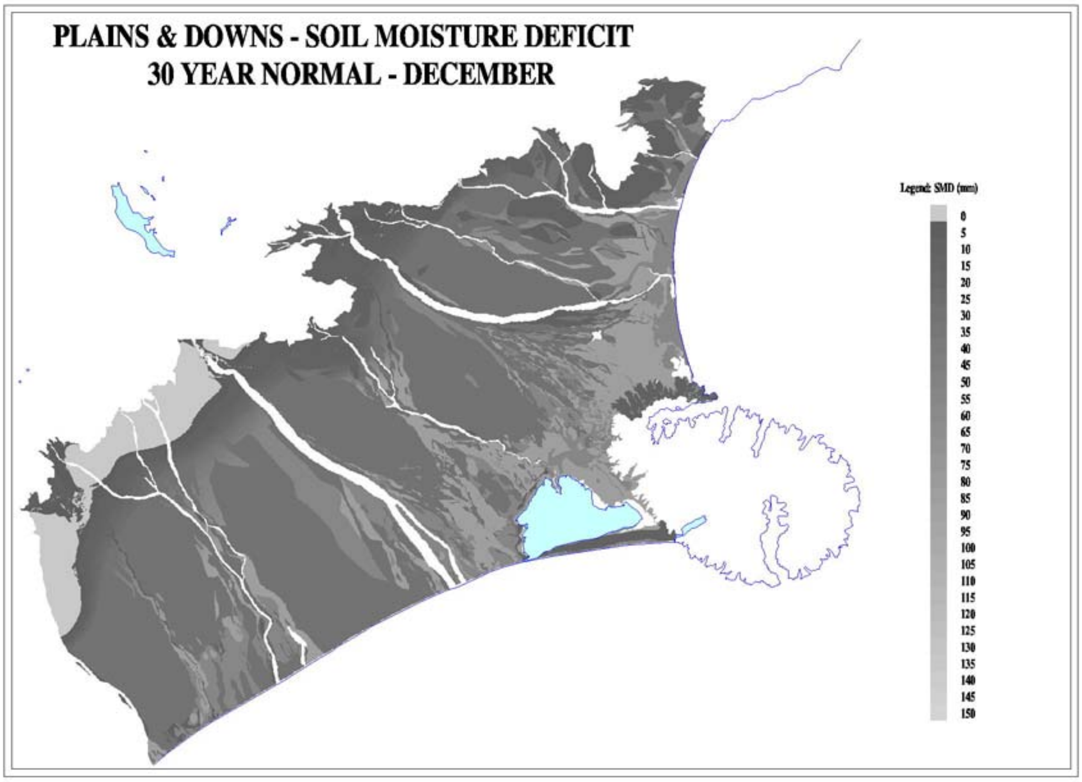

Figure 4: *Map of soil moisture deficit for midsummer 30-year normal conditions, illustrating the combination of variability associated with both climatic variation (best seen along the inland margin of the Canterbury Plains where increasing rainfall dominates) and soil variability (best seen over the central Canterbury Plains where differences in PRAW dominate).*

An obvious alternative might seem to be to run the model on a shorter time increment, but we are presently constrained by computational demands that make this impractical. For example, calculating splined surfaces and generating gridded surface data takes approximately 45 minutes for a single rainfall surface for the area shown in Figure 4. This is an area of 750 000 ha, with 326 rainfall data points. The surface has a spatial resolution of 100 m (1260 by 1280: 1.6 million cells) and is calculated using a ULTRASPARC 100 workstation, with 496Mb RAM running SOLARIS 2.6 and ARCINFO 7.2.1. Although some of the five splined input surfaces that have to be generated take less time than this, computational time are currently a limitation on temporal resolution.

Even should these issues be resolved with a more powerful computer, there are significant difficulties associated with interpolating input parameters over short time increments. The task of interpolating rainfall illustrates this problem well. An important assumption in most interpolation procedures is that the parameter being interpolated must vary smoothly in space. Over months or years this assumption holds reasonably well for rainfall, but over days or weeks it does not. It is quite common to have short-duration localised rainfall events that can produce significant rainfalls (20 mm +) while nearby locations receive no rainfall at all. This means that below approximately a monthly time increment it is inadvisable to interpolate rainfall data spatially without additional data such as weather radar maps, which are not widely available.

A more promising solution may lie in utilising knowledge of rainfall variability at daily time scales (from CLIDB) to establish whether there is a relationship between the variability of parameters measured daily like rainfall, and errors in estimated SMDs based on monthly estimates (Bian, 1997). From the discussion above, we might expect that our monthly model will underestimate SMD in months with rainfall distributed unevenly through the month. This may mean that, while it is not feasible to model spatially at time scales of less than a month, we may be able to incorporate a measure of the distribution of rainfall within each month so that the model can account for temporal scaling of rainfall.

Spatial scaling also represents a problem in terms of model accuracy. It is well known that soil classification is inherently limited by scale, so that an area mapped as a homogeneous soil class at one scale will in fact contain inclusions of other soil classes that are too small to be differentiated independently at that mapping scale (Fisher, 1989). Such errors can be treated as inclusions (Fisher, 1991), noise, or error in the map (McBratney, 1992). These errors may be sufficiently significant that the variability of a soil property within an identified soil type (class) may exceed the difference in the mean of that property between two soil types (Burrough & McDonnell, 1998; Webster & Oliver, 1990). As a result, considerable uncertainty is added to that already attributable to the temporal scaling issues discussed above (as uncertainty errors are propagated through the modelling process). Improving the spatial precision and accuracy of the input data may reduce this uncertainty, but the cost of such an exercise is prohibitive for large areas, and because of the variability inherent in soils over very small distances, this can never completely resolve the problem. Fisher (1991) discusses the use of stochastic methods for generating both uncontrolled (no knowledge of the structure of uncertainty) and controlled (some knowledge of the structure of uncertainty) random variations of model input parameters. These are known as Monte Carlo simulations, which vary model input parameters to produce multiple but equally probable soil maps. These maps can be used to assess the impact of error on model output. Although computationally demanding, this methodology could be applied to soil moisture modelling to yield results that show likely patterns of spatial variability in SMD, and likely patterns of spatial variability of errors in estimates of SMD.

Another issue relating to scale is the spatial error in climate surfaces. The resolution of the climate layers (100 m) is considered to be within the scale of process variability. However, while ANUSPLIN provides statistics on how well the surfaces fit the data, it is not entirely clear how well the surfaces model local climate variation in New Zealand conditions. Ideally stations should be evenly distributed spatially, as well as sampling the full range of climate variation. In practice climate stations are not evenly or randomly distributed in geographic space, and do not sample the full range of climatic variation. All stations are on flat sites, very few are above 500 m, and most are located in the more populated areas of New Zealand. In addition, while rainfall and air temperature are widely recorded, other climate measurements are not. For example, total sunshine hours is not as frequently measured. We have assumed that it is still valid to use ANUSPLIN to interpolate sunshine, even though from a reduced number of stations, because it is less variable than other climate parameters. As a result, we expect significant variation in the accuracy of climate surfaces, both spatially within specific surfaces where point data is sparse or natural variability is greater (e.g., rainfall in mountainous areas), and also between surfaces depending on availability and quality of input data (e.g., sunshine hours versus temperature).

Because of the scale issues discussed above, the modelled SMD patterns are the subject of considerable spatial and temporal uncertainty. Because we have limited ability to reduce that uncertainty due to scaling and logistic constraints, it is vital that the degree of uncertainty in the model output be well described. To fulfil this requirement a rigorous validation process is important in determining that model output is accurate in absolute terms. In addition, methods are required for dealing more explicitly with the uncertainty introduced by temporal and spatial variability. The use of stochastic methods to deal more explicitly with spatial variability in soil PRAW in particular, but also spatial variability in climate, may be important. In addition, utilisation of techniques to transfer knowledge of high-resolution temporal variation in climate and its impact on the low-resolution SMD model output need to be investigated. At the very least we need to be able to identify periods where the model accuracy at monthly time increments is expected to be good, and those where it is expected to be poorer. Ideally we might anticipate being able to improve model accuracy by incorporating a model parameter based on the degree of temporal variability at higher temporal resolutions than the model is run at, for example, the 1-D fractal dimension of rainfall.

Combining these approaches offers the prospect of taking account of both spatial and temporal scaling factors, and should provide a much more objective statement on model accuracy that can be incorporated into error propagation calculations when the data are subsequently used in other models (e.g., crop yield modelling).

6.0 CONCLUSIONS

There are a number of significant temporal and spatial scaling issues in developing regional-scale models of soil moisture. Inevitably there is a compromise between the level of temporal and spatial detail that can be modelled due to computational and computer storage limitations. More importantly the scale of spatial variability in input parameters like rainfall dictates the minimum resolution. At very fine spatial and temporal resolutions, rainfall is too variable. We don’t have the knowledge or input data to accurately model at fine spatial and temporal resolutions. However, by aggregating, noise can be smoothed out to a level at which variability relates to the topography. In this manner we can develop a model of water balance that realistically maps soil moisture at regional and monthly scales. An “interpolate first - model later” approach was used to develop these maps: raster input layers for key climate layers were derived from weather station data and a DEM, which were then combined with the best available soil data. Validation has shown the results to be reasonable.

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