Interpolation of Growing Degree-Days in Non-Homogeneous Terrain

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ABSTRACT

This paper investigates the spatial interpolation of growing degree-days (a measure of heat accumulation for crops) in Southland, New Zealand. This type of climate map aids land-use management and identifies high quality climates suitable for more profitable, high value crops. The use of an automated spatial interpolation technique (ANUSPLIN) speeds the production of climate maps and makes the process objective. The results of this study indicate that the accuracy of the spline model interpolated surface is comparable with that of traditional, hand-contoured maps. However this accuracy decreases with increasing topographic complexity. The density of the data network also affects the accuracy of the interpolated maps; results indicate that a less dense network than that used is sufficient for the desired level of accuracy and scale.

***Keywords and phrases*:** interpolation, temperature, climate map, splines, ANUSPLIN, Topoclimate South

1.0 INTRODUCTION

It is well known that climate is modified by topography, leading to the development of 'topoclimates' (Hutchinson et al., 2000), and the topic is given considerable treatment in classic texts by Geiger (1957), Yoshino (1975), and Oke (1987). The interaction between elevation, slope, aspect, and airflow (Oke, 1987) that creates topoclimates is not entirely understood, but many features can be explained by the theory of boundary layer climates. The climate may be altered to such an extent that it can significantly alter crop growth and production (Purdie et al., 1999). The Topoclimate South project (1998-2001) used growing degree-day (GDD) maps to identify and evaluate the climate resources of farmland in Southland, New Zealand (Topoclimate South, 2002). The study gathered short-term temperature data at ~2550 field sites, related these to long-term data from climate stations, and used interpolation to produce GDD maps from point data.

Climate determines plant growth, and the viability and productivity of land, and can vary significantly on a local scale. Thus standard networks of synoptic climate stations are inadequate: knowledge of local scale climates is critical for agricultural activities (Sturman and Tapper, 1996). GDDs express the relationship between crop growth and temperature (Richards, 2000; Sturman and Tapper, 1996), i.e. the amount of heat accumulated at a site in a season that can be used for a plant to grow. GDD heat units are computed as the sum of average daily temperatures above a chosen base temperature for a stated period, usually one year or one growing season (Richards, 2000; Sturman and Tapper, 1996), as can be seen in the following equation:

$$GDD = \sum \frac{(T_{Max} + T_{Min})}{2} - B \qquad (1)$$

where T_{max} is the maximum and T_{min} the minimum temperature for each day, and B is the base temperature for the crop (Hutchinson et al., 2000). The latter varies for different crops, e.g. with most temperate grasses such as coxsfoot and ryegrass, growth is activated when the temperature exceeds 4°C (Richards, 2000), but white wine grapes require 10°C. The GDD model implies that each crop must receive a certain number of GDD annually to be viable in a particular region (Sturman and Tapper, 1996). Despite flaws, GDDs have been successfully applied to crop selection and scheduling, leading to efficient use of land and produce processing facilities (Sturman and Tapper, 1996).

This paper reviews interpolation methods, and reports on an ongoing project to determine and implement the best method for interpolating climate data. The project uses data from the Topoclimate South project to create GDD maps for Southland. Results will be compared with traditionally contoured maps. The project will also address: i) the optimal amount of input data required for accurate results; ii) how accuracy changes as less data is used; and iii) how answers to i and ii change with increasing topographic complexity.

2.0 SPATIAL INTERPOLATION

Spatial interpolation creates a continuous field of data from point data, without having to measure the data at every point, or even at regularly spaced points. Interpolation becomes very useful when the cost of a dense sampling network becomes high, but a continuous, discretised surface of variation of the attribute over space is required (Burrough and McDonnell, 1998). Interpolated surfaces may be used to create maps of the attribute, or as inputs for geographic models of natural or agricultural systems (Jarvis and Stuart, 2001a).

There are many techniques with different underlying models that can be used for interpolating a variable's value in space. These can be broadly divided into global and local interpolators. Global interpolation methods use all available data to make predictions for the whole area (Burrough and McDonnell, 1998). Therefore, if a change or addition is made to the data set, or one of the data points is removed, then this change would have an effect throughout the entire domain (Franke, 1982). Local interpolators, on the other hand, operate within a small zone to make estimates using only data from the immediate neighbourhood of the point being estimated.

Interpolation techniques can be also divided into exact and inexact interpolators. The former are forced to predict the attribute value at a sample point that is identical to that measured (Burrough and McDonnell, 1998). The latter predict values at sampled points that are not the same as the measured value, but predictions are generally similar to those measured (Burrough and McDonnell, 1998).). Inexact or data smoothing methods aim to remove local fine scale variation at each data point in order to minimise predictive error of the interpolated function across the whole region being analysed. Table 1 shows the types of interpolation techniques that were reviewed, dividing them into local and global methods, and exact and inexact interpolators.

Table 1: Spatial Interpolation Techniques Reviewed.

Local Interpolators	**Global Interpolators**	
Exact	**Exact**	**Inexact**
Nearest Neighbours	Trend Surface Analysis	Thin plate Splines
Inverse Distance Weighting		
Kriging		

2.1 Smoothing Splines

A review of relevant literature indicated that, a tri-variate thin plate smoothing spline model is likely to be appropriate for interpolating climate. A univariate spline is a piecewise cubic polynomial that is continuous and has continuous first- and second-order derivatives (Burrough and McDonnell, 1998). Multi-variate splines satisfy analogous higher dimensional smoothness conditions but are not composed of cubic polynomials. Their calculation is more involved than univariate splines but efficient computational procedures have been developed.

Spline functions were initially applied to spatial interpolation problems by Wahaba in 1979 (Hutchinson, 2002), and were later developed to be applicable to larger data sets, and to incorporate parametric sub-models. Splines can be viewed as standard multi-variate linear regression in three dimensions, where the parametric model is replaced by a smooth non-parametric function (Hutchinson, 2002).

Smoothing spline analysis involves the decomposition of the observed point data into a signal and noise. The signal is then spatially coherent and able to be mapped, while the noise is not (Hutchinson, 1991). The data model underlying a spline function is:

$$y_i = z(\mathbf{x}_i) + \varepsilon_i \qquad i = 1, \ldots, n \tag{2}$$

where there are n data points y_i at positions $\mathbf{x}_i$, the term $z(\mathbf{x}_i)$ is the unknown smooth function describing the variation of the attribute, and ε_i denotes the spatially discontinuous noise (Hutchinson, 1993). The $\mathbf{x}_i$ often represent spatial coordinates in two-dimensional euclidean space, for example latitude and longitude, but higher or lower dimensions are possible (Hutchinson and Gessler, 1994). The error term ε_i represents independent random errors with a mean of zero and variance $d_i\sigma^2$. The d_i are known weights, while the σ^2may not be known (Hutchinson, 1991). This error term includes random measurement errors based on the assumption that there is no systematic instrumental drift, and microscale variation (Hutchinson and Gessler, 1994).

2.2 Tri-variate Thin Plate Smoothing Splines

Instead of using an exactly interpolating spline surface, a locally smoothed average surface can be calculated, which does not necessarily have to pass through the measured data point, rather it is assumed to pass as close as possible to the data points, while at the same time making the surface as smooth as possible (Burrough and McDonnell, 1998). This is done to avoid any local extremes in an exact spline surface that may be caused by natural variation or measurement error in the data set. A thorough overview of the theory of thin plate smoothing splines and its application to spatial interpolation is given in Hutchinson (1991).

Three dimensional thin plate spline models have three fully independent spline variables. These trivariate spline models view the data as being fully dependent on position and elevation h:

$$\mathbf{z} = f(x_i, y_i, h_i) + \varepsilon. \tag{3}$$

Such models are often used for interpolation of climate variables such as temperature, precipitation, and evaporation (Hutchinson, 1991). Because temperature declines approximately linearly with elevation, some temperature surfaces are well described by spline models with only two independent spline variables (latitude and longitude) and a single linear dependence on elevation, such models are referred to as partial splines (Hutchinson, 1991):

$$y_i = z(\mathbf{x}_i) + \beta h_i + \varepsilon_i \qquad i = 1, \ldots, n \tag{4}$$

where β is a parametric (usually linear) sub-model based on the elevation, h. It is possible to include many parametric sub-models to include other auxiliary information such as soil type, the proximity of a site to a coast or urban areas (Jarvis and Stuart, 2001a). A quintvariate spline including two parametric sub-models, β_1 and β_2, would look like:

$$\mathbf{z} = f(x_i, y_i, h_i) + \beta_1 p + \beta_2 q + \varepsilon. \tag{5}$$

The $z(\mathbf{x}_i)$ in the spline model are estimated by the smooth function f, which minimises:

$$\sum_{i=1}^{n} \left(y_i - f(\mathbf{x}_i)\right)^2 + \lambda J_m(f) \tag{6}$$

where λ is a positive number representing the smoothing parameter, it is chosen automatically from the data, and $J_m(f)$ is a measure of the roughness of the function f (Hutchinson and Gessler, 1994). λ determines the balance between the fidelity of the surface to the measured data and the roughness of the surface, it is calculated by minimising the generalised cross-validation (GCV) (Hutchinson, 1991). This is a measure of the predictive error of the fitted surface. It is calculated by removing each data point in turn and summing (with weighting) the squares of the difference of the data point from the surface fitted to all the other data points (Hutchinson, 1991). This gives a measure of the accuracy of the fitted surface.

Thin plate smoothing splines are often used for interpolating elevation to produce digital elevation models, as they interpolate large data sets quickly and efficiently. Splines are known to be very good predictors, provided that errors in data measurement are small, they are also good at retaining small-scale features that other techniques may smooth over. Because of their continuity, it is easy to find derivatives of the surface and analyse the surface geometry or topology. Another advantage is the possibility of incorporating linear parametric sub-models, so that it is easy to include dependent variables. A noted drawback of the spline model is that they sometimes produce unrealistically smooth surfaces when applied to some situations; for example, they are not very good to use when estimating attribute values for numerical models (Burrough and McDonnell, 1998), and discontinuous surfaces, such as cliffs in digital elevation models are also smoothed.

2.3 Comparison of Spatial Interpolation Techniques

Local interpolation methods, such as nearest neighbours and inverse distance interpolation, rely on partitioning the region into smaller areas and fitting simple functions on each area. Results of such methods can be sensitive to the positioning of the data points in the area to be interpolated, especially when the data is irregularly spaced. Local interpolation methods are also difficult to use in more than two dimensions, and are not generally useful in smoothing noisy data (Hutchinson, 1991).

The inclusion of physically meaningful relationships such as temperature lapse rates for air temperature interpolation has been found to improve prediction accuracies by up to 35% compared to traditional methods of spatial interpolation (Wilmott and Matasura, 1995). It has been found that when parametric sub-models are not included in thin plate spline models, surfaces are produced with accuracies of the same order as other spatial interpolation techniques such as spatial regression, kriging, and inverse distance weighting (Wilmott and Matasura, 1995).

Kriging extends easily to higher dimensions. Like splines, kriging attempts to achieve minimum error interpolation. However, kriging depends on first estimating the spatial covariance function or variogram. The assumptions about the form of this variogram are important for the interpolation process (Burrough and McDonnell, 1998). However, if the variogram is well chosen, then interpolation results can be similar to those of splines (Hutchinson, 1991).

When comparing splines to kriging, splines have been found to be easier to use due to the fact that only λ has to be estimated and this is done automatically by minimising the GCV (Hutchinson, 1991). Furthermore, the terms in the spline expression can be interpreted to be relevant to the problem: the residual term must be consistent with the errors in the data, and the roughness term, $J_m(f)$ can be seen as a measure of the spatial coherence of the variable being interpolated. Other advantages of splines over kriging are the ease with which parametric sub-models may be incorporated, and the way spline packages easily handle large data sets (Hutchinson, 1991; Jarvis and Stuart, 2001b).

2.4 Interpolation of Climate Variables

In a comparative study by Jarvis and Stuart (2001b), daily maximum and minimum temperatures were interpolated over England and Wales at a resolution of 1 km using partial thin plate splines, ordinary kriging, trend surface analysis, and inverse distance weighting. Partial thin plate splines were found to have the best accuracy. This study found that kriging and splining require fewer guiding variables or sub-models than the other methods used to achieve similar estimation accuracies. They explored partial, bivariate and trivariate splines. Partial splines with two or three parametric sub-models worked best for both maximum and minimum temperature.

When incorporating a linear sub-model to represent temperature lapse rates with elevation in a spline function, the coefficient of the sub-model is determined automatically from the data. There is no need to specify it *a priori*, as would be the case with kriging (Hutchinson, 1991). This also allows for broad changes in the temperature regime with position, as the coefficient of the sub-model may vary.

Despite the close affinity of thin plate splines to kriging, splining has some advantages not enjoyed by kriging as can be seen in Table 2. Because splines require no identification of areas of similar topographical relief, they work well where knowledge of the study area is limited (Custer et al., 1996). Spline predictions are based on elevation, latitude, longitude and climate measurements, this has a physical basis for climate interpolation. Kriging, on the other hand, is purely based on variation between data points in space, and does not automatically include dependence on elevation.

In application to a Tasmanian data set, the average lapse rate for maximum and minimum temperature throughout the year was determined by the thin plate spline routine to be approximately 6°C km^{-1}, which is a commonly accepted value. The lapse rates also varied through the year in ways that were physically reasonable (Hutchinson, 1991).

In a study by Custer et al. (1996), measured annual precipitation for an area of mountainous Montana was interpolated using thin plate splines and digitally compared to maps drawn from the same data by an experienced hydrologist. The resultant precipitation maps were very similar in appearance, but had some systematic differences. It was found that the spline function was not as accurate in areas where extreme values and scarcer input data points coincided. This study also highlighted the need for consideration of data points near the boundary; the spline would have been more accurate if nearby stations outside the study area had been included.

Table 2: Advantages of thin plate splines over kriging for climate interpolation.

	Splines	**Kriging**
Computer load	Small	Moderate
Climate covariates	Not required	Required as input
	Able to vary in space	Assumed stationary in space
GCV minimisation	Automatic	Subjective
Weighting	Automatic	Subjective
Radius of influence	Not required	Required as input
Identification of similar topography	Not required	Required as input
Information network	May be sparse / irregular	Data must be sufficient to compute variogram
Error Assessment	Automatic	Dependent on variogram and data distribution

2.5 Topoclimates in New Zealand

In New Zealand, topoclimate mapping (by whatever method) has received surprisingly little attention, despite the importance of agriculture to the nation. There are exceptions: Turner and Fitzharris (1989) and Cossens and Johnstone (1988) mapped topoclimates for areas in Central Otago and the Waitaki Valley, and recent large-scale topoclimate studies include the completed Topoclimate South, and ongoing Grow Otago projects.

During 1998-2001, the Topoclimate South project mapped long-term mean annual GDD for 802,000ha of Southland, using automatic data loggers at a spatial distribution of ~170 ha. Loggers measured air temperature at each site for one year, every six minutes and at a height of 1.2m. Transects were used to sample features of special interest (Purdie et al., 1999). Locations and elevations were recorded using a Global Positioning System (GPS). The short-term data were temporally extrapolated using data from nearby climate stations with long (~30-year) records (Purdie et al., 1999) and a linear regression technique (Turner and Fitzharris, 1989). The project produced GDD maps which were contoured by hand, using expert climate/terrain knowledge. A threshold temperature of 4°C was used because the main landuse in Southland is pastoral cropping, and most cool-climate grasses are active only above this threshold. The driving force for the project was a need to identify and capitalise on climate resources, to grow more valuable crops and, hence, increase farm profits, regional wealth and employment (Southland District Council, 2002; Topoclimate South, 2002).

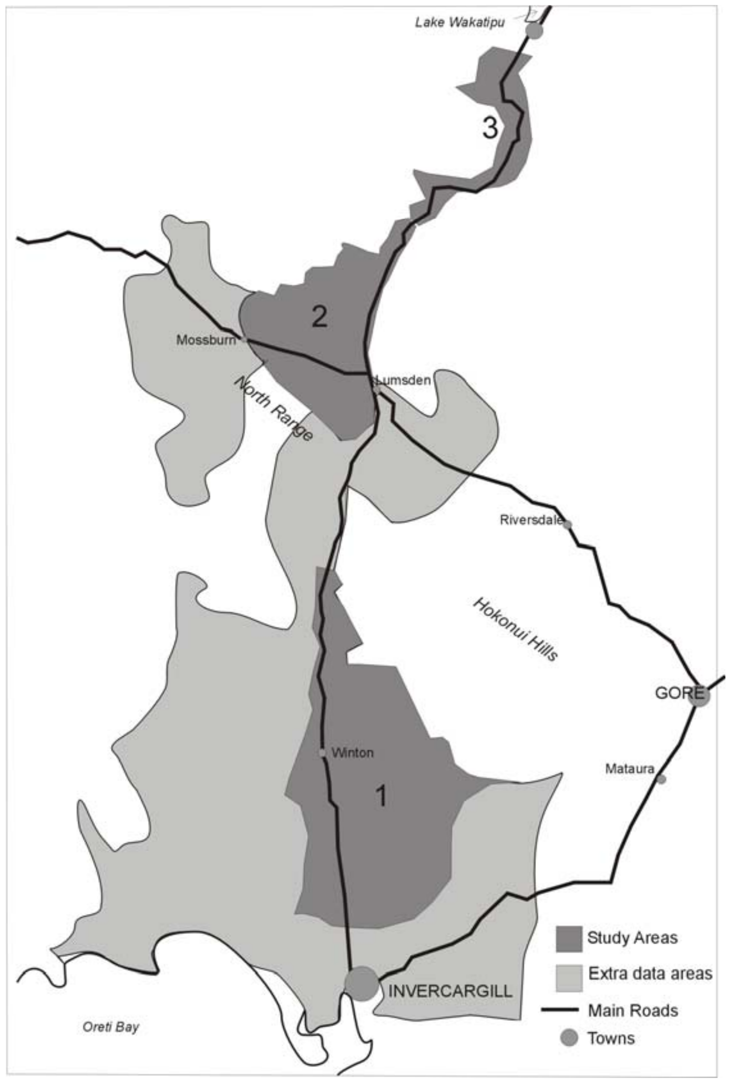

Figure 1: Study areas (dark grey) and areas with additional data (light grey) used in the edge effects analysis.

3.0 METHODS

3.1 Study Areas and Data

The study presented in this paper covers only a fraction of the original Topoclimate South survey area. The three study areas in this project were chosen to have topography of contrasting complexity (Figure 1).

Area 1 is flat with some isolated hills, on the Southland Plains north of Invercargill, and contains 186 data sites. To the north, Area 2 incorporates the Five Rivers plains and a steeper area on the northern flanks of the Hokonui Hills; it contains 128 sites and features a narrowing valley in the northeast corner. Area 3 adjoins Area 2 and includes 56 sites. It consists of a steep valley of Quaternary glacial origins; the north of the valley opens out, with a series of river terraces on the valley sides.

GDD values for a base temperature 4°C for the 370 data logger sites within the chosen study areas, as well as from loggers that were located in the areas adjacent to them were obtained from Topoclimate South. In all, data from 951 sites was used.

A digital elevation model (DEM) was downloaded from the *Geographx New Zealand* website. This is based on elevation data sourced from LINZ's 1:50,000 topographic vector dataset and had a resolution of 500m. The DEM of the three study areas was extracted from the original DEM and grids of the interpolated GDD values interpolated surfaces and their spatially distributed standard errors were fitted to this DEM.

3.2 Interpolation

The spline routine model supplied by the Australian National University (ANUSPLIN) was utilised to interpolate GDD in these areas. As outlined in its manual, this package was primarily developed for fitting climate surfaces. It provides a facility for the transparent analysis and interpolation of noisy multi-variate data using thin plate smoothing splines (Hutchinson, 2002).

Using programs from the ANUSPLIN package, GDDs for base temperature 4°C were spatially interpolated. This involved calculating surfaces as functions of easting and northing and scaled site elevation. These surfaces were then combined with the DEM to calculate regular grids of long-term GDDs, at a spatial resolution matching that of the underlying DEM, 500m. These grids were then displayed using the ArcMap GIS. The grids were displayed with the GDD values divided into classes with 50 GDD intervals. This was done so that the resultant GDD maps would be comparable to those produced by the Topoclimate South Project.

Because GDDs at base 4°C are more influenced by daily minimum temperatures that daily maximum temperatures, three-dimensional splines, as opposed to partial splines were used in the interpolation. From previous studies it has been found that three-dimensional splines are more accurate for interpolating minimum temperatures than partial splines (Hutchinson, *pers. comm*., 2002).

Edge Effects: To investigate edge effects, data from areas surrounding the regions of interest were incorporated in the interpolation. The amount of extra data incorporated was increased so that the way in which the extra data points impacted on the accuracy of the interpolation could be seen. Margins were increased by approximately 5km in every direction for each of the study areas. A disjoint set of validation data was used for each study area to gain an estimate of the accuracy of the interpolation that could be compared for each study area and level of topographic complexity.

Data Network Density: To investigate optimal data network density, 5%, 10%, 15%, 20%, 25%, and 30% of the data points from each study area were removed and the accuracy of the resultant interpolated surfaces was compared. Data points were selected for removal with the program SELNOT in the ANUSPLIN package. This program selects the specified number of data positions by attempting to equi-sample the geographical space.

4.0 RESULTS

4.1 Interpolated GDD Maps

Figure 2 shows the resultant interpolated GDD map for all three study areas using all 950 data points. In this map, GDD ranges between 1731 and 2320. Lower values are found high on the northern slopes of the Hokonui Hills in Area 2, and on the upper north-west facing slopes to the south of Five Rivers. These areas have cooler climates because of their high elevation.

High value climates can be found on terraces on the slopes of the glacial valley in Area 3, and on the southern plains on the higher land between State Highway 6 and Springhills, south-east of Winton. Here long-term average annual GDD values are between 2200 and 2350. Probable explanations as to why these areas experience warmer climates are their slightly raised topography, which allows for drainage of cold air. In the glacial valley, reduced wind speeds caused by the sheltering effect of the valley probably also contribute to the higher climate values.

A map of spatially distributed standard errors produced in conjunction with the spline surface is shown in Figure 3. This map shows that standard errors range between 41 and 59, with most errors being below 45 standard errors. This represents a mean error of 2%. Areas where errors are highest are on the upper slopes of the narrow glacial valley in Area 3, and on the southern foothills of the Hokonui Hills to the west of Glencoe in Area 1.

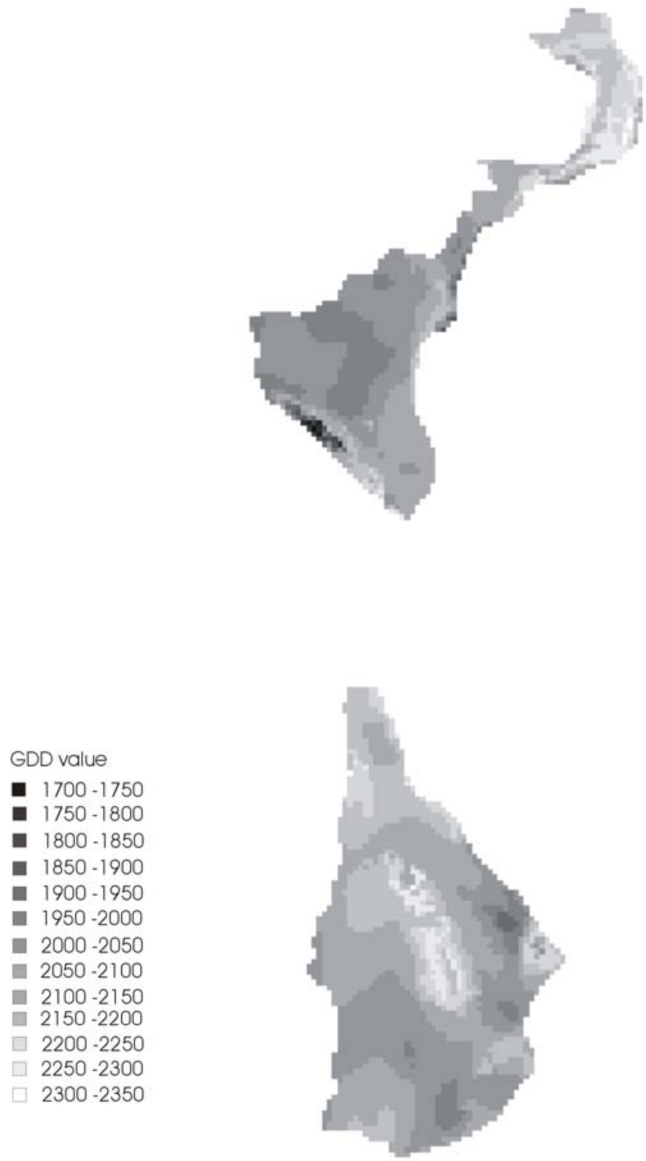

Figure 2: Growing Degree-day map for the study area in Southland (original maps are in colour).

4.2 Data Distribution Studies

Edge Effects: Initially, estimated errors are relatively higher around the edges of the study areas, however, the RMS values (residuals between the validation data points and the fitted surfaces, which indicate the accuracy of the interpolated surfaces) are reduced by the inclusion of extra data from beyond the margins of Area 1. Spatially distributed error estimates show that errors along the edges of the study area are most improved by the inclusion of this extra data. The inclusion of the first 5km of extra data has the most significant effect.

In Area 2, however, interpolation accuracy decreases as more and more data is included from outside the study area. This is thought to be because, for the spline function, extra data is only helpful where the topography is similar to that in the study area. Interpolated GDD surfaces become less accurate when extra data is included from outside an area where the topography is very complicated (as in Area 2). The inclusion of extra data forces the spline function to be more complex than it needs to be.

Data Density Study: Results show that the errors of the interpolated surfaces are changed by a relatively small amount when the data density is changed. This indicates that the spline function is strongly dependent on elevation, and reasonably robust with regard to changes in data network density.

Removal of 10% to 15% of the data points, served to make little difference to surface accuracy in Areas 1 and 2. This indicates that future such studies should aim for this density of data points (approximately one point representing every 3.8 km^2, in Area 1 and 3.4 km^2 in Area 2). This also proved to be the most accurate data density in Area 3.

4.3 Comparison to Hand-drawn Maps

Comparison with Topoclimate South maps show that spline-drawn maps are very similar, with around 20% of the area having GDD values that differ significantly from those on the Topoclimate South maps (Table 3).

The automatically interpolated surface is generally very similar to the published Topoclimate South map: a similar range of GDD values are found in both maps, and GDD values vary spatially in the same way. Most of the large-scale variations in GDD values (greater than about 4 km^2) identified in the published maps are present in the spline-interpolated surface. The thermal belt on the North Range is identified in both maps, as are the higher GDD values in the valley terraces of Area 3. Many small-scale features are also similar, however some smaller scale variations that are not identified in the interpolated map. These are generally small areas.

Table 3: Comparison of published and interpolated maps: Percentage of area with different GDD values in the Topoclimate South maps and interpolated maps. Maps differ by up to two or more GDD classes (each class spans 50 GDDs).

Map Area	Percentage of land area differing in GDD value	
	1 class	*2 classes*
Area 1	22%	3%
Area 2	20%	<1%
Area 3	20%	5%

5.0 CONCLUSION

Cross validation has shown the interpolated climate map to be very accurate. This indicates the usefulness and appropriateness of interpolating climate with splines. The climate maps that were generated for the study areas show the variation of climate in space and how this is influenced by topography, creating topoclimates. High on the slopes of the North Range, long-term mean annual GDD accumulation is as low as 1731 GDDs, while areas on the Southland Plains accumulate up to 2350 GDDs annually on average.

Inclusion of extra data from beyond the margins of the area being studied has been shown to improve interpolation accuracy when the surrounding topography is similar. Inclusion of data out to a distance of 5km significantly reduces errors along the margins. However inclusion of data at greater distances than this is also of value.

Investigations into the effect of changing the density of data positions within the study area show that more dense data networks lead to more accurate interpolated maps. However, network densities may be reduced without significantly compromising the accuracy of the interpolated surface. Based on the results of this study, a density of approximately one data point for every 3 to 3.2 km^2 is recommended, depending on the complexity of the terrain, and the required accuracy and resolution. These conclusions should prove useful for the design of future projects that involve the mapping of climate.

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