Spatial Modelling of New Zealand Climate Variations

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Abstract This study compares two methods of modelling the variability of climate over the New Zealand region. Spatial modelling of the variation of standard deviation of long term mean monthly temperature was examined for a data set of 72 New Zealand stations. Two modelling methods, a partial thin-plate smoothing spline model and the Cressman model, were used to interpolate the monthly temperature variation to a national scale. A computer routine was developed to determine the optimal influence radii for the Cressman method objectively. Though the thin-plate spline method demonstrates better results in general, comparison of these two models shows the Cressman method is satisfactory for interpolation of the variance of climate variables, if computational simplicity and efficiency are also of concern.

Introduction

Climate change impact studies have been mainly focused on the effects of mean changes of climate variables (e.g., Cooter, 1990; Mendelsohn et al., 1994; Rosenzweig and Parry, 1994). Recent studies have shown that the mean climate changes only provide limited information on the impact of the future changes on agricultural and ecological systems. It is known that changes in variability can have serious effects on agricultural yields (Parry and Carter, 1985; Carter and Parry, 1986). Studies on the sensitivity of crop models and climatic extremes have also revealed that changes in variability can have more profound effects on crop yield and on the probability of extreme weather events than simple changes in the mean values (Semenov and Porter, 1994, 1995; Mearns et al., 1996). The frequency of extreme events has shown to be better correlated with changes in the variability of climate variables than with changes in the mean values (Katz and Brown, 1992).

The effects of variability of climate may, in addition, change regionally (Anderson and Hazell, 1989). Consequently, the most common approach to the study of the spatial variability of climate is 1) generating different variability characteristics at point stations by manipulating the parameters of stochastic weather generators, such as that of Richardson (1981) and Richardson and Wright (1984); and 2) interpolating the point station results to required unsampled points, or to a required grid scale. Therefore, spatial analysis and modelling of climate variations is one of the preliminary requirements for the impact assessments of climate change. This is a particular requirement that has been identified for further development of the CLIMPACTS integrated model system for New Zealand (Kenny et al. 1995, 1996; Warrick et al., 1996).

This study investigates the spatial analysis and modelling of variability of climate. A comparison was made between two interpolation methods to determine their utility for generating the map of variability of monthly temperature means over New Zealand.

Spatial Interpolation

The objective of this study is to provide a gridded map of climate variation for New Zealand at a 0.05° latitude-longitude resolution. The interpolation method adopted will be integrated into a climate impact assessment software package (the CLIMPACTS system, Kenny et al., 1995, 1996; Warrick et al., 1996; Sims et al., 1996). Hence, in addition to the accuracy of the interpolation results, computational efficiency and simplicity also need to be considered. Two interpolation methods are selected for this study. The first method combines use of the Cressman technique (Cressman, 1959) to interpolate the irregular station data to a gridded scale at a relatively coarse resolution (0.5° latitude-longitude) and then to further interpolate this result to a finer resolution (0.05° latitude-longitude) using a cubic spline fit. The second method involves use of a partial spline interpolation technique. The software package used for this method is ANUSPLIN (Hutchinson, 1991, 1994).

Cressman Method: Cressman is a simple mathematical method which has become a standard and long-used technique in meteorological data interpolation (i.e. Trenberth 1977; Dey, 1989). Only observations within an influence area surrounding the point being estimated are needed. Other interpolation methods often require a knowledge of the error covariance matrices in advance, or a first-guess field and measured error covariance for all sites as input (kriging approaches also require the error covariance matrix and the assumption of spatial homogeneity). Estimation of the covariance matrices is often difficult. Although the Cressman method also requires a first guess field as input, it can normally be set objectively as the mean of the observed values or some climatology. However, Cressman interpolation requires a radius of influence as an input. The selection of an appropriate radius could be quite subjective. To choose the influence radius subjectively may give the advantage to the user to select the most appropriate map for a certain purpose, for example, increasing the radius if the fitted surface is too rough, and vice versa. This also implies that the final output may vary with different users.

In order to avoid the subjective selection of the influence radius, a computer routine was developed to determine the optimum radius. Firstly, a group of stations (selected station group) was chosen from the available stations according to the data quality and/or representativeness of the station locations. The method then involves withholding each selected station in turn and interpolating a grid with the remaining points. An error (square residual) was calculated for the withheld station according to its observed data and the interpolation result at the withheld station's location. The performance of the model under such a radius was measured by the total error which was obtained by accumulating the square residual for all selected withheld stations. The initial radii can be set to a range of values (a range of grid-sizes were chosen in this study). The best initial radius was determined by comparing the total error of each radius in the range. The routine then searches iteratively around the selected best radius to find the final optimized radius.

As a simple interpolation technique, the Cressman method requires a certain degree of spatial data density to work properly. Its result will likely be inferior to other more complex techniques at high resolution interpolation.

Thin-plate smoothing spline method: The thin-plate smoothing spline interpolation method has been applied to a number of meteorological problems (Hutchinson and Bischof 1983; Hutchinson et al 1984; Kalma et al 1988; Hutchinson 1990; Mitchell 1991). It has the advantage of not requiring a first-guess field or an error covariance matrix, and allowing influences from well beyond the immediate region of the point being estimated (Zheng and Basher, 1995). A key requirement is the estimation of the model's smoothing parameter, which determines a compromise between model accuracy and the output map smoothness. The smoothness of the fitted surface increases as the smoothing parameter increases. To avoid subjectivity and guesswork, a general cross-validation approach was developed as a fully objective method of choosing the smoothing parameter (Wahba and Wendelberger, 1980).

ANUSPLIN is the computer software package for thin-plate spatial interpolation used in this study. The ANUSPLIN method provides the user with a comprehensive set of criteria to indicate the model performance. A signal is also calculated in ANUSPLIN to indicate the degree freedom of the model based on the effective number of parameters being used. The signal characterises the degree of complexity of the fitted surface or indicates the model appropriateness. For example, too small or too large a signal indicates that the surface fitting procedure fails to find a genuine optimum value for the smoothing parameter. Both of these conditions are flagged by an asterisk in the output.

Results and Discussion

The standard deviation of the long term monthly mean temperature of New Zealand was analyzed using the two methods described above. The analysis was carried out for North and South Islands separately. Seventy two temperature stations around New Zealand which have satisfactory observation records were selected for this study. Of the 72 stations, 37 are in the North Island and 35 are in the South Island. Figure 1 shows the location of the stations.

Only latitude and longitude were considered in the interpolation of the variability of the climate variables. The implication of such an assumption is that the influence of other physical attributes, such as elevation and aspect, have been sufficiently represented in the normal climate variables.

The study window for North Island has a latitude from 42°S to 34°S and longitude of 172° to 179° while the

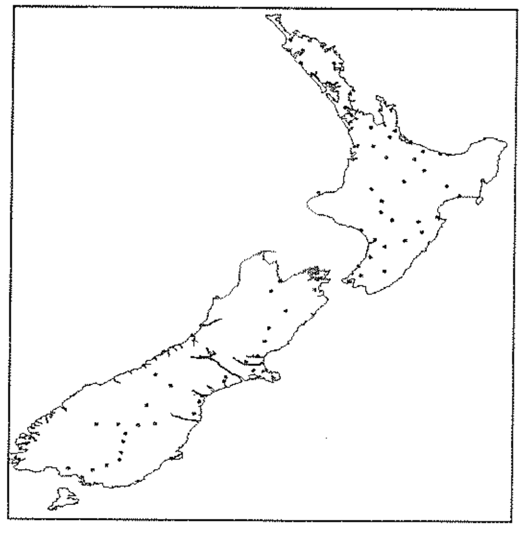

Figure 1: Station locations

Table 1 Final optimum radii and their corresponding mean square residual of standard deviation of monthly mean temperature at 0.5° latitude-longitude.

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
North Island												
R_{opt} (grid-size)	3.975	4.138	4.476	4.028	3.715	3.259	3.903	5.413	4.099	4.104	4.035	4.028
MSR at R_{opt} (×10°C)	0.855	0.989	0.341	1.109	0.537	0.340	3.556	3.506	0.608	0.426	1.230	1.430
MSR at 4 grid-size (×10 °C)	0.856	1.055	0.428	1.111	0.555	0.513	3.594	4.703	0.634	0.432	1.245	1.432
South Island												
R_{opt} (grid-size)	3.596	4.604	4.604	3.564	4.969	4.437	4.301	4.607	4.606	2.835	3.564	3.564
MSR at R_{opt} (×10°C)	0.337	2.153	1.213	0.458	0.617	0.428	1.580	1.166	0.781	0.359	2.063	3.081
MSR at 4 grid-size (×10 °C)	0.376	2.599	1.309	0.528	0.591	0.411	1.760	1.193	1.052	0.364	2.041	3.555

window for the South Island has latitude of 48°S to 40°S and longitude of 166° to 175°. The final resolution required for the temperature variance interpolation is 0.05° latitude-longitude. As for Cressman, since it demands much extensive spatial information at high resolution interpolation, a rather coarse resolution (0.5° latitude-longitude) was used as the initial calculation. At such a resolution (grid size of 0.5°), the windows under study have 15 columns × 17 rows and 19 columns × 17 rows for North Island and South Island respectively. All stations for both islands are selected into the group mentioned above (selected station group) to determine the optimum radius for the Cressman method. The influence radius was initially set from range of a grid-size of 3 (3 × 0.5° latitude-longitude) to the maximum width or height of the window used for the interpolation (i.e. 17 for North Island and 19 for South Island). Figure 2 shows the calculation results for each month. It is clear that for both islands, a radius of 4 provides the smallest accumulative square residual for all months. The final optimized radii and their corresponding accumulative square residuals for the standard error of the long term monthly temperature are listed in Table 1. The 0.5° latitude-longitude interpolation was then carried out after the optimum radius were selected. The output of the 0.5° interpolation was then used as an input to obtain the final 0.05° latitude-longitude resolution using a cubic spline technique. Table 2 lists the results of the mean square residual of the Cressman and ANUSPLIN interpolation results for both islands at the 0.05° latitude-longitude resolution. In general, the partial spline demonstrates better performance than the Cressman. For March in the North Island and July in the South Island, the signal of the ANUSPLIN method indicates that the spline package failed to find a genuine smoothing parameter for these two months. ANUSPLIN performs remarkably well for October for

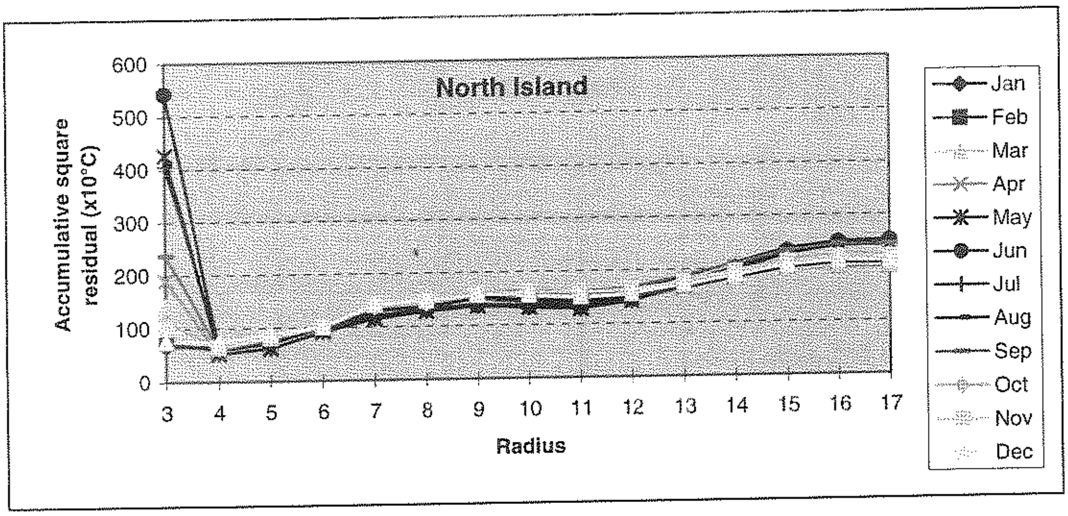

Figure 2(a) Accumulative square residual of mean monthly temperature vs. Radius (North Island)

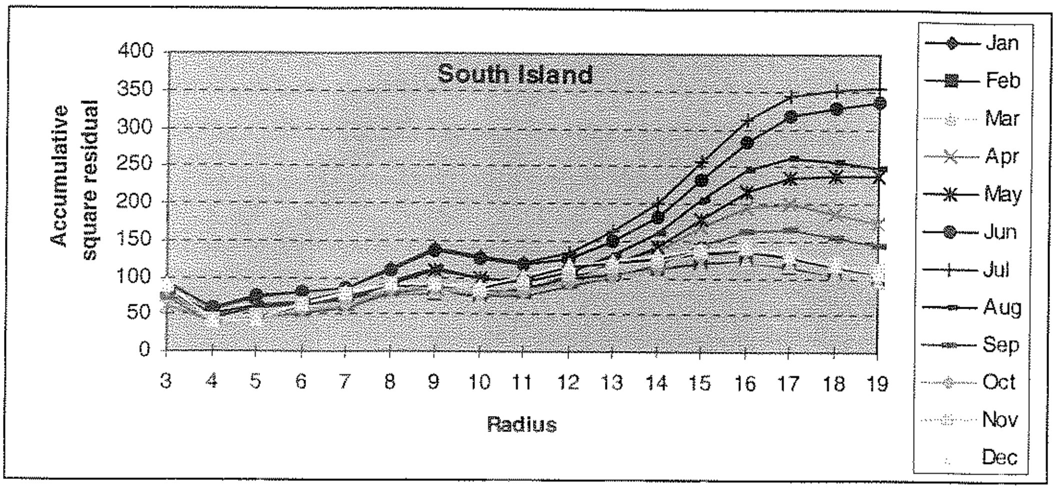

Figure 2(b) Accumulative square residual of mean monthly temperature vs. Radius (South Island)

Table 2 The mean square residual (×10°C) of Cressman and ANUSPLIN at 0.05° latitude-longitude.

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
North Island												
CRESSMAN	46.324	71.237	23.690	34.162	40.800	32.785	143.560	124.726	41.081	31.995	61.100	78.600
ANUSPLIN	26.239	32.134	*****	33.329	37.500	27.550	125.842	135.445	40.557	2.451	42.772	52.949
South Island												
CRESSMAN	33.465	66.639	36.978	24.752	27.035	53.186	120.095	60.558	37.191	33.950	84.444	91.494
ANUSPLIN	10.344	46.870	42.363	17.640	16.457	9.862	*****	6.993	14.494	5.631	32.381	81.690

both islands, compared to both the Cressman method and the ANUSPLIN results for other months. Although the signal of ANUSPLIN result for October does not indicate the failure of the model for this month, its magnitude demonstrates a large number of effective parameters being used in the fitted model which implies a high degree of freedom of the model. The two methods produce quite similar interpolation results for all other months. Figure 3 illustrates the February in the North Island and August in the South Island. Although for these two particular months, the spline model has a relatively better result than Cressman, the spatial distribution predicted by these two methods is quite similar. A comparison of several objective analysis methods by Seaman and Hutchinson (1985) also demonstrated that the simple Cressman successive correction method ranked only slightly below the two best statistical interpolation techniques.

Conclusion

Two interpolation methods were compared in this study to test their utility for spatial modelling of the variability of climate. With a built-in computer routine to determine the optimum radius, the Cressman method demonstrated its appropriateness for incorporation within CLIMPACTS system, given its mathematical simplicity and computation efficiency, which also need to be taken into account.

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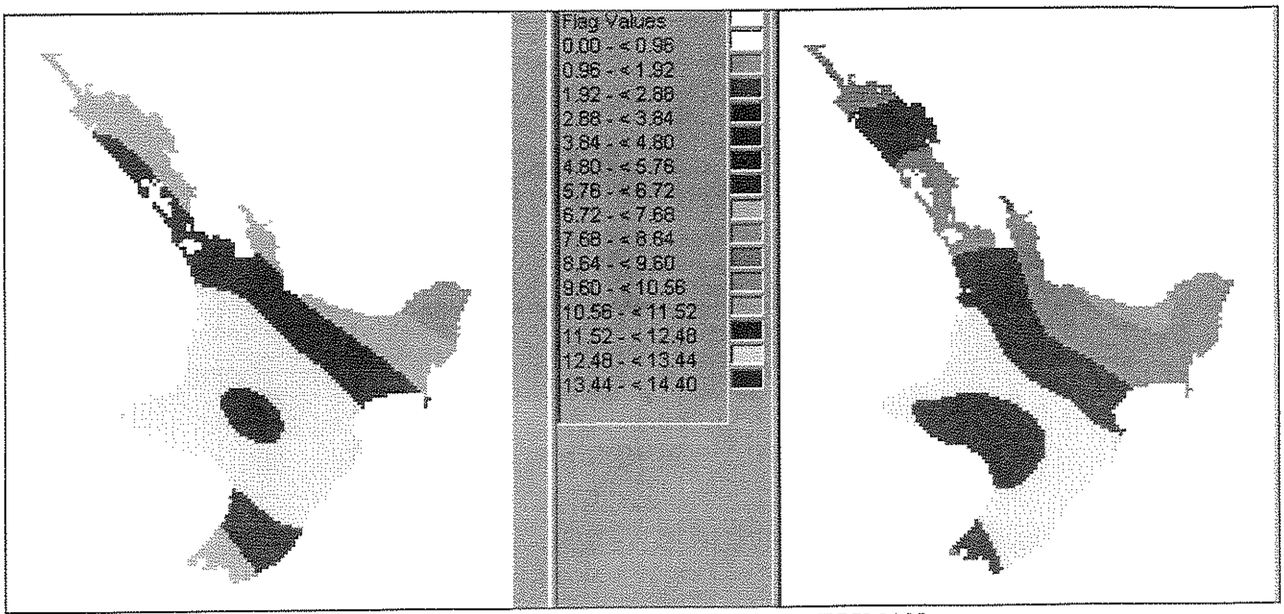
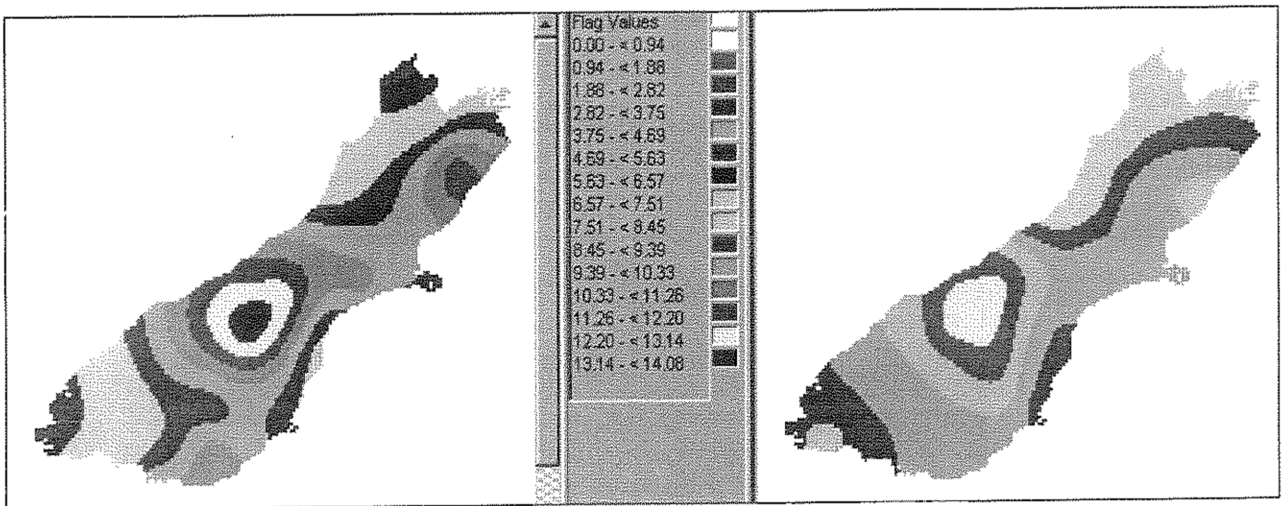


ANUSPLIN CRESSMAN

Figure 3a. ANUSPLIN and CRESSMAN interpolation result of the standard deviation of mean temperature. (North Island, February).



ANUSLIN CRESSMAN

Figure 3b. ANUSPLIN and CRESSMAN interpolation result of the standard deviation of mean temperature. (South Island, August).

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