Estimation of Long-Term Climate Information at Locations with Short-Term Data Records

JOHN SANSOM AND ANDREW TAIT
National Institute of Water and Atmospheric Research, Kilbirnie, Wellington, New Zealand

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ABSTRACT

The accurate mapping of climate has widespread interest and benefit and depends on the availability of long-term data. Accuracy increases with the amount of data, but, often, insufficient data exist for the desired accuracy. To produce accurate maps within a short time frame, a scheme for estimating long-term climate statistics at locations with only short records is required. A general method is described that involves thin-plate smoothing-spline interpolation. Using data from the long-term stations, two independent interpolations are made to the short-term sites: first, the climate element’s distribution and, second, the percentile for the period of observation at the short-term sites. Together these imply a value for the period of observation, but actual values are, of course, available for this period. The difference between the actual and implied values at the short-term sites provides an adjustment to the estimated distribution. It is also demonstrated that for short-term station deployment the better strategy is to have stations at sites for only 1 yr and then to move them to other sites rather than to have them at fewer sites for more than 1 yr.

1. Introduction

Identification of the potential for growing certain crops by accurately mapping the local-scale climate has huge economic value. In New Zealand, for example, horticultural crops are often grown in small niche climates where conditions are only just suitable. In many cases, a small increase in the number of frosts and a slight decrease in direct-beam solar radiation between one side of a valley and the other, for example, is enough to make the growing of these crops uneconomical. Thus, accurate local-scale climate maps are vital for aiding in crop location decisions and, hence, for quantifying and reducing the risk of crop failure.

It is well recognized that the best way to map the climate accurately at the local scale (0.1–10 km) is to have a dense network of measurement sites (Yoshino 1975; Skaar 1980; Turner and Fitzharris 1986). However, long-term climate stations are generally spread too far apart for local-scale climate mapping, and, although temporary climate stations can be installed in dense networks, data collection is often limited to a short period of time, typically one season or 1 yr. In this paper, a new method is used to estimate long-term climate information at short-term temporary climate station locations, enabling the production of climate maps of long-temporal-scale climate statistics that show well-estimated small-spatial-scale detail. The information sought is generalized by considering the estimation of deciles (i.e., minimum, 10th percentile, . . . , median, . . . , 90th percentile, maximum), which provide the non-parametric distribution of the climate statistics.

The problem of estimating long-term climate information at locations with short data records is not new. Turner and Fitzharris (1986) used a linear-regression method to estimate the average accumulated warm-season (November–April) growing degree days at several sites in a small valley in Central Otago, New Zealand. They correlated daily maximum air temperature at each temporary site with daily maximum air temperature at a permanent nearby climate station and did so similarly for daily minimum air temperature. Similar regression equations were pooled using a covariance analysis. These pooled regression equations were then used to estimate the mean monthly maximum and minimum air temperatures over the warm season for each group of sites, and the mean accumulated warm-season growing degree days were estimated from the monthly values.

In a similar way, Hunter and Elliot (1994) describe a regression-based method of estimating long-term mean wind speed at a site based on short-term measurements and long-term data from a reference station located in the vicinity. The authors remark that regression equations have been successfully applied at the regional scale (5–20 km) in complex terrain to predict mean electrical power output and wind speed using weekly, rather than daily, values.

Corresponding author address: John Sansom, National Institute of Water and Atmospheric Research, Ltd., P.O. Box 14-901, Kilbirnie, Wellington, New Zealand.
E-mail: j.sansom@niwa.co.nz

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The primary condition for regression to be valid is that the variance of the dependent variable—observations at a short-term station—is constant over the whole range of the independent variable—observations at a long-term station. However, many climate variables have a lower bound: rain, wind, and sunshine, for example, can all be zero in dry, calm, and cloudy conditions, respectively. This is especially so when they are measured over short periods: daily rainfall is often zero, but most months in New Zealand would have some rain, and similar for wind, and so on. Thus, regressions of a bounded variable between stations are likely to be invalid because the bound restricts the variance at low values of the variable to be smaller than at high values; that is, it is not constant over the range of the independent variable.

Temperature is bounded by absolute zero, but this value is so far below any observed climate temperatures that they will seem unbounded and thus the regression method (Turner and Fitzharris 1986) is valid. For wind, Hunter and Elliot (1994) used weekly values to shift values away from the origin and produce a pseudo-unbounded dataset. The technique of accumulating observations into long periods to enable valid regression could be applied to rainfall, sunshine, and so on. However, for a fixed period of deployment for the short-term stations, the size of the dataset for the regression decreases as the accumulating period increases, leading to poorer estimations.

Also, some climate variables (e.g., rainfall) have large spatial variability with low contemporary correlation between stations and, again, require accumulation into longer periods, leading to the same degradation in regression. Furthermore, there are some situations in which the nearest permanent climate station is not near to the short-term site (greater than 75 km for some remote areas of New Zealand). In these cases, regression models may account for less than 50% of the explained variance.

The application of the regression method to temperature data is described to provide a basis for comparison with a new method that uses a thin-plate smoothing spline, described in the next section. The spline method was developed to provide detail for mapping to small spatial scales, but, because it is independently applied to individual points, it is appropriate to validate it over a range of environments, such as the South Island. An attempt has also been made to answer the question: If a large area is to be mapped with limited resources, is it better (a) to spread any additional instrumentation over the whole area for the whole duration of the deployment of the short-term stations or (b) to divide the area and concentrate the instrumentation for a part of the duration into each of the subareas in turn?

2. The thin-plate smoothing spline

As noted above, regression is of limited applicability, whereas the method of estimating long-term climate information at short-term data locations presented in this paper applies to all climate parameters. It uses thin-plate smoothing spline interpolation (Hutchinson 1989, 1995) as implemented in a software package called “AN-USPLIN” available from the Centre for Resource for Environmental Studies at the Australian National University in Canberra. The interpolation implemented in this package not only seeks to determine the data’s dependence on latitude and longitude, but also, if appropriate, seeks dependency on other variables with continuous spatial variation such as altitude or slope or, perhaps, annual rainfall total as a surrogate for cloudiness when determining the spatial variation of solar radiation. For climate mapping, altitude is generally included and a surface is fitted to the data such that some error is allowed at each data point, and so the surface can be smoother than if the data were fitted exactly. A single parameter controls the smoothing and is normally chosen to minimize the mean-square error between the actual value at the stations and their values predicted by all of the other stations. That is, each station is omitted in turn from the estimation of the fitted surface and the mean error is found. This process is repeated for a range of values of the smoothing parameter, and then the value that minimizes the mean error is taken to give the optimum smoothing. This is called the method of generalized cross validation (GCV).

For many climatological datasets, which often have few data and are noisy, GCV can result in unrealistically smooth maps with unacceptably large differences between the data and the spline fit. To address this problem, Zheng and Basher (1995) manipulated the signal and error characteristics of the data and spline fit and found that enforcing a global value for the ratio of signal to error—a quality measure available from the spline-fitting procedure—provided a useful and intuitive method for understanding and controlling the fitting. The larger the signal-to-error ratio is, the closer the fitted surface passes through the data and the smaller the error of the fitted values is.

3. Regression versus spline

a. Regression estimation from data at short- and long-term stations

Stations throughout the South Island of New Zealand with long-term air temperature data, including, in particular, March, April, and May of 2001—which will be referred to as “autumn 2001”—are shown in Fig. 1. From these stations, one-quarter (18) were chosen to play the role of a network of short-term stations from which it was supposed that data were only available for autumn 2001. In reality, these 18 stations all had more than 10 yr of data, which included autumn 2001. For each short-term site, the nearest long-term station with autumn 2001 data and a long record (greater than 10
yr) was identified. Both the short-term and the long-term partners are indicated in Fig. 1.

Daily mean temperatures at each short-term station were regressed against the contemporary daily mean temperatures from its long-term partner, and the regression $R^2$ values are presented in Table 1. It can be seen that most of the station pairs are correlated well; however, there is one notable exception. Haast and Tara Hills are separated by the greatest distance, 99.4 km, and their $R^2$ is only 0.53. Other station pairs separated by large distances (e.g., Kaikoura and Culverden: 81.0 km) are located in the same general climate zone, but Haast and Tara Hills are located in two very different climatic zones separated by the Southern Alps mountain range (see Fig. 1) and are thus less likely to be highly correlated.

The deciles of daily mean temperature for autumn at each long-term partner station were calculated from all of the autumns of its long record. The regression provided a linear transformation that was applied to the deciles to give estimates of the deciles at the short-term station. However, because the short-term stations do have long-term data, their actual deciles could also be calculated, and, thus, the absolute difference between the estimate and the actual at each decile could be found. The thick solid line on Fig. 2 shows the variation with decile value of the mean over the short-term stations of these differences for the autumn season.

Aside from the minimum (i.e., zero decile), the mean absolute difference for autumn using this method is less than 0.5°C. The general decrease in error from the minimum to the maximum decile is attributed to a negative skew in the long-term autumn temperature data. Thus, cold autumns are colder than might be expected with a nonskewed distribution, which would give a mean error distribution that is more “U” shaped, with the minimum error at the median value. The larger error at the minimum and maximum decile arises because the standard error of the estimation of percentiles is larger for the more extreme percentiles (for normal data, e.g., the standard error for the 1st percentile is 3 times that for the median). Thus, the larger spread at the extremes, together with taking the mean of the absolute differences, results in the noted larger error.

The mean absolute differences for South Island winter, spring, and summer mean temperature are also
Table 1. Autumn 2001 daily mean air temperature regression $R^2$ values for short-term vs nearest long-term partner stations. The identification (ID) numbers beside the short-term station names refer to the numbers on Fig. 1.

<table>
<thead>
<tr>
<th>Short-term station (ID No.)</th>
<th>Nearest long-term partner station</th>
<th>Distance apart (km)</th>
<th>Regression $R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Takaka (1)</td>
<td>Farewell Spit</td>
<td>42.6</td>
<td>0.87</td>
</tr>
<tr>
<td>Lake Rotoiti (2)</td>
<td>Nelson</td>
<td>61.4</td>
<td>0.88</td>
</tr>
<tr>
<td>Haast (3)</td>
<td>Tara Hills</td>
<td>99.4</td>
<td>0.53</td>
</tr>
<tr>
<td>Nelson (4)</td>
<td>Takaka</td>
<td>58.5</td>
<td>0.87</td>
</tr>
<tr>
<td>Grassmere (5)</td>
<td>Blenheim Airport</td>
<td>35.4</td>
<td>0.88</td>
</tr>
<tr>
<td>Kaikoura (6)</td>
<td>Culverden</td>
<td>81.0</td>
<td>0.82</td>
</tr>
<tr>
<td>Harper River (7)</td>
<td>Craigieburn Forest</td>
<td>18.4</td>
<td>0.83</td>
</tr>
<tr>
<td>Christchurch International Airport (8)</td>
<td>Akaroa</td>
<td>50.2</td>
<td>0.91</td>
</tr>
<tr>
<td>Le Bons Bay (9)</td>
<td>Akaroa</td>
<td>15.4</td>
<td>0.79</td>
</tr>
<tr>
<td>Orari Estate (10)</td>
<td>Peel Forest</td>
<td>21.6</td>
<td>0.89</td>
</tr>
<tr>
<td>Naseby Forest (11)</td>
<td>Lauder</td>
<td>32.9</td>
<td>0.89</td>
</tr>
<tr>
<td>Palmerston (12)</td>
<td>Taiaroa Head</td>
<td>31.5</td>
<td>0.74</td>
</tr>
<tr>
<td>Manapouri Airport (13)</td>
<td>Lumsden</td>
<td>71.0</td>
<td>0.79</td>
</tr>
<tr>
<td>Queenstown Airport (14)</td>
<td>Cromwell</td>
<td>39.4</td>
<td>0.92</td>
</tr>
<tr>
<td>Clyde Dam (15)</td>
<td>Cromwell</td>
<td>16.7</td>
<td>0.94</td>
</tr>
<tr>
<td>Winton (16)</td>
<td>Tiawai Point</td>
<td>43.0</td>
<td>0.90</td>
</tr>
<tr>
<td>Balclutha, Finegand (17)</td>
<td>Nugget Point</td>
<td>16.6</td>
<td>0.82</td>
</tr>
<tr>
<td>Tautuku (18)</td>
<td>Nugget Point</td>
<td>29.4</td>
<td>0.91</td>
</tr>
</tbody>
</table>

The mean absolute difference over the short-term stations at each decile for the regression method for autumn (thick solid line), winter (dotted line), spring (dashed line), and summer (thin solid line) mean air temperature.

Figure 2 shows that winter temperature is also negatively skewed and that spring and summer are positively skewed. Skewed temperature distributions are not uncommon, with preliminary work showing pockets of positively and negatively skewed sea surface temperatures around New Zealand, similar in magnitude to the well-known positive skew in sea surface temperatures in the eastern equatorial Pacific Ocean “Niño 3” region (Burgess and Stephenson 1999; A. B. Mullan, NIWA, 2002, personal communication).

In general, the regression method produces good estimates of the long-term autumn air temperature deciles. A 0.3°C-0.5°C error level is generally acceptable for climate mapping, depending upon the use of the information. It will be shown in the following sections that by using a thin-plate smoothing spline a similar error level can be obtained.

b. Spline estimation from data at long-term stations

The deciles of autumn total rainfall at all long-term stations were calculated from all of the autumns of their long records. Also, the deciles of daily mean temperature for autumn of the remaining long-term stations (i.e., those stations that closed before autumn 2001) were calculated to accompany those calculated earlier. Thus, 22 datasets (11 rainfall deciles at 848 long-term stations and 11 temperature deciles at 166 long-term stations) were available, and the spatial variation of each was found by fitting thin-plate smoothing splines.

However, deciles at a point form a monotonically increasing set, and if each decile dataset was fitted directly (i.e., separately and with no reference to its neighboring deciles) there would be no guarantee that all points would conform to this requirement. Some early results suggested that this problem could exist, and to build in some dependency between the decile surfaces the following scheme was adopted. Only the median was fitted directly; each percentile above the median was transformed to be the difference between itself and the adjacent lower one (e.g., 60th percentile becomes 60th percentile minus the 50th percentile). For the percentiles below the median, the difference was taken the other way (e.g., 40th percentile becomes 50th percentile minus the 40th percentile). Then the decile variations were recoverable by suitably adding the resulting fitted fields together.

There could still be problems because the scheme
described depends upon the resulting spatial fields being positive everywhere. For any point where that was not the case the monotonic increase of the deciles would not hold. This condition could have been addressed by further transformations to map the positive half of the real line to the whole of the real line before the spline fitting, which would then be followed by the reverse transformation. However, the concern was only with the estimates at the locations of the short-term stations, and there, at least, no negative differences were found.

Despite the concern that the spline fits using the GCV method may give unrealistically smooth spatial variation, the method was used because it allows the smoothing of their spatial variations to be optimized to the full potential of the spline’s ability to differentiate actual spatial variation from noise. The diagnostics from the spline fits had signal-to-error ratios of approximately 1:1, showing that the GCV method had provided adequate fits. Such a ratio indicates that a coherent signal had been detected, but, as cautioned by Hutchinson and Gessler (1994), the ratio should not exceed unity—otherwise the spatial patterns lose robustness and become sensitive to extra data. Estimates for the deciles at the short-term sites were found from these fits by estimating the transformed deciles at the grid points of a 5-km grid and linearly interpolating them to their actual locations.

As for the regressions, the short-term stations do have long-term data, and so their actual deciles could also be calculated: the absolute difference at each decile could be found for temperature and the absolute percent difference (i.e., $100 \times |\text{estimate} - \text{actual}| / \text{actual}$) could be found for rainfall.

For both autumn mean temperature and total rainfall, Fig. 3 shows the variation with decile value of the mean of these differences over the short-term stations. Note that data from the 18 short-term stations were not used to generate the spline fits. Because these 18 stations do have long records, the overall spline fit would have been significantly improved if these data were included. Thus, the spline errors shown here are likely higher than they otherwise would have been if all available data were included. As with the regression method, there is a general decrease in the air temperature error from the minimum to the maximum, which is again attributable to a negative skew in the autumn temperature data. The decrease is less marked for rainfall, indicating that South Island autumn rainfall totals are more symmetrically distributed.

c. Comparison of regression and spline estimates

A comparison between Figs. 2 and 3 shows that from the long-term stations alone (i.e., without using any additional data from the short-term data sites) the spline gives estimates for temperature at the short-term sites that, on average, are only slightly worse than those made by the regression method (the average regression-method error across all the deciles is 0.37°C as compared with 0.51°C for the spline method). A comparison between the methods cannot be made for rainfall because the regression method could not be used for rainfall; thus, the spline method is better because it is a general method that can be used with most data types.

Figures 2 and 3 also show that scope exists for further improvement, and a scheme for incorporating the short-term data in the spline method should yield benefits. A straightforward method starts by fitting a spline to the data from the long-term sites for just that period during which observations were made at the short-term stations (autumn 2001). From this spline, estimates of the “observations” can be made for the short-term sites, and, hence, a set of differences from the actual observations that were made can be calculated. By assuming that the differences would be similar from year to year, these differences can then be added to the spline of the long-term climate statistic (e.g., autumn median temperature). The result is an estimate for the long-term statistic in which the short-term data have been incorporated.

This method was tried on the South Island autumn air temperature dataset. Figure 4 summarizes the results and, for ease of comparison, repeats the equivalent results for autumn air temperature from Figs. 2 and 3. It can be seen that adjusting the estimated deciles using the differences derived from the short-term data period results in an increase in the mean absolute difference.
of about 0.1°C over the spline method with the long-term station data only.

Upon inspection of the adjusted spline estimates at each of the 18 short-term stations, it was found that, at most of the sites, the adjustment improved the estimate of the actual deciles, as expected; however, at three sites there was no improvement (stations 2, 7, and 15) and at three further sites (11, 13, and 14) the adjustment significantly worsened the decile estimates. All of these six stations are located in inland mountainous regions (Fig. 1), and at each location the autumn 2001 mean temperature estimate was higher (by as much as 1.8°C) than the actual temperature.

It is probable that the overestimation of the long-term autumn temperature deciles at these inland stations and the resultant increase in the mean absolute error is the result of a slightly different relationship between elevation and temperature as compared with that at the coastal sites, perhaps caused by more snow cover and/or enhanced cold-air drainage in the mountainous areas. Furthermore, the optimum smoothing parameter in the spline model is most likely tuned more tightly to the coastal areas where the majority of the climate stations are located. The implication is that, in order to make best use of any additional temporary station data, the estimates of the observations for the period of the temporary stations must be made relative to the long-term estimates at the temporary sites. The relative estimates of the observations will thus incorporate any local differences in the relationship between elevation and temperature. The next section describes the implementation of this method.

4. Improved spline method

a. Adjusting long-term spline fit by using short-term data

In the previous example, a spline was fitted to the temperature data from the long-term sites for just that period during which observations were made at the short-term stations (autumn 2001). In this case, a spline is fitted to the percentile of the autumn 2001 temperatures at the long-term stations. The autumn 2001 percentile spline surface is much smoother than that derived from the actual temperatures, because it is the fit of the autumn 2001 temperatures relative to the long-term mean autumn temperature.

Thus, the estimate of the long-term deciles at the short-term sites involves three steps, which are outlined on Fig. 5. Step 1 is the estimation of the distribution of the long-term mean autumn temperature at the short-term site using spline fits of each decile of the long-term station autumn temperatures. This method is the one outlined above that uses long-term station information only. Step 2 is the estimation of the percentile for the autumn 2001 temperature at the short-term site using spline fits of the percentiles of the long-term station autumn temperatures. If both the estimated distribution and percentile are correct, then the “estimated value” and “actual value” marked in Fig. 5 would coincide. Thus, step 3 is the adjustment of the estimated long-term decile distribution by the difference between the estimated and the actual autumn 2001 temperature.

Figure 6 shows the mean absolute differences over all of the 18 short-term stations for the regression method, the spline method, and the percentile-adjusted spline method for mean autumn temperature, and Fig. 7 shows the spline method and the percentile-adjusted spline method for autumn rainfall total. It can be seen that the percentile-adjusted spline method results in errors that are lower than those of the simple spline method by around 0.2°C for temperature and 2% for rainfall, except in the case of the minimum and first decile. The percentile-adjusted spline method also results in errors that are lower than the regression method for deciles 2–10 for temperature.

A common statistic for assessing the degree to which a set of data derives from a given distribution is the Kolgomorov statistic (e.g., Conover 1971), which has an associated probability, or p value. The higher the p value is, the more likely it is that the data come from the given distribution. For the regression method, the median p value over the 18 stations was 4%; for the percentile-adjusted spline method it was 26%, with the significance level of this difference being about 10%. Thus, in general, the distributions estimated by the per-
Fig. 5. Schematic diagram that shows the three steps involved in the estimation of long-term deciles of mean autumn temperature at short-term station locations based on adjustment by the percentile. The thick solid curve is the estimation of the mean autumn temperature distribution at a short-term site based on interpolation of splines of the deciles from long-term stations. The dotted curve is the solid curve shifted to the right by the difference between the actual short-term (autumn 2001) value and the estimated value, which has been derived from the intersection of the estimated autumn 2001 percentile and the estimated long-term temperature distribution.

Fig. 6. The mean absolute difference over the short-term stations at each decile for mean autumn air temperature for the regression method (solid line), the spline method (dotted line), and the percentile-adjusted spline method incorporating the short-term data (dashed line).

Results for winter, spring, and summer temperature were similar to the results for autumn, with the percentile-adjusted spline-method errors being the same or slightly lower than the regression-method errors across deciles 2–10. Of interest is that the regression-method errors were consistently lower for deciles 0 and 1 for every season when compared with the percentile-adjusted spline-method errors (as is shown in Fig. 6), and in the case of summer the regression error was also lower for decile 10. This suggests that the spline method is less suited to the estimation of the extreme values.

b. Dense/short network as compared with sparser/longer network

A common question that arises in climate mapping studies is the following: If a large area is to be mapped with limited resources, is it better (a) to divide the area and concentrate additional instrumentation for a part of the duration into each subarea in turn or (b) to spread the instrumentation over the whole area for the whole duration of the deployment of the short-term stations? The framework of this study can be used to address this question.

Suppose that for the 18 short-term sites used above only six sets of instruments were available for deployment for a 3-yr period. These six sets could be installed at sites 1–6 (see Fig. 1 and note that any six sites would suffice, but here it was convenient to group by the site number) for 1999, then moved to sites 7–12 for 2000,
and then finally moved to sites 13–18 for 2001. As an alternative, they could be installed at six sites only and left for the entire 3 yr, which raises the additional question of which 6 of the 18 should be used.

To answer these questions, at each of the 18 short-term stations the percentile-based spline method described above was repeated using autumn temperature data from 1999 and 2000. Thus, the absolute differences between the estimated and actual deciles were calculated at every short-term station for each of the 3 yr of 1999–2001. Selections from these could be used directly to produce a figure similar to Fig. 6 for option “a.”

For option “b,” the long-term deciles were estimated at each of the 18 short-term sites by taking the mean of the three percentile-based adjustments for each year [i.e., steps 2 and 3 on Fig. 5 were repeated 3 times (for each of 1999, 2000, and 2001), and the mean adjustment was found]. However, only six sites were supposedly available, and so several selections of 6 of the 18 short-term stations were chosen based on the criteria that they were well spread out and at varying distances from coastlines. It was found that the mean absolute difference over the six stations varied by up to 0.5°C, depending upon the selection of sites. The lowest mean error was obtained from the selection of stations 2, 3, 9, 11, 15, and 17. From Fig. 1 it can be seen that this selection may have been chosen based on their location alone, without any a priori knowledge of the mean error reduction.

Thus, two spline fits of the long-term autumn temperature deciles for the South Island were produced. The first used the estimated long-term deciles at all 18 short-term stations (where the estimates for stations 1–6 were based on 1999 data, stations 7–12 were based on 2000 data, and stations 13–18 were based on 2001 data) plus the actual deciles from the long-term stations. The second spline fit was based on the estimated deciles at the six 3-yr short-term sites listed above plus the long-term stations. When applying the spline method, the number of years of record is generally used as a weight on the station data. However, because the estimation of the long-term deciles at the short-term stations incorporates long-term information, the actual short-term station length of record (i.e., 1 yr) is not a valid weight. The median length of record over all of the long-term stations (12 yr) was chosen as a weight for all of the short-term station estimates.

Rather than display two figures similar to Fig. 6, Fig. 8 shows the difference between the mean absolute percent differences at each decile for the two short-term station deployment options. The solid line on Fig. 8 shows that, aside from the zero decile, the deployment of the six stations at sites 1–6 for 1999, 7–12 for 2000, and 13–18 for 2001 (i.e., option a) results in an average improvement of the mean absolute difference of around
0.2°C over all of the short-term stations when compared with option b (i.e., where the six stations are spread out and are not moved for 3 yr). The dashed line shows that, at the 12 short-term stations at which no data were collected under option b, the mean error is considerably higher (by around 0.25°C, with the exception of the zero decile) when compared with the error arising from option a.

Of particular interest is the comparison, shown by the dotted line in Fig. 8, of the errors from the two deployment options at the six sites at which the stations were left for 3 yr in option b. At these stations, the mean absolute difference using option a was still lower than that using option b, aside from the zero decile, indicating that the most important factor when interpolating station data using a spline model is maximizing short-term station coverage rather than minimizing the estimation error at the short-term stations.

5. Summary and conclusions

Apart from setting out a method of incorporating data from short-term stations into a climate-mapping exercise, this paper also supports the view that using thin-plate smoothing-spline interpolation provides maps of acceptable accuracy. This conclusion is because, even without including the short-term data, rainfall deciles were predicted by the spline with a mean error of 10%—12%, and temperature deciles were predicted to about 0.5°C. An obvious step to decrease these errors is to include more data, which, of course, can only be from short-term stations because the maps will undoubtedly also be required in the short term. Hence, the thrust of this paper: What strategy should be used in station deployment, and how can the data be used?

For temperature, a regression method of relating observations at the short-term stations to those at long-term stations was shown to give deciles estimated to within 0.4°C, marginally better than the 0.5°C given by interpolation from observations at other sites. However, not many other climatic data types are suitable for regression, because most are bounded and would require amalgamations into relatively long periods to make them pseudounbounded, which would decrease the size of the dataset for any regression and, hence, the prediction accuracy.

A straightforward method of using the spline to incorporate the short-term data led to a 0.1°C increase in error rather than the decrease that extra data might be expected to give. It seemed likely that the spline had not sufficiently allowed for topography (if it had then the extra stations would be superfluous), which could be circumvented by estimating percentile values rather than actual values. Thus, whatever a station’s altitude or general situation, its percentile value should relate more closely to its neighbors than should its actual value; for example, over relatively large areas generally cold or dry conditions might be expected to apply. Using a percentile method led to a 0.2°C decrease in decile estimation errors. This result was a little better than that achieved for temperature by the somewhat simpler regression method, but the proposed method is more flexible, with applicability to all data types.

For the choice of deployment strategy, it was clearly shown that it is better to shift resources around for limited periods rather than to concentrate them at limited sites for longer times. This result might well be expected because it ensures that the climate will have been sampled over the widest possible area. However, it needs to be emphasized that the method is very much dependent on the existence of an adequate set of long-term stations. Such a network is needed to establish the spatial variation of the general form of a data type’s distribution (i.e., its deciles) and its percentiles during the period of the short-term stations. The method could also be applied to stations within the long-term set that have only a few years of data.

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REFERENCES


