The spatial structure of monthly temperature anomalies over Australia

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Thirty years of quality controlled surface data from a network of 95 stations have been used to examine the limits which spatial sampling place on the analysis of Australian temperature variability. Use has been made of two methodological paradigms, with the goal of documenting the ability of a typical climate network combined with modern analysis techniques to support the monitoring of short-term climate variability over Australia. In the first, the representativeness of stations' observations has been investigated through a parameter-based description of the scales and errors of monthly station data. This has revealed temperature anomalies to be highly coherent, with decorrelation scales longer than the typical distance between stations in our operationally feasible network, and for the associated observational error variance to be relatively modest, being typically 10 per cent to 20 per cent of the total variance.

The parameter-based results have been complemented by a series of experiments in which objective analysis techniques were applied to the independent estimation of observed monthly anomalies. The methods examined were successive correction (Barnes), statistical interpolation, and Laplacian smoothing splines, chosen because of their relative popularity, and because of their differing approach to the analysis problem. For each method and both mean monthly maximum and minimum temperature the root mean square error in estimating observed values was near 0.6°C, with a ratio to the standard deviation of approximately 0.45. The most important determinant of this error was found to be local station density, with an approximate doubling of errors from the well observed southeast through to the sparsely observed northwest of the continent for all methods. The intercomparison of analysis methods has revealed statistical interpolation to be most accurate, followed by the second order (*m*=2) Laplacian smoothing spline and then successive correction. The differences in root mean square error between the techniques show wide statistical significance, but are otherwise modest, typically amounting to less than 0.1°C. Collectively, the results of this study imply that station temperature observations are representative of the variability over a substantial area of surrounding space, and networks such as that used here are sufficient to support the monitoring of Australian temperature variability with reasonable accuracy.

Introduction

The use of conventional surface temperature data for the monitoring of climate variability and change presents a major challenge. Meaningful analysis is only possible with consistent station records spanning many years, and networks which are sufficiently dense to sample the variability of interest (Karl et al. 1994; Weber and Madden 1995). In reality, the conventional networks are generally sparse and irregular, while few long-term sta-

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tion records are free of error and temporally consistent, in the sense that variations are solely a function of the ambient weather and climate (Conrad and Pollak 1962). Together, the fallibility of individual records (temporal errors) and the discretised sampling of the continuous atmosphere (spatial errors) make climate monitoring necessarily approximate, and introduce uncertainty against which all findings should be assessed.

The limits to climate monitoring and analysis which are imposed by the imprecision of individual station records are contributed to by true data errors, for example due to observer misreading, as well as by changes in instrumentation, observer practice, and local station environment etc. (P.D. Jones et al. 1986; IPCC 1990, 1996; Torok and Nicholls 1996). These issues are widely recognised, and the past few years have witnessed considerable effort devoted to developing tools for the routine detection and correction of errors and inhomogeneities in station series (P.D. Jones et al. 1986; Easterling and Peterson 1995; Torok and Nicholls 1996; Trewin and Trevitt 1996; Gallo et al. 1999). The recent scientific literature provides many examples where these techniques have been applied in the preparation of homogenised station temperature datasets whose quality is believed to be sufficient to support the detection of climate change and variability (e.g., P.D. Jones et al. 1986; Karl et al. 1993; P.D. Jones 1994; Plummer et al. 1995; Torok and Nicholls 1996; Easterling et al. 1997).

The limits which the discrete and (often) sparse conventional networks impose on climate monitoring are more nebulous and technique dependent than their observational error counterpart (Trenberth et al. 1992; Daley 1993; Karl et al. 1994; Shen et al. 1994; Weber and Madden 1995; P.D. Jones et al. 1997). It is not surprising, then, that these have received less attention in the literature, and those results which exist are not readily generalised to different domains or analysis methodologies. This imbalance has hitherto been of limited importance, as many past climate studies have focussed on specific locations, in which case the network only limits the number of points available, or integrated values over large areas. In the latter case, the tendency for sampling errors to be spatially uncorrelated means areal averaging acts as a powerful filter, and a modest network is often capable of providing an accurate estimate of the spatial integral of temperature variability (P.D. Jones et al. 1986, 1997; Trenberth et al. 1992; P.D. Jones 1994; Karl et al. 1994; Shen et al. 1994; Weber and Madden 1995).

The limits imposed by the discrete observational networks are most obvious and significant when the goal is a spatially continuous description based on point observations. Because climate and its variability are spatially varying, it is axiomatic that the continuous three (two space and time) and eventually four (three space and time) dimensional description of climate variability must be the goal of climate monitoring. When forming analyses from point observations, spatial sampling becomes a central issue, due to uncertainties associated with observation representativeness and the under-sampling of spatial variability (Daley 1993). These impose limits on the accuracy with which the temporal evolution of climate can be described at points spatially removed from stations, regardless of the fidelity of the basic data, and the ability to monitor climate in a complete sense.

In this study we seek to address two questions fundamental to the monitoring of Australian surface temperature variability on monthly and longer timescales, these being:

(a) What are the random observational error and spatial covariance characteristics of anomalies of monthly mean maximum and minimum temperature over Australia? and

(b) With what accuracy are present day meteorological analysis procedures able to reproduce the true spatial structure of Australian temperature anomalies on monthly time scales?

The first question underlies the appropriateness of generalising temperature observations at stations through space, and the scientific basis for analysing short-term climate data over Australia. The errors of observation dictate the fidelity with which station data should be paid by analysis schemes, and provide an upper bound on the skill of analyses in estimating independent observations (Gandin 1963; Koch et al. 1983; Seaman and Hutchinson 1985; Daley 1993).

A knowledge of the covariance structure of a field to be analysed is of interest for both theoretical and practical reasons (Seaman 1982a; Daley 1993; Shen et al. 1994; P.D. Jones et al. 1997). Fundamentally, the covariance function (being the inverse Fourier transform of the spectrum) provides a convenient parameter-based description of the spatial scales of the field being analysed. Given that spatial analysis can be viewed as the optimal separation of signal from noise (Thiébaux and Pedder 1987; Seaman 1989; Daley 1993), the spectrum of the observations and associated data errors should provide a constraint on the spectral response of any analysis procedure, and be reflected in the analysed surfaces.

From a more practical viewpoint, the covariance structure provides a basis for assessing the adequacy of networks, the appropriateness of analysis, and should provide guidance when tuning parameters for analysis schemes (Gandin 1963; Seaman 1989; Daley 1993; P.D. Jones et al. 1997). For most spatial analysis methods the range of appreciable correlations (covariances) provides a limit to the distance to which data should be extrapolated from observation points (Gandin 1963). Hence, a first step when performing spatial analysis should be an assessment of the correlation length scales in comparison to the spacing of data points, with analysis only proceeding if the data density is sufficient to provide useful information across the analysis domain.

It is not possible to definitively answer the second question, firstly because we do not know the truth, and because of the diversity of meteorological analysis methods (Gandin 1963; Creutin and Obled 1982; Franke 1985; Seaman and Hutchinson 1985; Lorenc 1986; Daley 1993). Without the truth, the technique we use to evaluate analysis performance is based on comparison against independent observations, the details of which are provided below.

The analysis techniques which are examined in this paper are the Barnes successive correction, statistical interpolation (SI) and bivariate Laplacian smoothing spline. Each of these has found widespread use in meteorological data analysis (Franke 1985; Seaman and Hutchinson 1985; Lorenc 1986; Daley 1993), and is used within the Australian Bureau of Meteorology for analysing near-surface variables. Importantly, these span the three general classes of meteorological analysis methods: empirical interpolation, statistical interpolation and function fitting (Gandin 1963; Thiébaux and Pedder 1987).

Data

The reliable description of climate variability and change is only possible with data of the highest quality. The basic data for this study come from the quality-controlled daily temperature series for 103 Australian stations described by Trewin (1999). The preparation of this set involved the screening of the data for gross errors which affected a small number of observations, the identification of non-climatic inhomogeneities using the technique of Easterling and Peterson (1995) and the adjustment of data, at the daily time-scale, following Trewin and Trevitt (1996).

This study uses monthly mean temperature data for the 30 years 1961 to 1990, inclusive. We have chosen a month as our basic unit of time because it is sufficiently long to filter much of the variability associated with individual weather systems, while being short enough to allow the delineation of seasonal effects in climate variability and change. We note that the challenges faced when performing analysis on monthly time-scales are different to those on shorter (weather) and indeed longer time-scales, due to the tendency for meteorological data to scale simultaneously in space and time, and the differing availability of background first-guess fields (see Daley 1993; D.A. Jones and Simmonds 1993; Peixoto and Oort 1993).

Monthly means were calculated for each station in the set if the month had no more than five missing daily observations. For a station to be included in the study, it was then required to have a valid mean in at least 23 of the 30 years for each of the calendar months. The network used comprises 95 stations (Fig. 1), with four stations failing the data requirement, and Sydney, Melbourne, Adelaide and Brisbane rejected because of urbanisation. The used stations were all located in rural or semi-rural locations during the period 1961-1990, with the applied quality-control and review of station meta-data suggesting these may be used with relative confidence for monitoring climate change and variability. We note that this network has a density which is similar to that used in recent studies of Australian climate change (e.g. Plummer et al. 1995; Torok and Nicholls 1996; Wright et al. 1996).

The primary goal of this study is to examine our ability to monitor short-term climate variability, and so we confine our attention to anomalies of the monthly mean from the 1961-1990 base period. Using anomalies has the added advantage that it reduces the impact of temperature differences between stations arising from variations in topography and exposure, as much of this structure is accounted for in the mean. Hence, there is a reduced need to sample across a range of altitudes, and analysis can be performed using two-dimensional techniques. While each of the considered analysis methods may be generalised to three dimensions, allowing the analysis of the absolute rather than anomaly field, this is not pursued due to the very poor sampling of the vertical temperature gradients by the available network.

Analysis methods

In this study we seek initially to describe the characteristics of surface temperature anomalies on monthly time-scales. Having done this, we review the performance of three widely used objective analysis methods in independently estimating observed temperature anomalies.

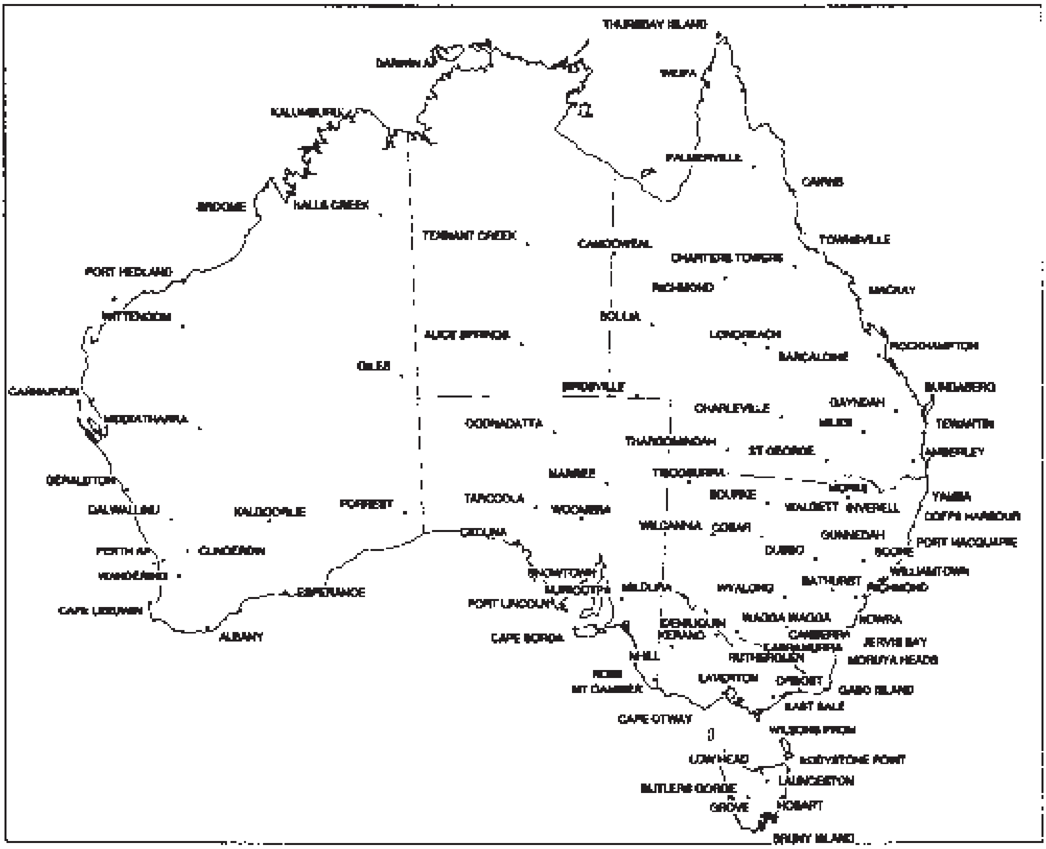
Covariance and observational error analysis

Linear interstation correlations are used to describe the length scales and observational errors for monthly temperature. The correlation has been calculated for all station pairings in each month, and for observations of the variable O (temperature) at stations k and l is defined as:

$$R_{kl} = \frac{\overline{(O_k - \overline{O_k})(O_l - \overline{O_l})}}{\sqrt{\overline{(O_k - \overline{O_k})^2}\,\overline{(O_l - \overline{O_l})^2}}} \qquad ...1$$

where the over-bar implies a time average.

Fig. 1 The distribution of the 95 stations used in this study.



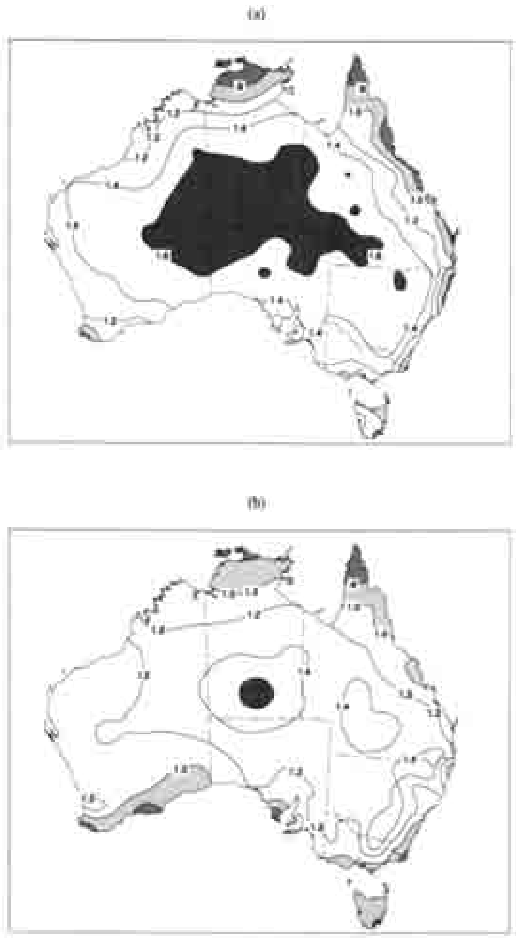
We use established analysis theory to explore the errors associated with observations, as outlined in Daley (1993). Observational errors in the station data mean that the observational correlations are a systematic underestimate of the true field correlations, and at small station separation (that is, for almost coincident stations) do not equal 1. For homogeneous covariances and random errors with variance E_o^2 the correlation of true values is scaled by $E_T^2 / (E_o^2 + E_T^2)$ where E_T^2 is the true variance and $(E_o^2 + E_T^2)$ the observed variance. When combined with an analytic or empirical functional form for Eqn. 1, it is a straightforward process to estimate the error variance, the true field variance, and the length scales (or spectrum) of the observations and truth using these relationships.

As a background to this study, in Fig. 2 we show the observational standard deviation for monthly mean maximum and minimum temperature anomalies (mapped using the Barnes successive correction technique). The standard deviation is characterised by relatively small values near the coast due to the moderating influence of the ocean, while elsewhere values are typically between 1.2 and 1.7°C. For the most part, the maximum temperature standard deviation is larger than that for the minimum temperature, though differences are quite small.

Meteorological analysis schemes and validation

It is not simple to assess analysis fidelity for objective methods applied to real data because the truth is unknown, all analysis schemes involve an element of subjectivity and conclusions may depend on the verifying statistic (Creutin and Obled 1982; Franke 1985; Seaman and Hutchinson 1985; Bussières and Hogg 1989; Daley 1993). Analysis fidelity has been assessed in this study through verification against independent observations, a method which has found widespread previous use in meteorology (e.g., Seaman and Hutchinson 1985; Seaman 1989; Hutchinson 1998).

Fig. 2 The average standard deviation of monthly (a) maximum and (b) minimum temperature (°C).



This has been achieved through cross-validation, whereby each station was individually removed from the available data for each of the 360 months, the analysis process performed using the remaining stations, and the resultant fields verified against the omitted observation. This technique provides a relatively unbiased estimate of interpolation accuracy (Michaelsen 1987; Elsner and Schmertmann 1994; Wilks 1995), without the need for assumptions about the statistical nature of the variables being analysed.

Analysis error has been assessed separately for the maximum and minimum temperature. The measure of skill which we use is the root mean square (rms) difference (or error), which is just one of many possible measures (Franke 1985; Wilks 1995). We note that the rms difference includes a contribution from both observational and analysis errors, being the error in predicting independent observations. However, because the observational errors will tend to be random and are independent of analysis method the validation errors provide a legitimate comparative measure of analysis accuracy.

Nominally, the analyses have been formed on 1°x 1° grid covering Australia, but in practice the SI and spline results are not grid dependent. In the following sections we detail the objective analysis method used, and some issues related to their application.

Barnes successive correction method

We have implemented the Barnes successive correction method as described by Koch et al. (1983), in which the grid values are generated using a two-step weighted sum of increments from a background field (zero field). The weight applied to an observational increment at station *k* (observed minus background, O_k-B_k) is determined by a Gaussian weighting function $w(r)$ whose value depends only on the distance (r) between observation and analysis points,

$$w(r) = e^{-\frac{r^2}{\gamma D^2}} \qquad ...2$$

Values for the analysis parameters (γ convergence and *D* length scale) were obtained by a search for that pairing which gave the lowest theoretical error following Seaman (1989). The temperature fields were modelled using an exponentially damped cosine function (see below) and a diagonal error correlation matrix. This minimisation was performed twice, being over all land points on our 1°x1° grid and at observation points (Methods 1 and 2, respectively).

Statistical interpolation

The SI procedure yields estimates of grid-point values (A_i) using a weighted sum of observation increments to a background value (B_i is a zero field here),

$$A_i = B_i + \sum_{k=1}^{N} W_{ik} [O_k - B_k] \qquad ...3$$

The weights (W_{ik}) in Eqn 3 are obtained from the column vector $\underline{W}$ (Daley 1993) given by,

$$\underline{W} = [\underline{\underline{B}} + \underline{\underline{O}}]^{-1} \underline{B} \qquad ...4$$

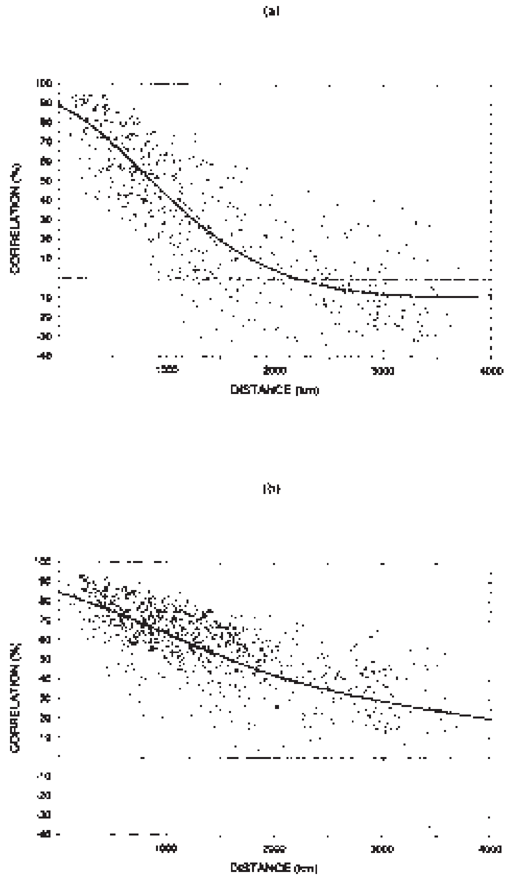
In Eqn 4, $\underline{\underline{B}}$ is an NxN symmetric matrix of background error correlations, $\underline{\underline{O}}$ is the matrix of normalised observational error covariance, and $\underline{B}$ a column vector containing the background error correlation between observations and analysis points.

It is usual in SI to represent the background error correlation by a positive definite function fitted to the observed correlations (Daley 1993). A large number of correlation models were examined, including a Gaussian, exponentially damped cosine, polynomial damped cosine and Markov function (Seaman and Hutchinson 1985; Daley 1993). The Gaussian function was found to be unsatisfactory, providing a poor fit to the observed correlations. Of the other tested models, the exponentially damped cosine function (Eqn 5) was found to provide a good fit to the observed correlations (Figs 3 and 4). This function is a generalisation of a first order autoregressive model, with the oscillatory term allowing for the location of spectral peaks away from the lowest wavenumbers. In the interests of brevity, we will concentrate on the use of this function noting that it is just one of many possible, and certainly suboptimal.

$$\rho(r) = (a-b+b\cos(r/d))e^{-r/L} \qquad ...5$$

When applying SI it was assumed that the background error correlation was homogeneous, while the observational errors were taken to be spatially uncorrelated. All covariances (Eqn 4) were calculated in a cross-validated sense. For example, the covariances used for January 1961 were calculated from observations for the 29 January months 1962 to 1990. The model parameters (a, b, d and L; Eqn 5) were estimated using non-linear least squares applied to the cross-validated interstation correlations.

Fig. 3 **Observation correlation coefficients (%) as a function of station separation for (a) January and (b) July maximum temperature. Overlayed in bold is the best fit exponentially damped cosine function.**



Laplacian smoothing splines

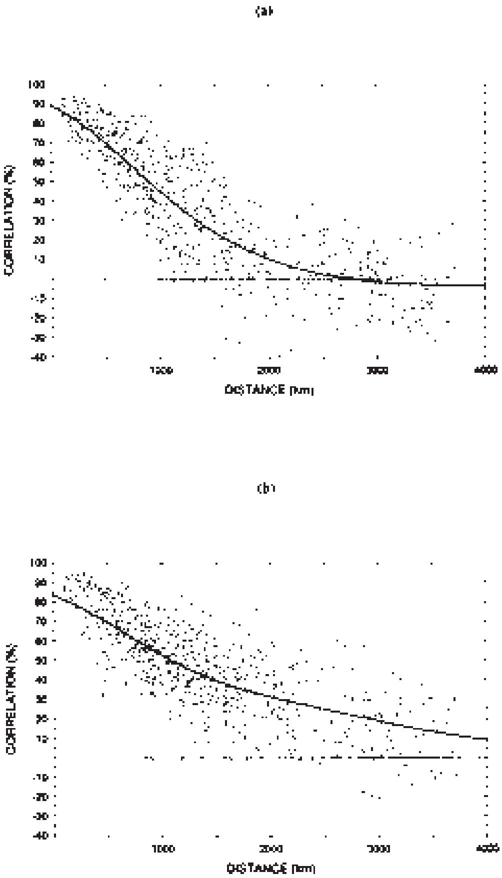
The bivariate form of the Laplacian smoothing spline is the third class of numerical analysis procedure used in this study (Wahba and Wendelberger 1980; Hutchinson 1995; Zheng and Basher 1995; Hutchinson 1998). The smoothing spline is a solution $f(x,y)$ to the constrained minimisation problem,

$$\frac{1}{N}\sum_{k=1}^{N}\left[\frac{f(x_k,y_k) - O_k}{w_k}\right] + \lambda J_m(f) \qquad ...6$$

where λ is a smoothing parameter, the w_k positive weights (taken to be 1) and $J_m(f)$ the Laplacian penalty function. The integer m (>1) is related to the spectrum of the interpolated surface and is the order of the spline ($f(x,y)$) which solves the constrained minimisation problem. λ is a smoothing parameter which determines a trade-off between data fitting and surface roughness. The larger λ, the greater the weight applied to the smoothing term, and the smoother the interpolated surface (see Wahba and Wendelberger 1980; Hutchinson 1991; Zheng and Basher 1995).

The Laplacian spline can be interpreted as the result of applying a low-pass filter to the observations (Wahba and Wendelberger 1980). The smoothing parameter controls the half-power point of the filter, and m the steepness of the roll-off, with larger values of m giving a greater attenuation of short waves. Application of the spline revealed that m greater than 3 (we tested 4 and 5) gave large errors, and hence we limit our discussion to m=2 and 3 (second and third order splines). We note that the m=2 (second order splines) are commonly referred to as 'thin-plate-splines', owing to their ability to be interpreted in terms of 'thin-plates' (e.g. Franke 1985). In the experiments we describe, the smoothing parameter has been determined by minimising the generalised cross-validation (Wahba and Wendelberger 1980; Zheng and Basher 1995). An important advantage of this technique over our implementations of the Barnes and SI methods is that the free parameters are determined

Fig. 4 As in Fig. 3 but for the minimum temperature.



directly from the observations being analysed. To assess the impact of this difference, we also applied the spline method but with *a priori* estimates of the error variance to define λ, which revealed analysis errors similar to (or greater than) those achieved through minimising the generalised cross-validation.

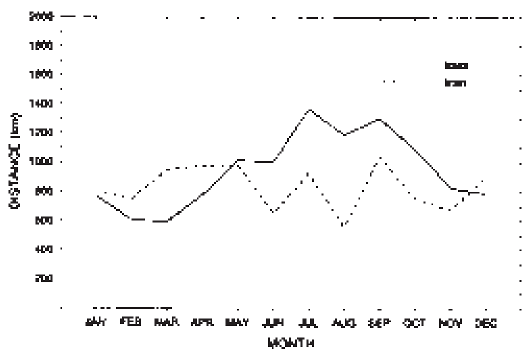
Correlation structure and observational errors for monthly temperature

Interstation correlations (Eqn 1) were calculated for all possible station pairings for each calendar month. As representative examples, Figs 3 and 4 show the correlation of monthly mean anomalies during January and July for the maximum and minimum temperature, together with the least squares fit provided by the exponentially damped cosine function (Eqn 5). An obvious feature is the presence of highly significant correlations at distances well in excess of the average (~200 km) or random (~300 km; Koch et al. 1983) station separation in our network. The scatter in these figures reflects spatial inhomogeneities and anisotropies in the correlation decay scales, as well as random sampling errors.

The interstation correlations are well modelled by the exponentially damped cosine function, and non-linear least squares has been used to fit this function to the observed correlations. To provide a measure of the characteristic length scales of the temperature data, in Fig. 5 we show the distance at which the best-fit function falls to 0.54 for each month. This correlation value is the 99.9% one-sided significance level for non-autocorrelated series of length 30 (Freund 1988). This measure of length scale is necessarily arbitrary, though we stress that definitions based on different correlation values (Briffa and P.D. Jones 1993), fractional reduction factors (Seaman 1982a), and the spectra yield very similar results.

This figure confirms the considerable large-scale structure in monthly temperature anomalies, with the length scales typically in the range 700 to 1200 km. To the extent that comparison is possible, these values are in good agreement with those estimated by Vinnikov et al. (1990), Weber and Madden (1995) and P.D. Jones et al. (1997) for the southern hemisphere, and consistent with the 1000 km estimate of Yamamoto and Hoshiai (1979) for the northern hemisphere. For the most part the maximum and minimum temperatures display similar length scales, with those for maximum temperature slightly larger. The robustness of this result is confirmed by D.A. Jones (1999), who found a similar dominance of the variability of

Fig. 5 Annual cycle of the observational decorrelation length scales (see text) for monthly maximum (tmax) and minimum (tmin) temperature (km).



maximum and minimum temperatures by the leading empirical orthogonal functions.

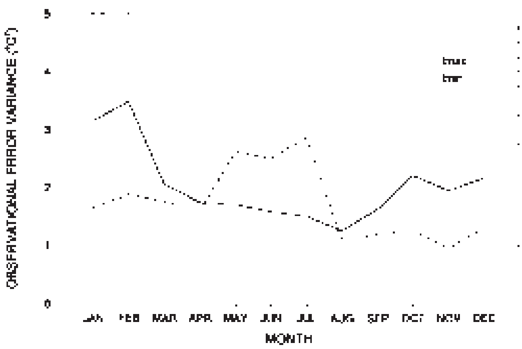
The length scales for the maximum temperature display a marked annual cycle, being longer during winter/spring. This seasonality is consistent with that observed by Yamamoto and Hoshiai (1980) for Europe, and by P.D. Jones et al. (1997) for seasonal means in the northern and southern extratropics. A close inspection has revealed that the winter scale lengthening comes from an increase in all radial directions, which is reflected in the spectra (not shown) as increased power at long wavelengths (>1000 km), in particular. We attribute the winter increase in decorrelation scales to the greater importance of baroclinic and very long wave activity during this season (D.A. Jones and Simmonds 1993; May 1999), and a reduction in the importance of sea-breezes. The minimum temperature length scales show little consistent variation with season, which may reflect the tendency for the near-surface atmosphere to decouple from the large-scale at night.

Under the assumption of spatial homogeneity and random errors, it is a relatively straightforward process to calculate the error variance of observations from the correlation functions and local variances (Daley 1993). In Fig. 6 we show the observational error variance of monthly mean maximum and minimum temperature for each month. These values estimate the error in defining the truth near observation points due to true data errors and also errors associated with small unresolvable scales (errors of representativeness; Daley 1993). In the context of analysis verification, these provide an effective lower bound for the rms differences shown later in this paper.

There is a pronounced annual cycle in the observational error variances for both variables, with a summer peak for the maximum temperature, and a late autumn to early winter peak for the minimum temperatures. To a large extent this seasonality of error variances mirrors that shown by the observed variance at stations (not shown), which peaks for maximum temperature in summer, and for minimum temperature in winter. Consequently, there is only a weak annual cycle in the noise-to-signal ratio.

Averaged across the twelve months the square root of the error variance for the maximum temperature is 0.45°C, while that for the minimum temperature is 0.42°C. These values lie between the daily estimate of Keenan et al. (1986) and climate estimate of Hutchinson (1991), and are remarkably similar to the value of 0.45°C for monthly mean temperature in the belt 0 to 60°S given by Vinnikov et al. (1990). For comparison, the average observational standard deviations for monthly maximum and minimum temperature are 1.29°C and 1.17°C.

Fig. 6 Annual cycle of the observational error variance (see text) for monthly maximum (tmax) and minimum (tmin) temperature (°C^2).



Objective analysis accuracy

Using cross-validation as described earlier, we have calculated the rms difference between withheld observations and interpolated values for each of the five analysis methods (see Table 1). These results are summarised in Tables 2 and 3, which give the rms difference across all stations for all months and also for each calendar season. Figures 7 and 8 show the spatial distribution of the rms difference across all months for monthly maximum and minimum temperature for Methods 2, 3, and 4. We note that the distribution of rms differences for Method 1 is very similar to that for Method 2, and similarly for Methods 4 and 5, and these have not been reproduced in the interests of brevity.

Spatially, the rms differences provide a legitimate method for assessing the relative performance of the individual analysis methods, but are more ambiguous in measuring the ability to estimate the truth. Most simply the rms difference values measure the ability of the analyses to estimate independent observations, being the square root of the analysis plus observational error variance (Seaman and Hutchinson 1985; Daley 1993). The true rms error will be somewhat smaller than the values shown, and may be estimated using the observational error variances shown previously.

The rms difference values are mostly in the range 0.4 to 0.8°C, being typically 30 to 50 per cent of the observational standard deviations (Fig. 2). In all cases the spatial distribution of the rms difference broadly parallels the density of stations (Fig. 1), with lowest values over eastern Australia and in the far southwest. We conclude that the most significant constraint on analysis accuracy is the local station density, with

Table 1. Technical details for the analysis methods described in the text.

Method	*Description*	*Details*
1	Barnes successive correction	D and γ calculated using technique of Seaman (1989). Optimised across all land points.
2	Barnes successive correction	D and γ calculated using technique of Seaman (1989). Optimised across all stations.
3	Statistical interpolation with exponentially damped cosine correlation function	a, b, d, and L calculated using non-linear least squares.
4	Laplacian smoothing spline	m=2 and λ calculated using generalised cross-validation.
5	Laplacian smoothing spline	m=3 and λ calculated using generalised cross-validation.

Table 2. Temporally averaged cross-validated rms differences (°C) between analyses and withheld data for the different analysis methods for all months, austral summer (DJF), autumn (MAM), winter (JJA), and spring (SON) for maximum temperature.

Method	*All Months*	*DJF*	*MAM*	*JJA*	*SON*
1	.605	.737	.582	.482	.619
2	.590	.720	.576	.465	.601
3	.519	.627	.505	.419	.525
4	.545	.667	.531	.428	.555
5	.596	.730	.580	.467	.607

Table 3. Temporally averaged cross-validated rms differences (°C) between analyses and withheld data for the different analysis methods for all months, austral summer (DJF), autumn (MAM), winter (JJA), and spring (SON) for minimum temperature.

Method	*All Months*	*DJF*	*MAM*	*JJA*	*SON*
1	.617	.595	.637	.646	.592
2	.616	.595	.633	.644	.590
3	.555	.534	.564	.578	.542
4	.597	.574	.603	.637	.576
5	.627	.612	.629	.658	.610

analysis method and local meteorological factors of secondary importance (see Seaman and Hutchinson 1985; Bussières and Hogg 1989). This underlines the importance of maintaining adequate climate networks for climate monitoring purposes.

For maximum and minimum temperature all methods have rms differences of around 0.4°C in the well-observed southeast, values which agree very well with the theoretical observational error variance for this region. We conclude that all methods are able to

Fig. 7 **Spatial distribution of the rms difference for maximum temperature. (a) Method 2, (b) Method 3, (c) Method 4 (see text, °C).**

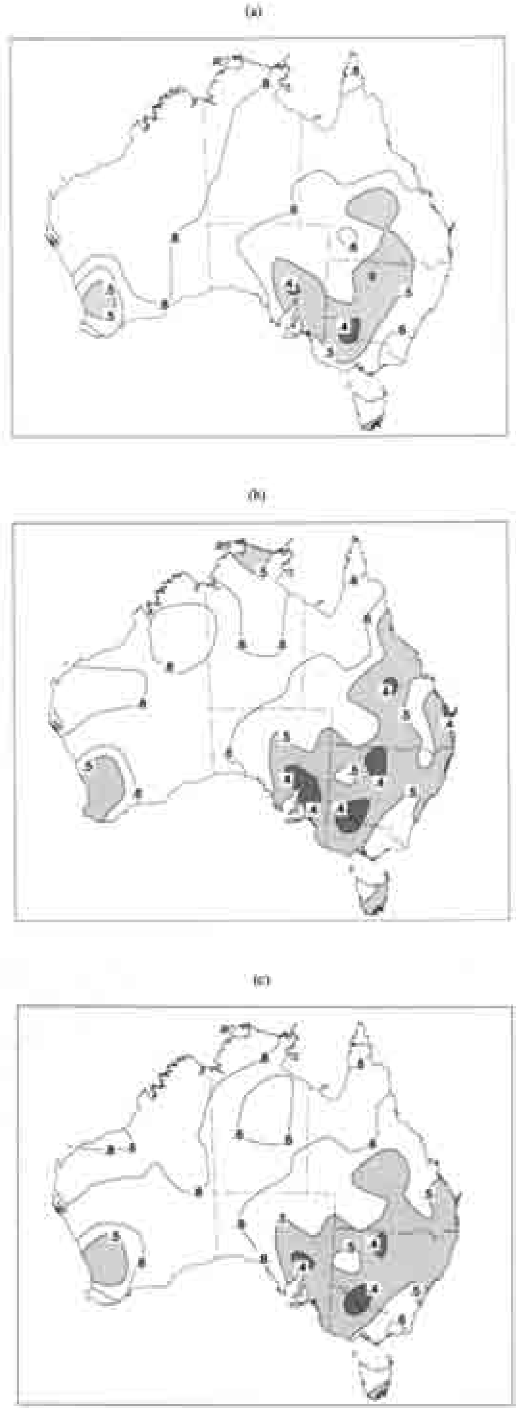


Fig. 8 **As in Fig. 7 but for the minimum temperature.**

achieve near-optimal accuracies in the best observed areas. In contrast, all methods perform rather poorly in the northwest where the station density is low. It should be remembered, however, that in regions of low data density the removal of a single station in the cross-validation has the effect of dramatically reducing the local station density, and the associated rms differences will be larger than for the full network. An extreme case occurs for Darwin (airport), where the rms difference values are similar to the standard deviation. This implies that without Darwin (or similar) in the network, there is very little skill in estimating monthly temperature variability over the Top End of the Northern Territory.

Of greater meteorological interest are the large errors on the subtropical west coast of Australia, in the vicinity of Carnarvon and Geraldton, where local factors greatly influence the climate. This is particularly so during the summer half year when all methods have rms differences of greater than 1°C, against an observed monthly standard deviation of 1.5°C. Summer maximum temperatures in this region are strongly influenced by local onshore breezes near the coast, leading to gradients of up to 0.3°C/km in mean temperature (Bureau of Meteorology 1998). The importance of small-scale factors in driving interannual temperature variability in this region is highlighted by the weak negative correlation which exists between January maximum temperature anomalies at Carnarvon and Meekatharra.

For minimum temperature the greatest rms differences occur near Alice Springs. The difficulty faced by the analysis methods in this area stems from the combined influences of low station density (Fig. 1), large interannual variability (Fig. 2; D.A. Jones 1999), and significant and diverse topography. It is to be expected that large variations in topography will be reflected in much sub-grid (network) spatial variability which is not simply related to altitude or the horizontal coordinate. Subsequently, interpolation errors would be expected to be large, due to a greater fraction of the spatial variance lying at scales which are poorly resolved by the (coarse) network. Further evidence for an inflation of errors near significant topography is apparent in southeast Australia and near the tablelands of northern New South Wales.

Under our experimental design, the smallest rms difference across stations (Tables 2 and 3) is achieved by the SI method, with the second order Laplacian smoothing spline ranked second. These rankings are robust across season and minimum and maximum temperature, and indeed across most of Australia as evidenced by Figs 7 and 8. The statistical significance of the differences (leading to the rankings) has been assessed using a paired t-test and a test of proportions (Wilks 1995). This has revealed that the differences between the SI and second (and third) order spline methods are in all cases significant at the five per cent level. A similar test of the differences between the m=2 spline and Barnes methods has shown these to be statistically significant.

The m=2 (second order) spline was found to outperform all other tested settings for m, while the interpolation error is only weakly dependent on whether λ is determined through generalised cross-validation or a prescribed error variance (see Zheng and Basher 1995). The spline analyses with m>3 verify poorly, with the surfaces being unrealistically smooth (see Wahba and Wendelberger 1980). The inflation of errors for the higher order splines due to the oversmoothness is compounded by very large errors on the edge of the data domain (not shown). The failure of the spline methods (particularly higher order) in extrapolation reflects the fact that these approach polynomial interpolation away from data points (linear for second order, quadratic for third order, etc.).

The Barnes successive correction procedure is the least sophisticated of the methods which we have used, and it is possibly not surprising that this is less skilful than either the SI or second order spline. It is to be expected that SI will outperform successive correction (Barnes), as both use a linear combination of observational increments to a background, and SI (with accurate estimates of the covariances) is by definition that (linear) method which will yield the smallest rms error. The placement of SI ahead of successive correction methods is common in studies of this type (e.g., Creutin and Obled 1982; Franke 1985; Seaman and Hutchinson 1985; Bussières and Hogg 1989). The suboptimality of the Barnes analysis method reflects the requirement that the weights at points sum to one, the failure to account for the spatial covariance of observational increments, and the inappropriateness of the exponential weighting function (Koch et al. 1983; Seaman and Hutchinson 1985; Daley 1993). There are no guarantees that the spline will out-perform the Barnes technique, and the relative performance of these will be largely determined by that whose filter response is most appropriate for the analysis variable, since both are essentially low pass filters (Wahba and Wendelberger 1980; Daley 1993). Indeed, the excessive filtering of shorter wavelengths in the m=3 (and particularly m>3) applications of the spline is reflected in rms differences which are similar or larger than for the Barnes method.

The Gaussian function provides a poor fit to the observed spatial correlation of meteorological fields on weather time scales (Julian and Thiébaux 1975; Thiébaux 1975; Seaman 1982a; Seaman and Hutchinson 1985), and this is also true for annual temperature (Hansen and Lebedeff 1987; Briffa and P.D. Jones 1993) and Australian monthly temperature (Figs 3 and 4). Thiébaux (1975) and Seaman and Hutchinson (1985) have demonstrated how the inappropriateness of the Gaussian function applied to a climatological first-guess can give a far from optimal performance for SI. To better understand the reasons behind the less good performance of the Barnes method compared to SI, we have repeated the SI analyses using an isotropic Gaussian function. Similarly, the successive correction analyses have been repeated, but using a Markov type weighting function $(1+r/(\gamma D))\exp(-r/(\gamma D))$, a functional form which has found widespread use in SI (Seaman and Hutchinson 1985; Daley 1993). This function provides a superior model for the observed correlations while still having just two parameters. The all months rms difference (equivalent to second column in Tables 2 and 3) using the Gaussian function in SI is 0.584°C for maximum temperature and 0.602°C for minimum temperature. These values reveal a marked degradation in performance, and are similar to those achieved by the Barnes method. The results using the Markov weighting function in the successive correction are a little less emphatic, though both maximum and minimum temperature show an improvement, with rms differences of 0.588 and 0.606°C, respectively. These results suggest that a substantial improvement may be possible with the successive correction method through the use of a more appropriate weighting function, and in fact it can be shown that a weighting function can be chosen such that the successive correction method approximates the optimal (linear) solution in a statistical sense (Bratseth 1986). From this perspective, the failure of the Barnes interpolation method to verify as well as SI reflects a weakness in the weighting function, rather than a weakness of the successive correction method. These results also underscore, that while SI appears to be the most accurate of the considered methods for spatially analysing temperature anomalies, this relative advantage is dependent on the specification of reliable covariance information.

We conclude this section by noting the value of the earlier consideration of length scales and observational error variances in providing an estimate of the 'best' achievable analysis accuracy and the variation of the rms difference across seasons and variable. The rms differences for maximum temperature are smallest during winter, coinciding with the season of longest decorrelation scales and smallest observational error variance, while rms differences for minimum temperature are largest during winter, being the season with the largest observational error variance. The seasonality of the observational error variances and length scales mean that the rms difference is larger for maximum than minimum temperature during summer, while the reverse is the case during winter.

Interannual variability of all-Australia means

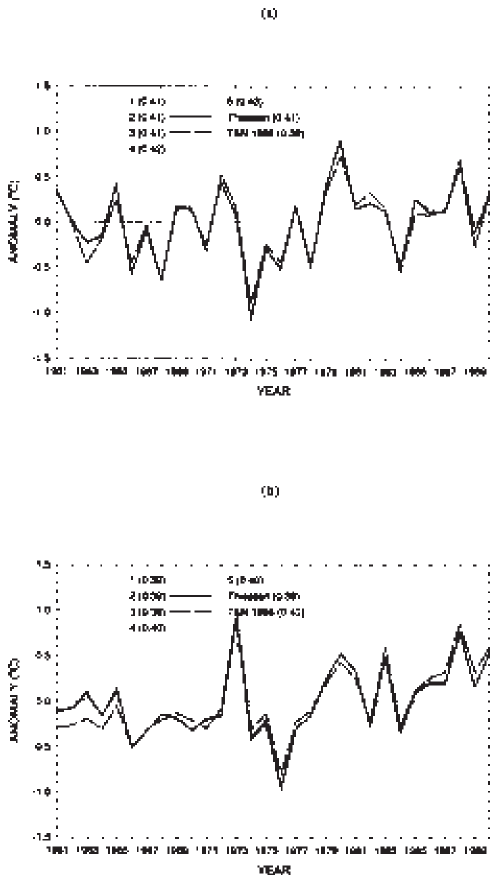
The objective analysis methods described in the previous section provide the opportunity to assess the robustness of less detailed monitoring methods and indices for Australian temperature. One measure of the Australian climate which has received considerable recent attention in the literature is the all-Australia annual temperature (Torok and Nicholls 1996; Wright et al. 1996; Nicholls et al. 1997; Collins and Della-Marta 1999). For each of the five analysis methods (Table 1), we have calculated this index through the simple numerical integration of the monthly anomaly fields (Weber and Madden 1995) across the land points on our analysis grid, and show the annual mean of these in Fig. 9. For comparison we also show the time series calculated using the method of Thiessen polygons (Louie 1977) applied to our station data, and the equivalent series from Torok and Nicholls (1996).

There is exceptional agreement between our (six) estimates of the annual temperature anomaly, with all series correlating at greater than 0.99 and having standard deviations within 0.02°C. We deduce that the all-Australia temperature anomaly is very robust across the different methods. This suggests that this index can be very accurately calculated with a relatively small number of reliable station values.

While none of the differences in interannual variances (or correlations) are statistically significant, the m=3 spline method tends to give slightly greater variances, which we attribute to the unrealistically large variability on the edge of the data domain. We also note that the variance of the area averages from the SI analyses for which the sum of the weights applied to observational increments are less than unity (Gandin 1963) is similar to that for the methods which formally impose normalised weights (Barnes and Thiessen polygons). This reflects the relative independence of observational errors, and the fact that the decorrelation scales are long in comparison to the distance between stations.

For the most part our maximum temperature series are very similar to those of Torok and Nicholls (1996), a fact demonstrated by the excellent agreement in standard deviations, and correlations which are all 0.97 or higher. Similar comments are applicable for the comparison of the arithmetic mean of our maximum and minimum series against the all-Australia (10-50°S, 110-160°E) means of P.D. Jones (1994)

Fig. 9 Time series of annual (a) maximum and (b) minimum temperature anomaly averaged over Australia (°C), for methods 1 to 5 of Table 1, for Thiessen polygons, and for Torok and Nicholls (T&N 1996). Shown in brackets is the standard deviation of each series.



(correlations 0.95). The minimum temperature series agree well with those of Torok and Nicholls (1996) on interannual time-scales (correlations ≥0.96). This, however, belies less good agreement on longer periods with our data warmer during the first half of the record, and mostly cooler during the second half. Subsequently, the linear warming trend in our series is only two thirds of that in the data of Torok and Nicholls (1996). This difference substantially reflects a differing treatment of inhomogeneities in the Alice Springs record, between Torok and Nicholls (1996) and this study. This provides a salient reminder of the importance of maintaining a high-quality network, as a single station discontinuity in this example appears to be more important than the method used to generate the all-Australia temperature index.

Discussion and conclusions

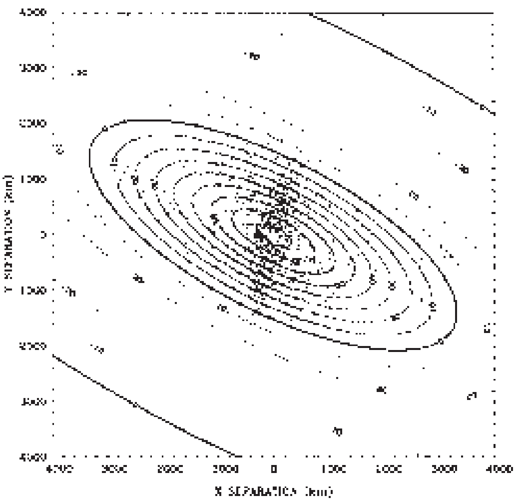
High-quality temperature data have been used under two methodological paradigms to investigate the practicality of describing the short-term variability of Australian temperatures using continent wide spatial analyses. The scientific basis for describing the spatial structure of temperature anomalies has been investigated through a parameter-based description of the scales and observational errors of Australian monthly temperatures. A more practical, but quantitative, insight has then been provided by a series of experiments in which the ability of objective analysis methods to replicate observed monthly temperature anomalies over Australia was examined.

Through the use of linear interstation correlations it has been shown that Australian temperature variability on monthly time scales is dominated by the large-scale, while the observational error variance is modest, being typically near 0.2°C^2. Statistically significant interstation correlations were found to typically occur over a distance of 700 km or more, being distances which are much greater than the average station separation in our network. This provides unambiguous evidence that the modest and operationally feasible network used in this study is capable of providing very significant information about the structure of temperature anomalies across most, if not all, of Australia.

The focus in this study has been on the isotropic component of the covariance of temperature, which assumes a constant correlation decay in all directions. In reality atmospheric fields are rarely isotropic, and indeed the maintenance of westerly flow in the southern extratropics against frictional dissipation is only possible due to the northwest-southeast elongation of transient eddy activity (Peixoto and Oort 1993). Seaman (1982a) provides a graphic illustration of this anisotropy on weather time-scales for the Australian region. For illustrative purposes, in Fig. 10 we show the result of fitting a generalised anisotropic form of the exponentially damped cosine function (Seaman 1982a) to the observational correlations of maximum temperature during January, together with the displacements at which correlation values have been calculated. In January (and in fact all months and for both temperature variables) length scales are elongated in the general northwest-southeast direction with ellipticity values (Seaman 1982a) close to 1.5.

This observation of considerable anisotropy is in

Fig. 10 Least square fit of a generalised exponentially damped cosine function to January maximum temperature correlations (%). The dots show the relative displacements at which correlation values have been calculated.



contrast with Hansen and Lebedeff (1987) for North America and Europe, but consistent with the model based results of Weber and Madden (1995). We also note the inappropriateness of the function used by P.D. Jones et al. (1997) for describing anisotropy (at least for Australian temperature), which limits the major and minor axes of the correlation ellipse to the zonal and meridional direction (see Seaman 1982b). Clearly, anisotropy represents an important characteristic of Australian temperature anomalies, which should be accommodated in analyses of Australian climate variability. Unfortunately, our experience has been that the highly irregular distribution of stations in our network, combined with spatial and temporal variability in the anisotropic correlation model, has precluded the in-depth use of this feature in analysis, as model parameters, length scales and error variances could not be accurately and robustly computed.

The practical limits which the observational network and modern analysis methods impose on the monitoring of Australian temperature anomalies has been examined through the quantitative assessment of interpolation accuracy for a number of analysis techniques. This has been done with a view to assessing the uncertainty associated with monitoring variability on monthly time scales, and to gauge whether such uncertainty is significantly dependent on how analyses are generated. We have detailed the results of exhaustive cross-validation experiments for two applications of the Barnes analysis method, SI with an exponentially damped cosine correlation model, and the second and third order (*m*=2 and 3) Laplacian smoothing splines. Additional analyses were performed using a modified successive correction scheme, SI with a Gaussian function, and the Laplacian smoothing spline with m greater than 3 and also the smoothing parameter determined from a prescribed error variance, to increase confidence in the results of this study and aid interpretation. The main results from these experiments are:

(a) Local station density provides the strongest control on analysis accuracy, with meteorological factors and analysis method of generally lesser importance. Each of the analysis configurations examined in detail, provided interpolation accuracies close to the practical limit implied by the observational error variance in the well observed southeast and southwest of Australia, whilst all performed rather poorly in the sparsely observed northwest. For the more accurate interpolation methods the average rms difference values are near 0.5°C with a ratio of rms difference to local standard deviation of approximately 0.4, ranging spatially from 0.25 in the southeast to greater than 0.5 in parts of the north and west.

(b) The best analysis accuracies were achieved using SI with the exponentially damped cosine function, with the *m*=2 spline ranked second. The Barnes and *m*=3 spline methods generally performed less well, and showed rms difference values which were quite similar. This general ordering is statistically significant and robust across season, variable and through space. The $m \geq 3$ spline methods were found to be unreliable for extrapolation. It is beyond the scope of this study to determine if the statistically significant, though rather modest, differences in analysis accuracy are of practical importance, or outweighed by other considerations such as robustness, computational efficiency and ease of use.

(c) The performance of the SI method is dependent on the appropriateness of the background correlation model. When the inappropriate Gaussian model was used, or in those regions where the local autocorrelations differed markedly from the global model, the analysis accuracies were significantly degraded. This result is in agreement with a number of earlier studies (e.g., Thiébaux 1975; Franke 1985; Seaman and Hutchinson 1985), and suggests that in those instances where the field covariances are not well known or modelled, analysis may be better performed using the more easily applied spline or successive correction techniques.

(d) All-Australia area averages obtained through the direct numerical integration of the temperature anomaly fields for each analysis method are for all practical purposes equivalent.

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