Weather and Climate, **29**, (2009), 24-44

Statistical Downscaling of New Zealand Climate

James A. Renwick*, A. Brett Mullan, and Alan Porteous

NIWA Wellington, New Zealand

Abstract

A statistical downscaling system has been developed for New Zealand daily climate variables, based on the perfect prognosis approach. Variables were daily precipitation, maximum, minimum and 10cm earth temperature, solar radiation, and wind run. A number of binary event-probability variables were also developed from the continuous temperature and rainfall values. A set of diagnostic regression equations was developed for 114 New Zealand sites, using as predictors 1000 hPa height and 850 hPa temperature fields from a long time series of reanalyses. A useful level of diagnostic skill was found in most cases. Explained variances, for anomalies from the seasonal cycle, were around 50% for temperatures and wind run, and 30-40% for precipitation and solar radiation. Tests on an independent data set suggested the downscaling system is relatively robust and reliable. Statistics of the fit reflect the geography of New Zealand and the strong forcing of its climate by orographic influences and interplay with the mean westerly circulation. The resulting downscaling system can be applied to a variety of model output, including climate model simulations and large-scale numerical weather prediction model runs.

1. Introduction

Many global circulation models used for climate simulation, numerical weather prediction (NWP) and global analysis/reanalysis, successfully capture the synoptic and larger scales of motion in the atmosphere, on horizontal scales of ~100 km or more. They generally do not pick up the details of local weather and climate that are often influenced by local topography, land/sea contrasts and details of local or regional land use. To infer such local detail, "downscaling" techniques are applied, either by the use of a nested dynamical model or by the use of statistical interpolation techniques (Benestad 2004; Giorgi and Mearns 1991; Kidson and Thompson 1998). Dynamical downscaling

* Corresponding author address:Dr J. A. Renwick,NIWA,Private Bag 14-901,Wellington,NEW ZEALAND.e-mail: j.renwick@niwa.co.nz

tends to be employed in climate change research, while statistical downscaling is commonly used in short-term weather prediction, or for investigation of current climate variability.

In the context of weather prediction, statistical downscaling has a long history and a large literature, using the Model Output Statistics (MOS) and Perfect Prognosis (PP) frameworks (Glahn and Lowry 1972; Marzban et al. 2006; Wilks 1995), both of which statistically relate large-scale circulation to local scale weather. PP or MOS downscaling systems are often defined in terms of sets of regression equations, although other methods such as neural networks, analogue techniques, and Kalman filters, are also employed.

The simplest approach is PP, which develops diagnostic downscaling relationships between analysed meteorological fields (temperature, winds, etc.) and local surface weather observations. The diagnostic relationships are applied to forecast fields predicted by an NWP model, to provide estimates of the surface weather that would occur if the forecast verified correctly. The assumption is that predicted fields exhibit the same statistical characteristics as the analysed ("observed") fields, hence are considered "perfect". Any biases in the NWP model fields are carried through into the downscaled predictions. The advantage of a PP approach is that it is portable and can be applied to any NWP model. Forecast skill will improve as the forecast model improves, without the need to change or update the PP downscaling system.

The more complex MOS approach uses relationships between observed surface weather and predicted meteorological fields, where the predictions come from a particular configuration of a particular NWP model, with separate statistical relationships defined for each forecast interval of interest. In this way, MOS takes account of bias and random errors inherent in NWP model output. However, a MOS system is not transferable between models or even between different versions of a single NWP model, but must be updated to take account of any changes to the model for which it is defined.

In New Zealand, statistical downscaling methods have been applied for NWP applications (Kidson and Renwick 1996; Renwick 1986) and for climate-related investigations (Kidson and Thompson 1998; Mullan et al. 2001). The location of New

Zealand in the mid-latitude westerly circulation, and the country's significant topography, result in many sharply-defined regional climates and strong topographic controls on weather and climate variability (Salinger and Mullan 1999). Because the topography exerts such an influence, it is often possible to develop strong statistical relationships between synoptic-scale variability and local weather, giving statistical downscaling techniques a lot of utility in New Zealand.

This paper summarises the development of a general statistical downscaling system for specifying daily climate variability around New Zealand from a small selection of fields of dynamical variables available from reanalyses or other gridded meteorological data sets. Part of the motivation for this work was to document how well local variability could be specified from standard meteorological fields. A second motivation was to investigate how well extended-range ensemble NWP forecasts could predict local climate anomalies around New Zealand, on the two-week to one-month time scale. That work is described in a companion paper (Renwick et al. 2009).

The paper begins with a description of data sets and statistical techniques, followed by a summary of statistical model performance, and a discussion of the approach and its utility for specifying local New Zealand climate variability.

2. Data and Methodology

Climate station data

Daily climate records for 114 locations were taken from the National Climate Database maintained by NIWA. Station locations were fairly evenly spread around New Zealand, as indicated in Fig. 1. For each station, six daily climate variables were extracted: precipitation (mm), maximum, minimum, and 10 cm earth temperature (°C), solar radiation (MJ m^{-2}) and wind run (defined as average wind speed over 24 h, in m s^{-1}). All were 24 h 9am-9am (New Zealand local time) values, except the earth temperature; that was an instantaneous measurement at 9am. Precipitation and max/min temperature measurements were available at all stations, but around a third of stations lacked wind run information, while around 45% of stations lacked either solar

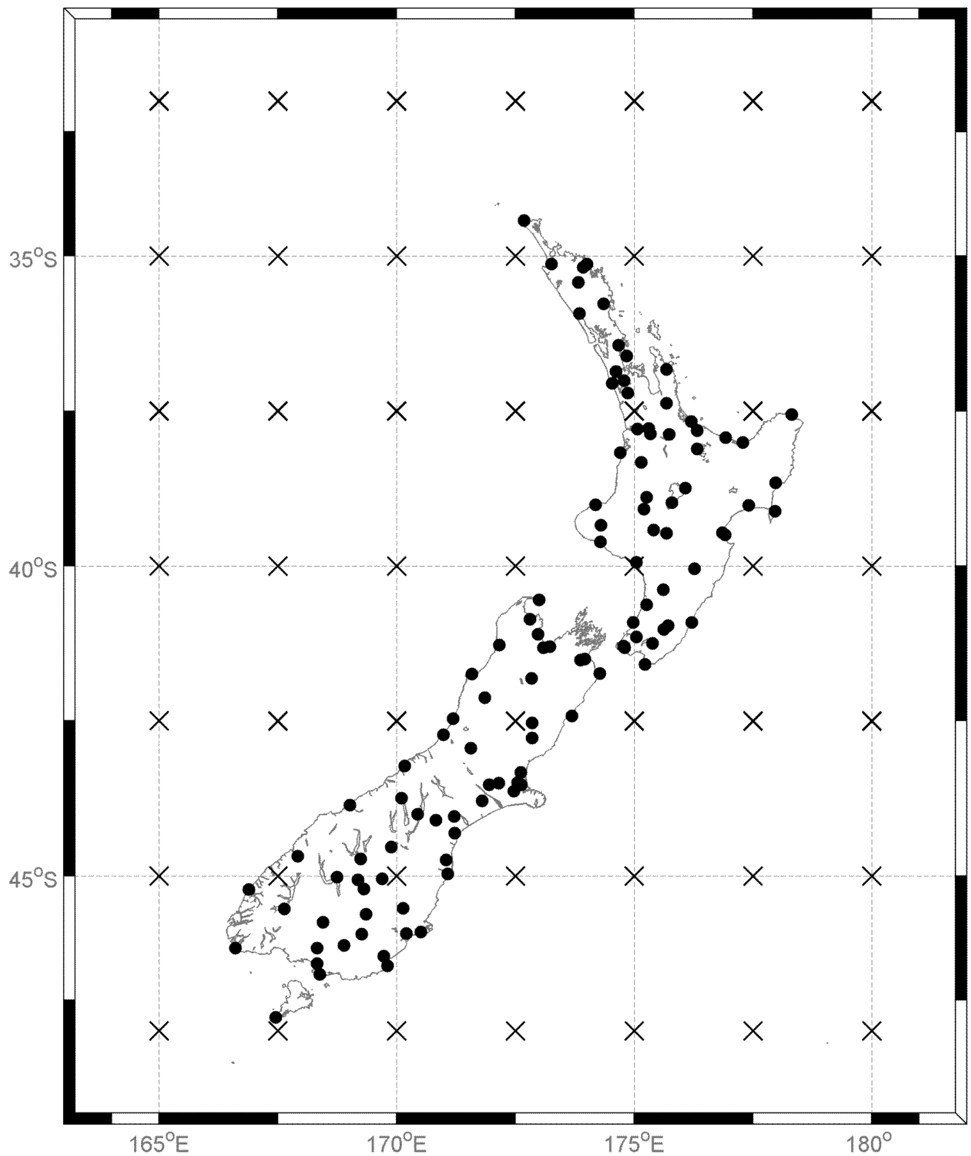

Figure 1: Map of New Zealand, indicating the location of climate stations used (dots) and the grid spacing of the NCEP/NCAR reanalysis fields (crosses).

radiation or earth temperature information. The period of record was in most cases the 34 years January 1972 to December 2005, often with missing data gaps, especially for solar radiation, earth temperature and wind run.

More complete station time series were generated by amalgamating sub-series from adjacent sites, to handle station closures or site changes. In those cases, records were merged and homogenised using a calibration procedure based on periods of overlapping record, using the longest continuous period of record from one site as the master record for that station. Biases were calculated for each month separately between the master sites and up to three secondary sites. Temperature and solar radiation time series were adjusted by subtracting mean biases, while precipitation and wind run were corrected in a percentage sense by scaling time series according to the ratio of the means between sites.

For each climate variable time series at each site, a smoothed daily climatology was calculated using a harmonic analysis with 12-month and 6-month period terms retained. Climatologies were defined in terms of daily mean values for temperatures and solar radiation, but daily medians were used for precipitation and wind run, since their distributions were significantly non-Gaussian in most cases. Medians were defined for 73 pentads spanning the full year, grouping across years, then the harmonic analysis was applied to the 73 median values. For development of statistical models, climate data were taken as anomalies from their daily climatological values. For the purposes of model fitting, a square-root transform was applied to rainfall, solar radiation and wind run, to make their frequency distributions more Gaussian in form.

From the basic set of six variables, eight binary event-related variables were derived: the occurrence of daily rainfall greater than 0, 1, 5, 10, 20 mm, and greater than median rainfall (as defined by the climatology); the occurrence of air frost (minimum temperature less than 0°C), and the occurrence of hot days (maximum temperature greater than 25°C). Also, the precipitation record was reduced to only those days with measurable rainfall, making a set of “wet day only” precipitation measurements. Climatologies of event occurrences were calculated as long-term monthly mean frequencies of occurrence, as the harmonic analysis approach was found to be unstable in some cases with such binary variables.

Large-scale fields

Large-scale meteorological fields were taken from the National Centers for Environmental Prediction/National Center for Atmospheric Research (NCEP/NCAR) reanalysis (Kistler et al. 2001). The fields used were the height of the 1000 hPa surface

(H1000) and the temperature at 850 hPa (T850) over the New Zealand region. The region used was 30-50°S and 160°E-170°W, a total of 117 points at 2.5° resolution (a slightly larger region than that indicated in Fig. 1). Fields were selected twice daily at 0000 and 1200UTC (midday and midnight New Zealand Standard Time, respectively). The total period of record used was 25 years, 1979 to 2003 inclusive. For development of the downscaling system, the 15 years 1989-2003 were used, with the 10 earlier years reserved for testing.

Other fields were tested in combination with the two listed above, such as 850 hPa winds, and 500 hPa heights, but were found to add little to the fit of the statistical models. Hence, for simplicity, the analysis was restricted to H1000 and T850. No moisture or precipitation fields were used in the development, despite a need to estimate daily rainfall. This constraint was imposed largely because of the anticipated application to ensemble NWP model output (Renwick et al. 2009). It was felt that reanalysed moisture fields were the most likely to exhibit different statistical character to those from an NWP system, while basic dynamical fields (heights and temperatures) were more likely to be consistent in their statistical behaviour from reanalysis to forecast model.

A monthly mean climatology was calculated for H1000 and T850, over the development period 1989-2003. Twelve-hourly fields were converted to anomalies from the respective monthly mean climatology. The anomaly fields were processed into a set of derived quantities, in two ways. First, the gridded fields were subjected to an Empirical Orthogonal Function (EOF) analysis (Wilks 1995) to reduce the number of independent variables available, and to define gradients in the height and temperature fields. Second, 850 hPa temperature and 1000 hPa gradient wind and geostrophic vorticity (derived from the 1000 hPa height field) anomalies were calculated and bilinearly interpolated to the location of each of the climate stations.

Statistical modelling

The statistical modelling framework used was multiple linear regression, with predictors chosen by a forward stepwise selection procedure (Draper and Smith 1981), in the manner of a traditional Perfect Prognosis (PP) approach. After each forward selection step, a backward step was taken, if any prior predictors were rendered non-significant as a result of adding the new variable. At all locations, the same basic set of 15 variables was made available (Table 1) for most variables. For wind run, absolute values of wind-related predictors were also included (local wind components, and H1000 PCs), in an attempt to capture non-linearities in relationships between local and large-scale wind flows.

Table 1: Candidate predictor variables made available to the stepwise regression procedure, for all variables and locations.

Predictor Variable	Comment
H1000 principal component (PC) time series	Leading 5 PCs
T850 principal component (PC) time series	Leading 5 PCs
1000 hPa wind u-component	Interpolated to station location
1000 hPa wind v-component	Interpolated to station location
1000 hPa wind speed	Interpolated to station location
1000 hPa geostrophic vorticity	Interpolated to station location
850 hPa temperature	Interpolated to station location

For precipitation and wind run, where the observed values are accumulated over a full 24 h period, predictor variables were made available from both 0000 and 1200UTC (Table 2). For minimum temperature measured at 9am local time (2100UTC, or 2000UTC during Daylight Saving Time), the time of occurrence was taken to be around dawn, so variables analysed only at the prior 1200UTC time were used. Conversely for maximum temperature and solar radiation, variables for 0000UTC were used, to represent conditions in the middle of the daylight hours. For earth temperature, a time lag was found between analysed atmospheric conditions and temperature at 10 cm depth. Hence, to estimate earth temperature measure at 9am, predictor variables from 0000 and 1200UTC the previous day were used. The change in observation time with Daylight Saving (from 2100UTC to 2000UTC) may have a small effect on the statistics. However, the analysis was carried out for each season separately, so the timing change would have an effect only in the transition seasons.

Table 2: Validity time of candidate predictors made available to the stepwise regression procedure, for each variable.

Predictand Variable	Predictor Validity time
Precipitation, 24h accumulation	00 and 12UTC
Probability of precipitation exceedance	00 and 12UTC
Maximum temperature	00UTC
Hot day probability	00UTC
Minimum temperature	12UTC, previous night
Frost probability	12UTC, previous night
Earth temperature	00 and 12UTC, previous day
Solar radiation	00UTC
Wind run	00 and 12UTC

Some daily climate variables were therefore allowed a potential pool of 15 predictors (or 22 for wind run), while others were allowed 30, the basic 15 at two different times. In all cases however, the stopping rules were the same: predictors were chosen by forward stepwise selection, with a 95% significance F-to-enter criterion and a maximum of 6 predictors selected. All variables were modelled in the same way, including binary event-occurrence variables such as frost occurrence, in an approach known as “regression estimation of event probabilities” (REEP) (Miller 1964; Wilson and Sarrazin 1989).

3. Results

EOF analysis

Reanalysis H1000 and T850 anomalies were converted to principal component (PC) time series through an EOF analysis. All times of year were included in the analysis, since the form of such EOF patterns does not exhibit much seasonal dependence (Kidson 1988; Renwick 1998). The leading 5 EOF patterns are illustrated in Fig. 2. Together, they accounted for 94 and 85% of the total variance of the H1000 and T850 fields, respectively.

For both fields, the leading EOF dominated, accounting for 55% of the H1000 variance and 38% of the T850 variance. Since the EOF analysis was based on

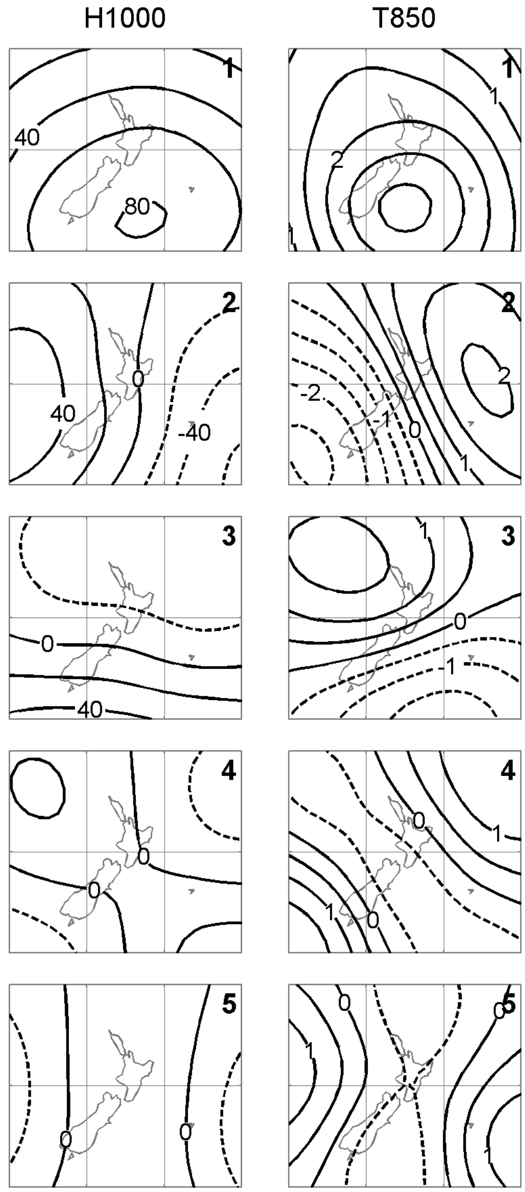

Figure 2: The leading 5 EOFs of the H1000 field (left) and the T850 field (right) over the New Zealand region, for the period 1989-2003. Fields are shown as regression maps, exhibiting typical amplitude for an amplitude time series (PC) value of +1 standard deviation. For H1000, units are geopotential metres and the contour interval is 20 m. For T850, units are K and the contour interval is 0.5 K. Negative contours are dashed throughout.

anomalies from monthly mean climatologies, the PC time series do not exhibit any significant seasonal cycle. The large variance associated with the leading EOFs merely reflects the tendency for the height and temperature fields to vary in unison over such a small region. Higher-order EOFs illustrate meridional and zonal flow patterns, then higher-order patterns with two sign reversals in the analysis region. Such a progression is common in limited domains (Buell 1978; Richman 1986), and is not necessarily related to preferred dynamical patterns or teleconnections. The EOF analysis has been carried out merely to reduce the dimensionality of the gridded data sets.

Station climatologies

The form of the station-based climatological estimates, and geographical variation

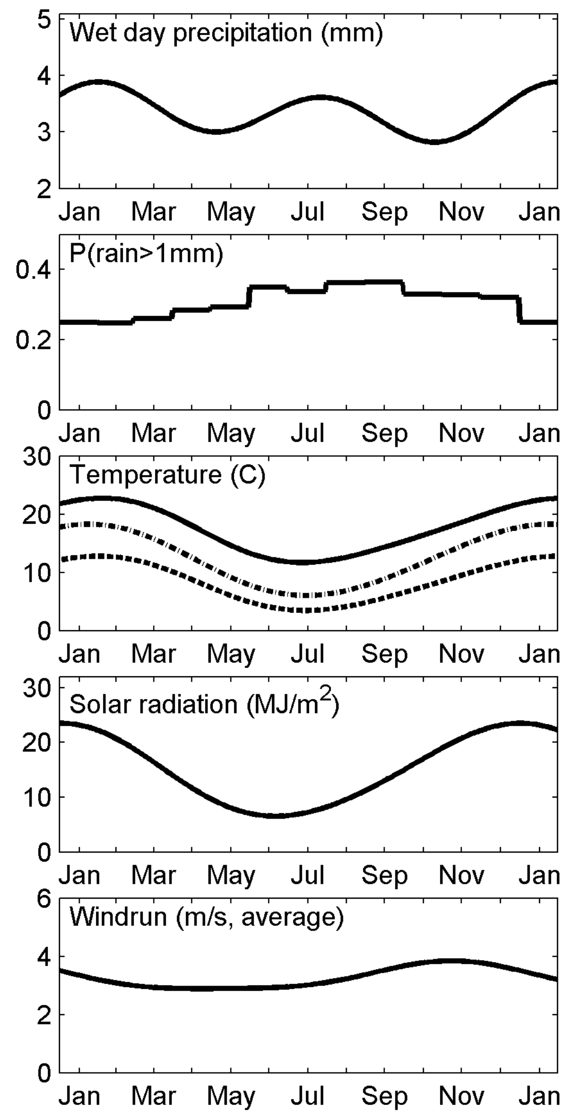

Figure 3: Example station climatology curves, for Rotorua (38.1°S, 176.3°E), for variables as indicated. In the temperature panel, the top (solid) line is maximum temperature, the middle line is earth temperature, and the lower line is minimum temperature. The tick marks on the x-axis indicate the 15th day of the month.

in the fit of the climatological models, gives some insights into New Zealand regional climate variation, quite apart from the formal downscaling exercise. Figure 3 illustrates the annual cycle for a number of variables, as calculated for Rotorua, a typical North Island station. The precipitation amount (conditional on there being some precipitation) exhibits a bimodal distribution in time, with both a winter and summer peak. However, the probability of at least 1 mm of precipitation exhibits a broad winter and spring peak, with a relative minimum in summer, typical of many North Island locations. Hence, winter is the overall wettest season. The temperature evolution shows maxima in late January and minima in early July, with the earth temperature slightly closer to the minimum temperature in winter, and slightly closer to the maximum in summer. The climatological wind run is fairly flat through the year, but does display a weak maximum in spring, typical of many New Zealand sites.

The overall mean amount of daily variance accounted for by the climatological fitting process is listed in Table 3.

Table 3: Percentage of total variance accounted for by the fitted climatology, for each climate variable, averaged across all stations.

Climate Variable	Average variance accounted for (%)
Wet day precipitation	0.2
Prob(precipitation>0mm)	2.0
Prob(precipitation>1mm)	1.3
Prob(precipitation>5mm)	0.7
Prob(precipitation>10mm)	0.4
Prob(precipitation>20mm)	0.2
Prob(precipitation>median)	0.8
Maximum temperature	63.4
Hot day probability	12.4
Minimum temperature	48.8
Frost probability	14.4
Earth temperature	81.9
Solar radiation	58.1
Wind run	5.7

The geographical distribution of the “explained” variance is shown in Fig. 4, for the six climate variables. Clearly, the mean annual cycle accounts for a physically insignificant fraction of the total rainfall variance at most locations. However, the climatological component was retained for each variable and location, for consistency.

As expected, temperatures and radiation showed the strongest seasonal cycles, while for wind run, the seasonal cycle accounted for a small but statistically significant fraction of the total variance at most stations.

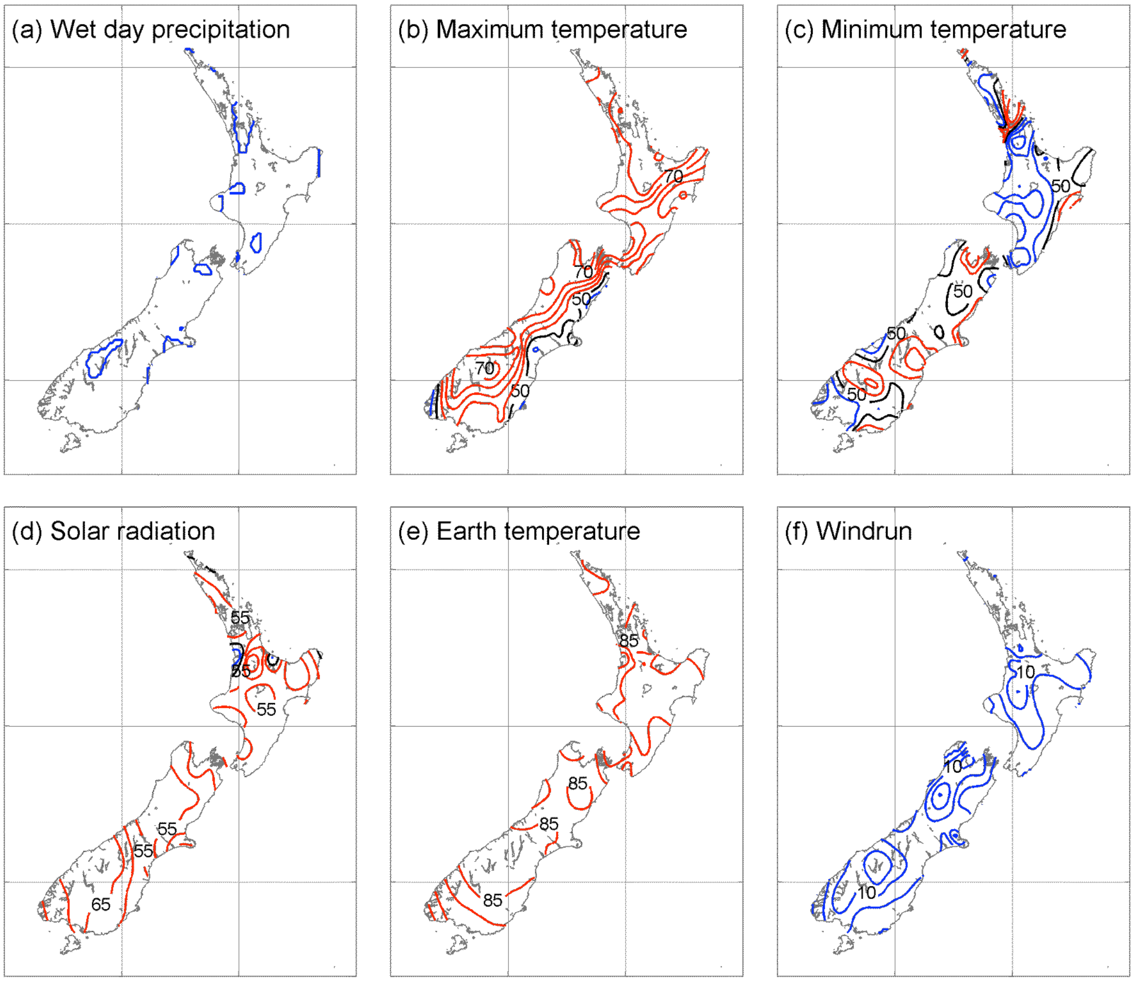

Figure 4: Geographical distribution of the percentage of variance accounted for by the smoothed daily climatology of (a) wet-day precipitation, (b) maximum temperature, (c) minimum temperature, (d) solar radiation, (e), earth temperature, and (f) wind run. The contour interval is 5%, the black contour is 50%, red contours above 50% and blue contours below. In panel (a) the only contour plotted is the 5% contour.

There are interesting differences between maximum and minimum temperatures in the geographical distribution of variance in Fig. 4. For maximum temperature, there is a west-east gradient, along with a latitude gradient component most evident over the North Island. The west-east gradient reflects the effects of topographically-related Föhn warming in many eastern regions that contributes to the larger temperature variability east of the main divide. For minimum temperature, distance from the coast appears to play a role in the North Island, while in the South Island, the pattern is not obviously tied to the land form. Note that the contours in Fig. 4 are drawn from a smoothed re-gridding of the 114 station values, and do not reflect in any detail the full geographical patterns of temperature seasonality.

Downscaling relationships

Regression equations were fit to climate station data separately for the four standard seasons: Sep-Nov, Dec-Feb, Mar-May, and Jun-Aug, being spring, summer, autumn and winter, respectively. With the 15 years' data used, each of the regression models was based on around 1000 observations, allowing for missing data. All regressions were against anomalies from the respective seasonal cycles, including those for event probabilities. As noted above, to help normalise the distributions of precipitation, solar radiation and wind run, a square root transform was applied. Almost all regression equations took the maximum of 6 predictors, although predictor selection was stopped by the significance criterion in 1% of cases, at between 3 and 5 predictors. For each climate variable, a single preferred predictor was often selected for the vast majority of site-specific regression equations, as outlined in Table 4.

In many cases, the most popular predictors listed in Table 4 were chosen 90% or more of the time. The choice of predictors and the sign of their coefficients usually make obvious physical sense. Cyclonic vorticity is negative in the Southern Hemisphere, hence a negative relationship with precipitation and a positive relationship with solar radiation (sunshine). Temperatures are strongly positively correlated with the matching T850 value. For maximum temperatures, the sign of the coefficient of the zonal wind component is dependent on season and location. Eastern locations generally have positive coefficients (Föhn warming). Western locations tend to have positive coefficients in winter and negative in summer, a reflection of seasonal changes in land-sea temperature contrasts (e.g., off-shore ocean surface is warmer than the land during

Table 4: Two most commonly selected predictors for each climate variable. For each climate variable, the first predictor variable listed was the most frequently chosen. The "D-1" for earth temperature indicates that the value from yesterday at 00UTC was selected. The third column shows the sense of the relationship between predictor and predictand.

Climate Variable	Most frequently chosen predictor variable	Sign of coefficient
Precipitation	Vorticity 1000, 12UTC	negative
	V-component 1000, 00UTC	negative
Maximum temperature	Temperature 850, 00UTC	positive
	U-component 1000, 00UTC	positive/variable
Minimum temperature	Temperature 850, 12UTC	positive
	Temperature 850 PC 1, 12UTC	positive
Earth temperature	Temperature 850, 12UTC	positive
	Temperature 850 PC 1, 00UTC D-1	positive
Solar radiation	Vorticity 1000, 00UTC	positive
	Wind speed 1000, 00UTC	negative
Wind run	Wind speed 1000, 12UTC	positive
	U-component 1000, 00UTC	positive

winter and hence stronger westerly flow promotes positive temperature anomalies over land).

The quality of the fit between local climate anomalies and large-scale predictors is summarised in Table 5, in terms of variance explained in the training samples. The fit is best for the three temperature variables, and for wind run, all of which attained mean explained variance around 50%. Solar radiation and precipitation amount performed similarly, with about one third of anomaly variance accounted for. The fit to event probabilities was poorer for the rarer events (large precipitation amounts, hot days in autumn, etc.). While such results are still very statistically significant, given the sample sizes, explained variances of 25% or less would result in rather low-amplitude downscaled patterns and anomalies, likely exhibiting some reliability but little sharpness (Wilks 1995).

Table 5: Percentage of anomaly variance accounted for by the downscaling regression, for each climate variable, averaged across all stations.

Climate Variable	Average variance accounted for (%)				
	Autumn	Winter	Spring	Summer	Mean
Wet day precipitation (sqrt)	33.6	39.1	35.5	29.5	34.4
Prob(precipitation>0mm)	32.2	33.3	33.7	31.0	32.5
Prob(precipitation>1mm)	35.1	38.9	36.2	31.7	35.5
Prob(precipitation>5mm)	31.1	35.1	32.1	27.3	31.4
Prob(precipitation>10mm)	27.4	30.1	28.4	23.9	27.5
Prob(precipitation>20mm)	27.3	28.8	28.6	29.4	28.4
Prob(precipitation>median)	33.6	37.3	35.1	29.6	33.9
Maximum temperature	51.3	48.8	56.0	56.1	53.0
Hot day probability	15.8		15.4	28.5	19.9
Minimum temperature	47.5	48.9	51.2	50.0	49.4
Frost probability	17.0	25.9	18.3		20.4
Earth temperature	49.6	51.6	51.4	54.3	51.7
Solar radiation (sqrt)	33.5	41.9	38.0	33.6	36.8
Wind run (sqrt)	52.0	52.5	50.1	45.9	50.1

The geographical distribution of fit is illustrated in Fig. 5, averaged across the four seasons, for all climate variables. For precipitation amount, explained variance tends to be highest at wet western sites, and is lowest in dry sites in inland Otago and south Canterbury. The fit to maximum temperatures shows little variation with season, and is best along the east coast, especially from mid-Canterbury to Hawkes Bay, where the explained variance is over 60%. The fit is generally worst in western regions, where the amplitude of the variability is smallest, falling to around 30% at some South Island sites. The minimum temperature fit exhibits a complex pattern, with explained variance over 50% in Bay of Plenty and Hawkes Bay, but only around 30% in eastern Otago and Southland. That pattern is more complex in winter, presumably reflecting the greater influence of nocturnal boundary layers and drainage flows then, while summertime explained variances are more uniform, between 45 and 55% at most places.

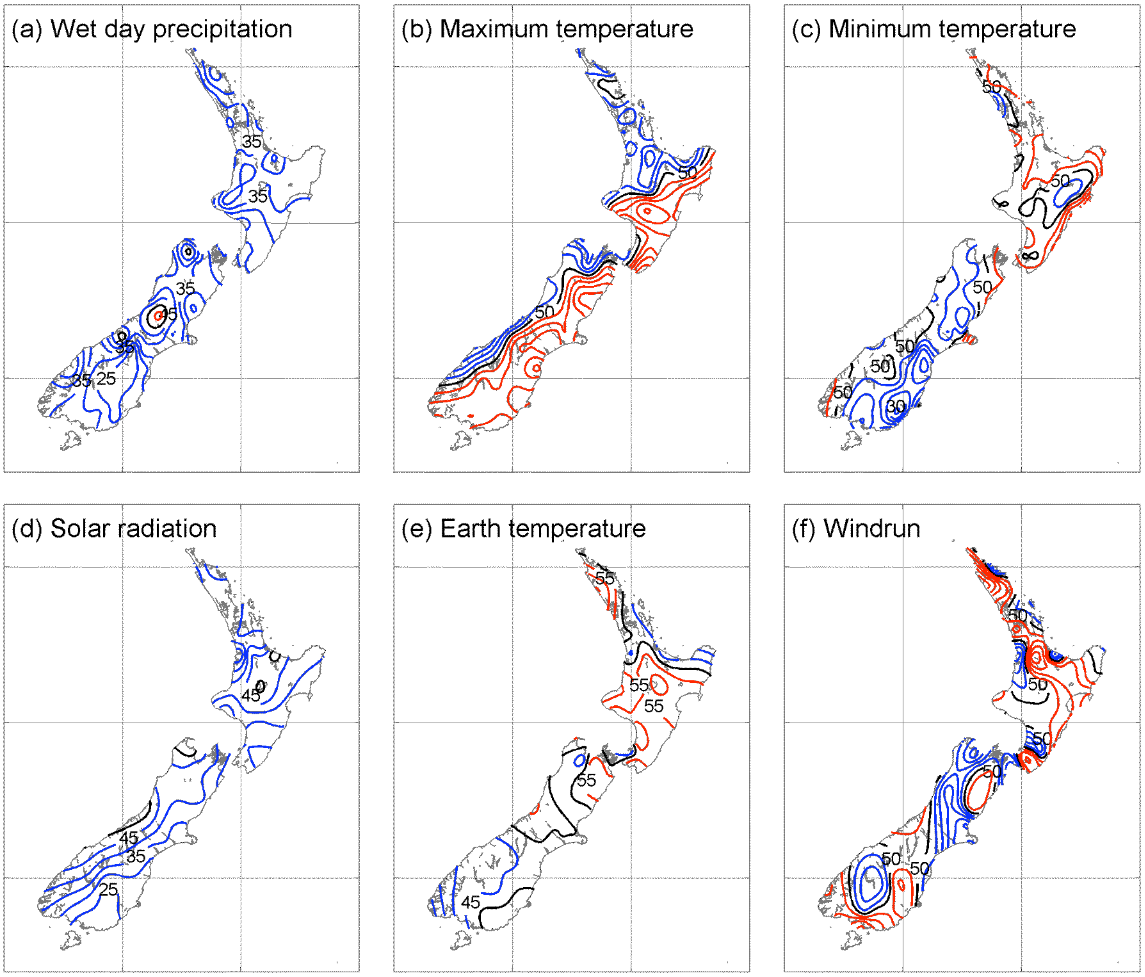

Figure 5: Geographical distribution of the annual average percentage of variance accounted for by the seasonally-specified downscaling regression fit to daily climate anomalies. The sequence of variables and the contouring conventions are as in Figure 4.

Independent trials

To test the skill of the downscaling system, local daily climate estimates were calculated over the independent period 1979-1988. Here, reanalysis fields of H1000 and T850 were processed in the same way as in the training period, using the climatology and EOF patterns calculated over 1989-2003, as above. Estimated daily climate parameters were compared to observations, in terms of explained variance, bias (mean error), root mean-square error (RSME), and ranked probability skill score for event

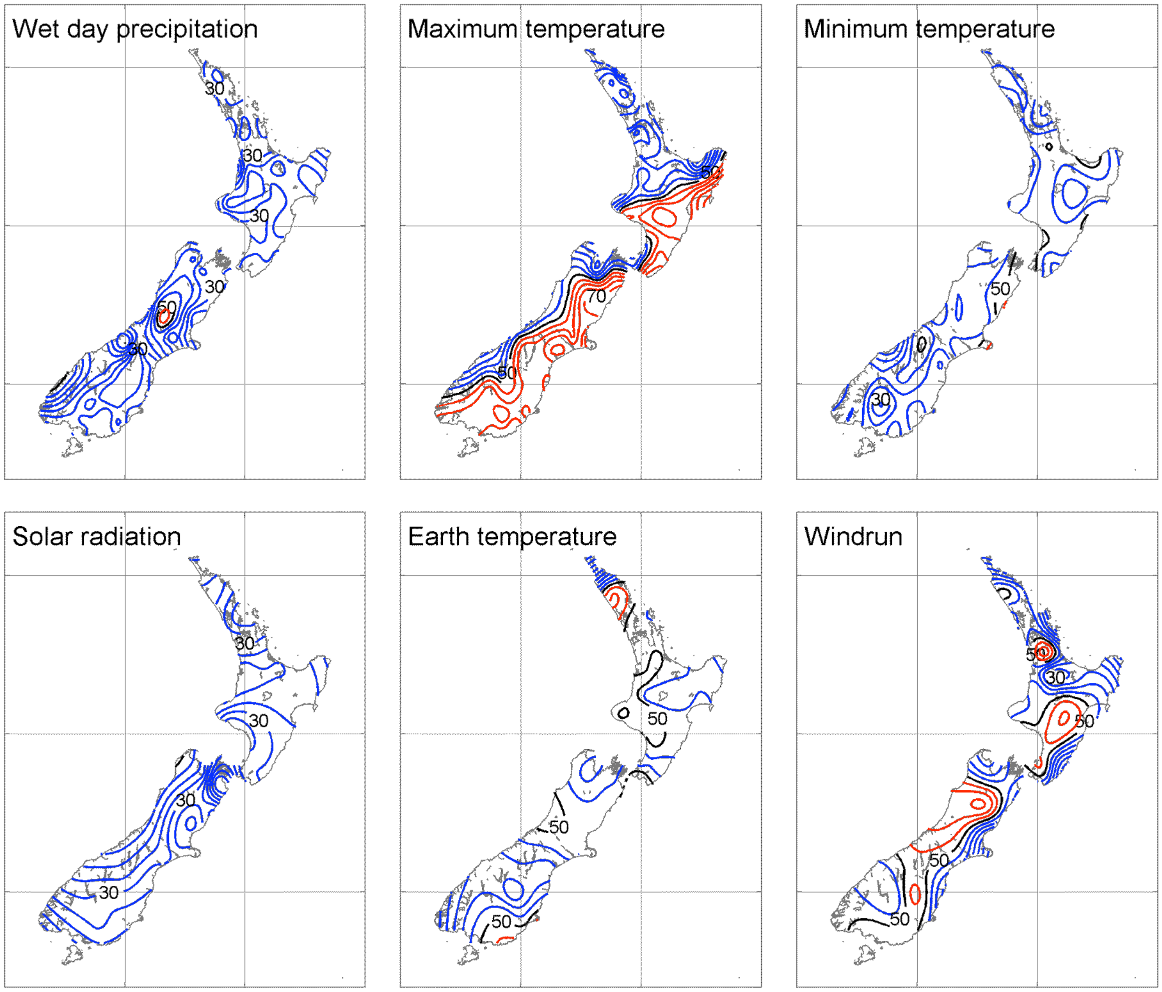

Figure 6: Geographical distribution of the percentage of variance accounted for during the independent trial period 1979-1988, for all seasons of the year. The sequence of variables and the contouring conventions are as in Figure 4.

probability forecasts (Wilks 1995).

Figure 6 shows anomaly explained variance (after removal of climatological variation) for each climate variable, averaged over all seasons during 1979-1988. Patterns of explained variance were broadly similar to those seen in the development sample (Fig. 5). On average, the explained variance during the independent test period was around 1-2% lower than during the development period, for temperatures. For precipitation amount, solar radiation and wind run, the decrease appears to be higher (5-10%). This is a function of the square root transform used in the development process.

The reduction in explained variance for the square-root transformed variables is comparable to that for other variables shown here. The statistics for the independent trials presented here were however calculated after conversion back to full values. Explained variance for the event probability estimates were generally consistent across development and independent samples.

There are many similarities in the distribution of precipitation amount explained variance between development and independent samples, but with generally slightly lower values in the independent period. The fit to maximum temperatures exhibits the west-east gradient seen in the development set (Fig. 5), with the poorest fit in western and northern regions. For minimum temperatures, the fit is quite spatially uniform, between 40 and 50% variance explained at most sites. This pattern is typical of the summer and autumn patterns seen in the development sample.

The use of a relatively long training period (15 years) and a maximum of only six predictors from a set of meteorologically relevant predictor variables seems to have resulted in a relatively robust fit to the available climate parameters, with minor decreases in explained variance in independent tests. It is therefore likely that such a set of downscaling equations would be reliable in other settings, such as for interpolating GCM output, or for medium-range weather forecasting (see companion paper, Renwick et al. 2009).

Over the independent trial period, the regression estimates showed only small biases, 1-2% for event probabilities, 1mm for precipitation, and less than 0.5°C for temperatures. Typical RMS errors were 5-10mm for precipitation, 1.5°C for earth temperature, 2°C for maximum temperature and 2.5°C for minimum temperature, 1-2m s^{-1} for wind run, and 4-5MJ m^{-2} for solar radiation. The ranked probability skill score for event probability estimates was around 30-35% for all variables.

4. Discussion and summary

A statistical downscaling system has been developed for New Zealand daily climate variables, based on a regression framework drawn from the "perfect prognosis"

(PP) approach used in statistical weather forecasting, and applied in statistical downscaling of climate model output. Using as predictors only 1000 hPa height and 850 hPa temperature fields from the NCEP/NCAR reanalyses, a useful level of diagnostic skill was found at most sites, for most variables. Tests on an independent decade of reanalysis data suggested the regression system is relatively robust and reliable. As such, it should be suitable for downscaling the output of general circulation models (GCMs), at least for present day climate states, and for statistical weather forecasting applications.

Statistics of the fit of the regression equations, and of the underlying climatological mean estimates, reflect the geography of New Zealand and the strong forcing of its climate by orographic influences and interplay with the mean westerly circulation. Precipitation is best estimated where there is most of it, along the west coast of the South Island, while the fit is poorest in the dry basins of inland south Canterbury and Otago, in the rain shadow of the Southern Alps. Maximum temperatures are best estimated, in terms of explained variance, in eastern regions where there is large variability associated with downslope warming in the lee of the orography. Minimum temperatures are well estimated in many regions.

The use of statistical downscaling with GCM output has been questioned, particularly for climate change experiments where the model climate is presumed to be outside the bounds of the development samples used to set up statistical schemes (e.g. Benestad 2004). Relatively simple schemes such as that developed here may however give useful guidance, for at least moderately changed climates. The basic dynamical links between synoptic-scale wind flows and temperatures are unlikely to change, even across a quite wide range of climate warming. The small expense of developing such a statistical downscaling scheme, and the negligible expense incurred in running it, make statistical downscaling an attractive option, perhaps used in conjunction with dynamical downscaling based on regional climate model (RCM) simulations.

For weather forecasting applications, the PP approach is well-known. It has fallen out of favour in recent decades, as more sophisticated model output statistics (MOS) schemes take explicit account of model error and bias. However, MOS is more costly to maintain, as statistical models must be updated whenever the dynamical model is updated, leading to the development of more adaptive and self-updating downscaling systems (e.g., Homleid 1995). One promising application of PP for weather prediction is in its use with ensemble forecasts, where the nature of the forecast error is implicit in the spread of the ensemble. By using a PP system directly with ensemble NWP output, one can obtain a forecast distribution of a number of meteorological variables at specific sites, including information on model error and predictability. Issues of model bias remain, but such an approach may be useful for local-scale interpretation of ensemble NWP output. A companion paper (Renwick et al. 2009) describes the application of the PP system developed here to a set of ensemble NWP model output, and its use in estimating one-month climate anomalies and short-term probabilistic climate predictions.

Acknowledgements

The authors are grateful to Andrew Tait, Darren King, and others for helpful discussions. The authors also thank the anonymous reviewers for a helpful comments on the draft manuscript. Thanks to NCAR and NOAA CDC for supply of reanalysis data. This research was funded by the New Zealand Foundation for Research, Science and Technology through contract C01X0202, and associated capability funding.

References

Benestad, R. E., 2004: Empirical-statistical downscaling in climate modeling. *EOS Transactions AGU*, **85,** 417.

Buell, C. E., 1978: The number of significant proper functions of two-dimensional fields. *J. Appl. Meteor.*, **17,** 717-722.

Draper, N. R., and H. Smith, 1981: *Applied Regression Analysis.* 2nd ed. Wiley Series in Probability and Mathematical Statistics Wiley, New York, 709 pp.

Giorgi, F., and L. O. Mearns, 1991: Approaches to the simulation of regional climate change: A review. *Reviews of Geophysics*, **29,** 191-216.

Glahn, H. R., and D. A. Lowry, 1972: The use of Model Output Statistics (MOS) in objective weather forecasting. *J. Appl. Meteor.*, **11,** 1203-1211.

Homleid, M., 1995: Diurnal corrections of short-term surface temperature forecasts using the Kalman filter. *Wea. Forecasting*, **10,** 689-707.

Kidson, J. W., 1988: Interannual variations in the Southern Hemisphere circulation. *J. Climate*, **1,** 1177-1198.

Kidson, J. W., and J. A. Renwick, 1996: Statistical forecasting of temperatures and winds at major airports. Report prepared for NIWA, report, to Met. Service of NZ Ltd. 1996/21-WN, 41 pp

Kidson, J. W., and C. S. Thompson, 1998: A comparison of statistical and model-based downscaling techniques for estimating local climate variations. *J. Climate*, **11,** 735–753.

Kistler, R., W. Collins, S. Saha, G. White, J. Woollen, E. Kalnay, M. Chelliah, W. Ebisuzaki, M. Kanamitsu, V. Kousky, H. van den Dool, R. Jenne, and M. Fiorino, 2001: The NCEP–NCAR 50–year reanalysis: Monthly means CD–ROM and documentation. *Bull. Amer. Meteor. Soc.*, **82,** 247–268.

Marzban, C., S. Sandgathe, and E. Kalnay, 2006: MOS, perfect prog, and reanalysis. *Mon. Wea. Rev.*, **134,** 657–663, doi: 610.1175/MWR3088.1171.

Miller, R. G., 1964: Regression Estimation of Event Probabilities. Report prepared for Travelers Research Center, Inc., Technical Report CWB 10704, 153 pp

Mullan, A. B., D. S. Wratt, and J. A. Renwick, 2001: Transient model scenarios of climate changes for New Zealand. *Wea. Climate*, **21,** 3-33.

Renwick, J. A., 1986: Objective guidance forecasts based on prognoses from the European Centre for Medium-Range Weather Forecasts. Report prepared for New Zealand Meteorological Service, Scientific Report 20, 38 pp

Renwick, J. A., 1998: ENSO-related variability in the frequency of South Pacific blocking. *Mon. Wea. Rev.*, **126,** 3117-3123.

Renwick, J. A., A. B. Mullan, C. S. Thompson, and A. Porteous, 2009: Downscaling 15-day Ensemble Weather Forecasts and Extension to Short-term Climate Outlooks. *Wea. Climate*, **29**, 45-69.

Richman, M. B., 1986: Rotation of principal components. *J. Climatol.*, **6,** 293-335.

Salinger, M. J., and A. B. Mullan, 1999: New Zealand climate: temperature and precipitation variations and their links with atmospheric circulation 1930-1994. *Int. J. Climatol.*, **19,** 1049-1071.

Wilks, D. S., 1995: *Statistical Methods in the Atmospheric Sciences.* International Geophysics Series, Vol. 59, Academic Press, San Diego, CA, 467 pp.

Wilson, L. J., and R. Sarrazin, 1989: A classical-REEP short-range forecast procedure. *Wea. Forecasting*, **4,** 502-516.

Submitted to *Weather and Climate* September 2008 Revised manuscript resubmitted May 2009