OBSERVATION AND PREDICTION OF WINTERTIME PRECIPITATION IN MOUNTAINOUS REGIONS OF AUSTRALIA

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ABSTRACT

Accurate analysis and prediction of precipitation are very important for water management and planning especially over a water catchment area. They are also relevant to the operation and assessment of cloud seeding projects, such as the Snowy Precipitation Enhancement Research Project (SPERP). However, even observation is difficult in the mountainous areas where precipitation may fall as snow in strong winds rather than rain and there are limited point measurements.

The Australia Bureau of Meteorology's Poor Man's Ensemble (PME) forecast for daily rainfall, in which quantitative precipitation forecasts are combined to give deterministic and probabilistic rainfall forecasts, provides forecast maps on a grid of roughly 100km by 100km (Ebert, 2001,2002). Snowy Hydro Ltd (SHL) maintains an independent network of high-quality observing sites across the Snowy Mountains region. These observations will be used to assess and calibrate the PME forecasts in the Snowy region. Statistical downscaling will also be applied in order to improve the accuracy of the forecasts at specific sites.

1. INTRODUCTION

The Snowy Mountains are located near the border of New South Wales (NSW) and Victoria and have the highest mountain peak on the Australia mainland. The Snowy Mountains Hydro-Electric Scheme is so far the largest engineering project in Australia. It diverts the flow of the Snowy River through tunnels in the mountains to storage dams. The water is then used by power stations to generate electricity, which provides about ten percent of NSW electricity needs.

The major rainfall in the Snowy Mountains happens during the winter period between May and October, while the summer precipitation is dominated by isolated showers. The snowfall over this region is an important source of water for hydro-generation, as well as irrigation and recreation. Thus the estimation of precipitation over the water catchment area is an important problem for water management and planning. However, the problem is difficult in mountainous areas where precipitation fall as snow rather than rain and where the representativeness of point measurements can be uncertain due to variations in the terrain. The problem is especially important for the assessment of a cloud seeding project, such as the Snowy Precipitation Enhancement Research Project (SPERP), where relatively small differences in precipitation need to be identified and quantified.

In ensemble forecasting, a numerical weather prediction model (NWP) is run multiple times with a series of perturbations to the initial conditions. Alternatively the predictions from a number of different models can be combined. The ensemble approach then allows one to estimate the probability of various events occurring such as precipitation. Ensemble forecasting has been extensively tested and used worldwide (Molteni 1996; Tracton and Kalnay 1993) with more recent studies having shown that ensemble forecasts out perform single model forecasts (Atger 1999; Ziehmann 2000). Ebert (2001) verified that the skill and accuracy of the Australia Bureau of Meteorology's Poor Mans Ensemble (PME) precipitation forecasts exceeded those of a single simulation. Due to the large spatial scale of the NWP model, these results cannot be applied to the mountainous terrain directly. Techniques have been developed to downscale information from larger scales to individual points. Statistical downscaling employs statistical relationships developed from historical observations to bridge this gap (von Storch, 1995). Statistical downscaling techniques were developed for NWP applications (Klein and Glahn, 1974) but are also currently used for climate applications. The major advantage of this approach is that it is computationally inexpensive and can be easily applied to the output from different models (Wilby and Wigley 1997, Fowler et al, 2007).

The classical approach to quantitative precipitation forecasting (Lorenz, 1969) is analogue-based, where one or more specific predictors (e.g. mean sea level pressure) is used to estimate a site-specific parameter (e.g. precipitation.) Duband (1981) employed this approach to forecast the spatial distribution of precipitation in the Alps. More recently, this approach has been successfully applied in climate studies (Martin et al. 1997, Timbal et al. 2001). Another possible approach to quantitative precipitation forecasting (QPF) is with a nonparametric, non-homogeneous hidden Markov model (NHMM). Such an approach is believed to be most successful in areas and/or seasons where precipitation is driven by synoptic scale systems (Hugh et al. 1999). This approach has successfully been used to downscale general circulation

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models to estimate climate change (Charles et al. 1999, Robertson et al. 2007). Both approaches are relatively computation inexpensive, but they require relatively long historical observations.

Snowy Hydro Ltd (SHL) maintains an independent network of observing sites across the Snowy Mountains region. This network was further enhanced to support the Snowy Precipitation Enhancement Research Project (SPERP). The combination of these local observations together with the historical records presents a unique opportunity to develop and test downscaled QPFs for the Snowy Mountain region.

2. COMPARISON OF DAILY PRECIPITATION ANALYSES WITH INDEPENDENT OBSERVATIONS

The accurate estimation of precipitation is a crucial problem for QPF. Comparison between precipitation observations in the Snowy Mountains region with the gridded analyses of daily rainfall was performed in order to identify the problem of measurement in the mountain area, especially in winter. The study draws on two data source. The 5-km analysis of daily rainfall across the Australia was obtained from the Australia Water Availability Project. The methods used to generate the data include successive-correction Barnes analysis for the anomaly fields and the three-dimensional smoothing spline methods for the background climates (Jones et al 2006). Hourly observation data were also obtained from the independent network of Snowy Hydro Ltd (SHL) for the period 1 May 1995 to 30 April 2003 and aligned with the Bureau time period (24 hours accumulation to 9 am each day). Bilinear interpolation from the nearest four grid points was used to estimate the analysed precipitation for all SHL sites. We simply define time series for winter as May to September when snowy is likely to fall and the rest of the year as summer. Figure 1 shows the Bureau and SHL observation sites in Snowy Mountain. Two sites Cabramurra and Khancoban are used both in the gridded analysis and the comparison tests.

2.1 Methodology

The first stage of comparison is for the days with little or no rain day (daily precipitation less than 0.5 mm by SHL observations). Then for days with rainfall, basic correlation coefficients are calculated for each site for daily and monthly precipitation. Quantile- quantile (Q-Q) plots were generated to identify the difference between distributions of variables. A simple linear regression is used to quantify the difference between the analyses and observations. Since there are errors in the precipitation measurements in the independent variables (SHL observations) as well as the analyses, orthogonal regression (Carrol et al 1996) is applied.

2.2 Results

The total number of sites that record daily rain less than 0.5mm over the summer and winter for gridded analyses and SHL sites are calculated. Figure 2 shows the probability of no rain at a specified number of sites for summer and winter. It appears in both summer and winter, rainfall is widespread across this 5000 km^2 area. The precipitation in winter tends to be more spatially variable than in summer. While rain occurrence tends to be more uniform in analyses due to its methodology. The agreement between rain days from the gridded analyses with the observations is very high in the summer. The agreement is slightly lower in the winter when precipitation is likely to be as snow rather than rain. Over the whole period, at least 80% of no-rain days were correctly estimated from the gridded analyses.

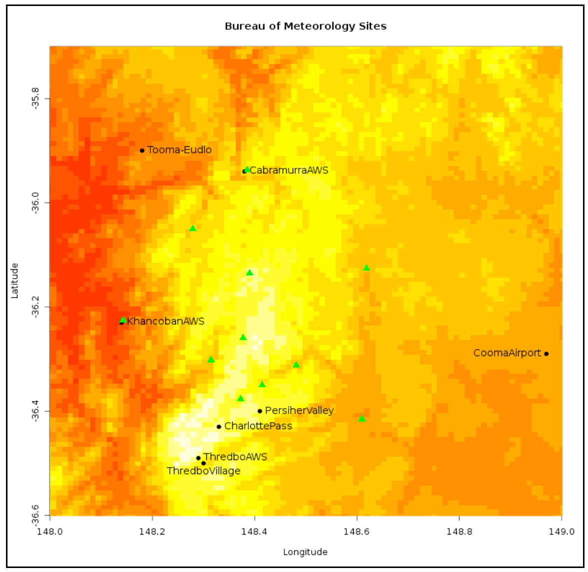

Figure 1 Sites used by Bureau of Meteorology daily precipitation analyses; green triangles indicate locations of SHL sites

The correlation coefficients between the daily analyses and observations tend to be greater than 0.8 with negligible P values, though the gridded analyses at a few sites are consistently underestimated. Generally speaking, the gridded analyses are reasonably consistent with the SHL observations of daily and monthly precipitation. However, there is evidence that the analyses underestimate winter precipitation, when there is likely to be snow rather than rain. It is also apparent that precipitation from localized severe convective storms may be underestimated in summer. On the other hand, monthly accumulations of precipitation can be overestimated in summer when daily falls are light and the analyses tend to overestimate the spatial extent of the rain.

Table 1 shows the results of the regression analyses for the winter periods at each site. The slope, confidence intervals on the slope, and the intercept are given. The regression slopes are generally near one, consistent with the results of the Q-Q plots. For the winter period, slopes less than 0.8 are found only for Geehi Dam, Cabramurra, Jagungal and Tooma Dam. All of these sites are at elevations greater than 1000 m. The slopes for summer daily precipitation are uniformly less than for winter, which is due to underestimation of extreme events (greater than 50mm). The spatially isolated storms are not being well represented in smoothed analyses.

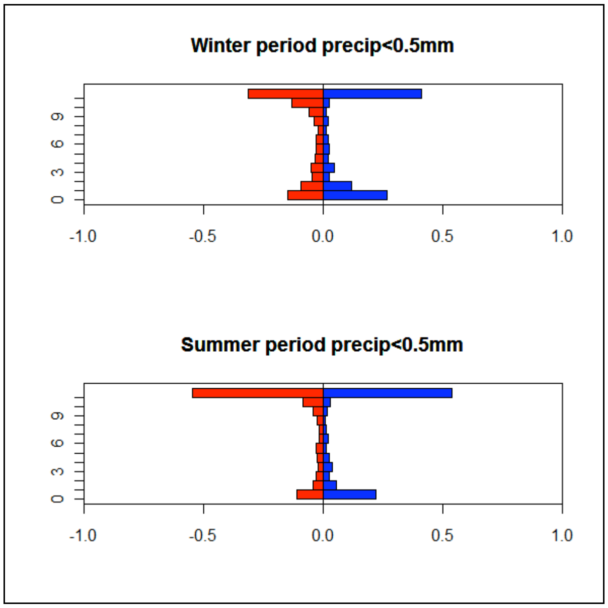

Figure 2 Probability of rain less than 0.5 mm at a specified number of sites (0 to 11) each day in winter and summer; red (negative values) for SHL sites and blue for gridded analyses

Location	Slope	CI1	CI2	Intercept
GuthegaD	1.038	1.037	1.039	0.286
Kerries	0.966	0.965	0.967	-1.046
IslandBend	1.070	1.070	1.071	0.123
GeehiD	0.589	0.589	0.590	1.419
GuthegaPS	0.862	0.861	0.862	-0.047
Cabramurra	0.669	0.668	0.669	0.404
Jagungal	0.743	0.742	0.744	0.834
Khancoban	0.894	0.894	0.895	0.709
ToomaD	0.472	0.472	0.473	1.251
EucumbeneD	1.020	1.020	1.021	-0.075
Jindabyne	0.951	0.950	0.951	0.084

Table 1. Results of orthogonal regression for daily precipitation at each site for the winter period

In summary, the analyses capture the observed distribution of precipitation quite well. Winter snowfall is systematically underestimated, thus a statistical adjustment may be able to improve the estimate of winter precipitation. Isolated summer storms are smoothed, leading to an under estimation of high rainfall events and causing isolated outliers in the linear regression.

3. PRELIMINIARY COMPARISON OF DAILY OBSERVATIONS WITH PME PREDICTION

A crucial issue for precipitation measurement in mountainous area is snow measurement. Most of the SHL gauges in the Part 2 study have heating devices for measuring winter precipitation, but none of these gauges have significant wind fences to reduce wind impact. For the SPERP project, a number of sites in the SHL network have installed proper wind fences. Preliminary analyses in some locations show improvement in the accuracy of snowfall measurement. These measurements will be used in the future study of the area. As a first stage, a comparison between PME forecast results and 2006 winter SHL sites with a wind fence, was performed to verify the PME forecast. The methodology applied here is similar to the Part 2 comparison.

The PME daily QPF is conducted twice a day and it provides forecasts up to three days ahead. Table 2 shows the correlation coefficients between SHL sites and PME forecast from now cast (time=0) to the forecast up to 60 hours ahead for raining days (SHL observed more than 0.5mm rain). The correlation is quite consistent for each location: for most of locations the location correlation value increased until 24 hours ahead then start decrease. It is worth noting, due to the inadequacy of data, the confidence intervals of correlations are large and these differences are not significant. For simplicity, we will focus on the 24-hour PME forecast.

Time	Perisher	Grey Hill	The Kerries	Guthega Dam	Waterfall Farm
0	0.46	0.22	0.52	0.42	0.6
12	0.47	0.23	0.49	0.43	0.49
24	0.53	0.19	0.55	0.47	0.53
36	0.51	0.18	0.48	0.44	0.47
48	0.36	0.19	0.37	0.34	0.4
60	0.51	0.21	0.51	0.45	0.5

Table 2. Correlation coefficients between SHL and PME for daily forecast from 0 hour to up 60 hours ahead

The majority of days in the 2006 winter were the no-rain or light rain day (as indicated in SHL sites). There were 123 no-rain days from a total of 152 days at Waterfall Farm, which is the driest site. PME predicted at least 75 percent of light rain days correctly for all 5 locations, which is quite good agreement between the two datasets.

Having put aside days with little or no rain days, linear regression is applied to the rest of the days as in

Part 2. The slopes of orthogonal linear regression are extremely low for all 5 locations, which are only around 0.1 to 0.4. The Figure 3 shows the Q-Q plots and back-to-back plot for Guthega Dam as an example. There is significant systematic underestimation by the PME forecast. It catches the occurrence of major events correctly most of the time, but the magnitude of events is underestimated. Considering the new wind fence improved the SHL measurement, while the calibration of the PME was done using the Bureau observation network only, the results are understandable. Thus it appears that the PME forecast could be used to estimate precipitation in the Snowy Mountains region, provided a statistical adjustment is applied.

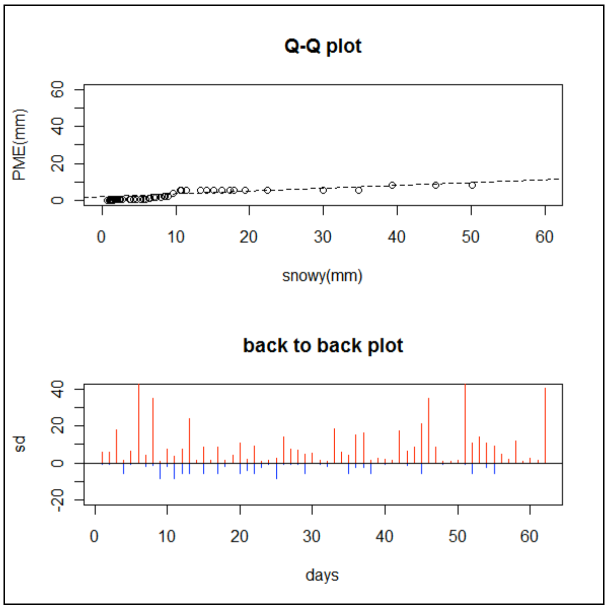

Figure 3 The Q-Q plot and back-to-back plot for Guthega Dam

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