South Eastern Australian
Climate initiative

Final report for **Project 1.3.1**

Development of the analogue downscaling technique for rainfall, temperature, dew point and pan evaporation

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Project Abstract - Executive summary

Initial Project objectives:

- Set up a statistical downscaling technique to relate large-scale changes to local variations in south-eastern Australia

Proposed methodology:

- Existing downscaling methodology will be expanded to include humidity variables (dew point temperature and pan evaporation) in addition to proven dataset (rainfall and daily temperature extremes).
- Large-scale predictors will be tested and the spatial variation of skill across south-eastern Australia will be assessed for all calendar seasons and the suitable stations data, following on recommendation from milestone 1.1.1.
- Methodology will be optimised for south-eastern Australia using identified coherent climatic regions

Summary of the findings:

- This project has seen the development and validation of a single downscaling method based on the idea of meteorological analogues to the entire SEACI regions and for all existing high quality climate surface networks: rainfall, temperature, dew-point temperature and pan-evaporation.
- The SEACI domain was divided into three climate entities: the Southern part of the Murray-Darling basin (SMD); east of the SMD, on the coastal side of the Great Dividing Range, the South-East Coast (SEC) and west of the SMD, the South-West coast of Eastern Australia (SWEA).
- Individual Statistical Downscaling Models (SDMs) were optimised for each region, each calendar season and each predictands; a total of 72 SDMs (3 regions * 4 seasons * 6 predictands).
- The optimisation comprised two steps: the selection of the best combination of predictors (step 1) and then setting up other critical parameters of the SDM.
- The skill of the SDMs are fairly consistent across the three regions, the four seasons and the six predictands, thus confirming that the analogue approach is a suitable downscaling method for mid-latitude temperate climate.
- The reproduction of the observed Probability Distribution Functions (PDFs) was assessed by checking the two main moments of the reconstructed series: mean and variance. The mean of the observed series is very well reproduced with the exception of rainfall but all the reconstructed series do under-estimate the observed variance, this underestimation varies from one predictand to another and is largest for rainfall.
- In the case of rainfall, because the daily PDFs is not near normally distributed the reduced variance leads to a dry bias, this dry bias can be reduced with a very simple and robust inflation factor.
- The skill of the SDMs was assessed by looking at the ability of the technique to reproduce day-to-day variability using correlation and Root-Mean Square Errors (RMSEs): the best correlations tend to be achieved for most variables during the “transition seasons” autumn and spring, correlations in winter are often low but with low RMSEs (i.e. not less skill), in contrast, for all variables but daily temperature extremes, the model tends to have less skill (low correlation and high RMSEs) in summer.

Technical details

Expand existing downscaling model to humidity dataset

The Australian Bureau of Meteorology has developed a SDM using the idea of meteorological analogues (Timbal and McAvaney, 2001). This is one example of a more general type of SDM based on weather classification methods in which predictands are chosen by matching previous (i.e., analogous situations) to the current weather-state. The method was originally designed for weather forecasting applications but was abandoned due to its limited success and lack of suitable analogues for systems with large degrees of freedom. The popularity of the method has recently increased with the availability of longer time-series datasets following the completion of reanalysis project and the recognition that the size of the search space must be suitably restricted when identifying analogues. Even so, the analogue method still performs poorly when the pool of training observations is limited and/or the number of classifying predictors is large. The Bureau SDM was first developed for daily temperature extremes (T_{min} and T_{max}) across the Murray-Darling Basin (MDB) (Timbal and McAvaney, 2001). It was then extended to rainfall occurrences (Timbal et al., 2003) and amount (Timbal, 2004).

As part of this SEACI project, the Bureau of Meteorology existing downscaling technique has being tested for new surface variables to complement previous work done on rainfall and temperature. These new surface variables are the most recent addition to the Bureau High Quality (HQ) climatological networks. Dew point stations were homogenised (Lucas, 2006) and are available in the HQ dataset from 1957 to 2003. 13 stations across the SEACI domain were considered. At each location, daily maximum, daily minimum, and 9am dew point temperatures are available but the optimisation of the SDM was applied only to daily extreme dew point temperature. Pan evaporation HQ stations have been also been assembled across Australia (Jovanovic et al., 2008) from 1975 to 2003. 24 stations are scattered across the SEACI domain. The Bureau pan-evaporation HQ dataset is a monthly dataset, the quality control was extended to daily values across the SEACI region, using monthly corrections for non-homogeneities at stations which required such correction (as part of project 1.1.1). The application of a SDM to these moisture variables is a very novel research as there is currently very few examples in the literature of fitting a statistical downscaling model to surface moisture variables (Huth, 2005 for a case study fro dew point across the Czech republic) and none as extensive as our study.

Overall, applying a single technique across a large region such as the SEACI domain and across a large range of predictands is a very large undertaking. This extensive work (a total of 72 individual SDMs were optimised: 3 regions * 4 seasons * 6 predictands) was possible due to the simplicity of the chosen downscaling method. The analogue approach used here is one of the simplest existing downscaling methods. Despite its simplicity which was paramount to be able to perform this work, this method has been shown to compare well with more advanced techniques (Zorita and von Storch, 1999). The simplicity, flexibility and robustness of the technique were important to ensure that a single technique could be used across a range of variables and several climatic regions.

Choice of coherent climatic regions

In order to apply the Bureau of Meteorology SDM to the SEACI domain, surface observations were gathered into three distinct *climate entities* (Fig. 1), roughly following the rotated Empirical Orthogonal Functions (EOFs) for rainfall suggested by Drosdowsky (1993): (1) the South-West of Eastern Australia (SWEA): southwest of a line roughly from Melbourne to the south of the Flinders' ranges and following the end of the Great Dividing Range (GDR) over Western Victoria, (2) the southern half of the Murray-Darling Basin (SMD) south of 30ºS in the north, limited in the west by SWEA and in the east by the GDR, and (3) the South-East Coast (SEC), a coastal band east of the GDR from Wilson Promontory in Victoria in the south all the way along the New South Wales coast up to the Hunter valley in the north.

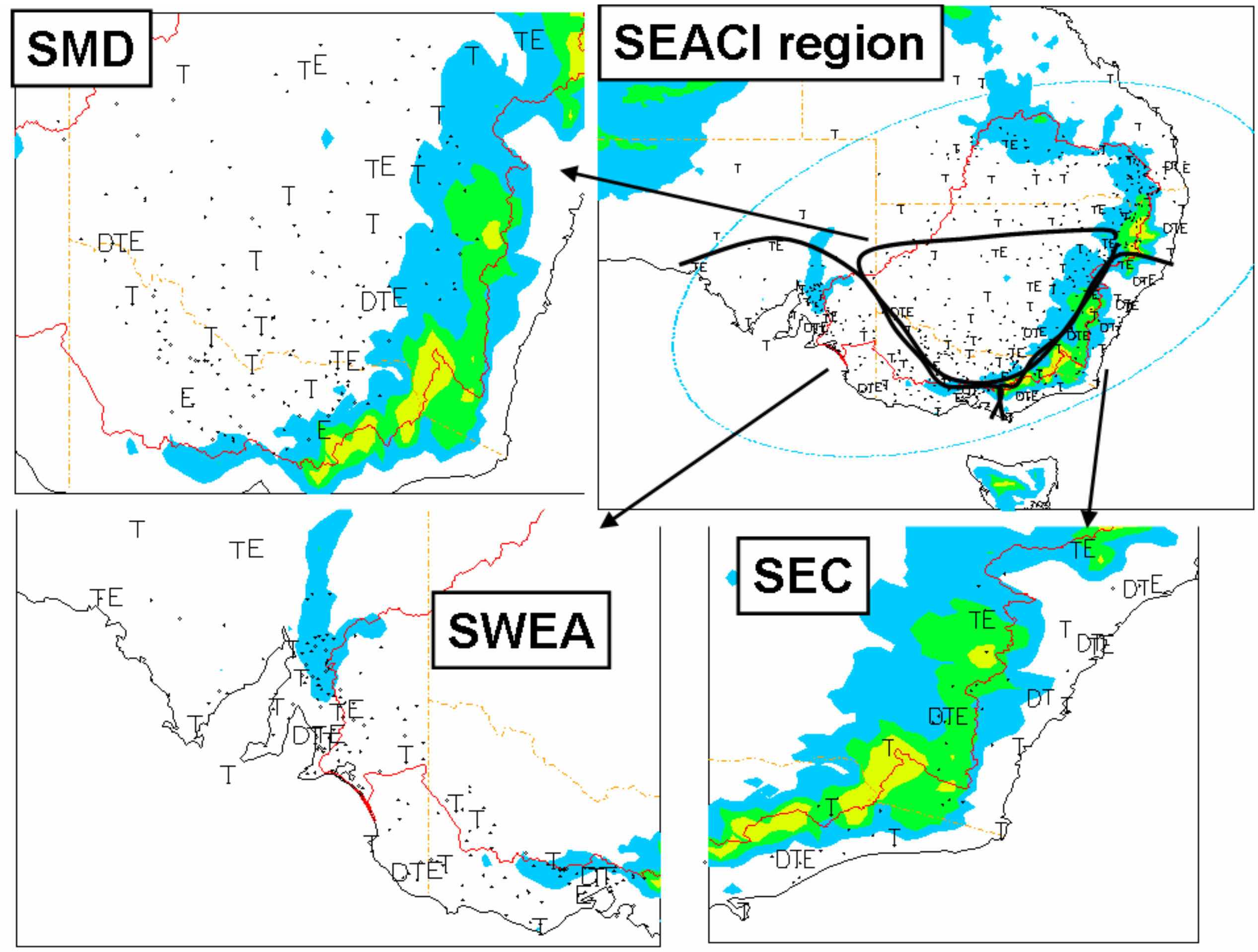

Figure 1: *Locations of the station data chosen for the SEACI program (upper right map) and for the three climatic entities used to optimise the statistical downscaling model: the Southern Murray-Darling Basin (SMD), the South-West of Eastern Australia (SWEA) and the South-East Coast (SEC). Different symbols are used for different surface predictands: D for dewpoint temperature, E for pan-Evaporation, T for temperature and the small points are rainfall station).*

The number of surface predictands available in each climatic region is summarised in Table 1. Although a small part of the Australian continent is covered by these three climatic regions, together they cover a large proportion of the number of HQ observation sites across Australia (between 30% for dew point temperature and 54% for rainfall. It underlines the fact that these regions are amongst the most populated in Australia: hence the relatively denser network of observations in particular for rainfall. A logical consequence is that they are amongst the most important for human related activities (e.g. agriculture). For rainfall, a large number of additional stations have been used as well to apply the SDM to: the number of additional rainfall stations per climate regions is also shown (Table 1).

Predictands		SWEA	SMD	SEC
Temperature (T_{max} & T_{min})		22	18	16
Rainfall	**HQ network**	31	24	11
	additional stations	133	137	30
Pan-Evaporation		6	8	6
Dew point (dT_{max} & dT_{min})		3	2	5

Table 1: *Number of stations considered in each climatic region for the four types of predictand*

For temperature some stations as well were added but only a handful (they are included in the number of temperature stations provided. Overall not all the SEACI relevant stations identified in project 1.1.1 (and shown in the top right of Fig. 1) are included in one of the three regions as the original stations lists cover a wider geographical area than the three climatic entities (inserts in Fig. 1).

Optimization of the predictors

The choice of the optimal combination of predictors constitutes the first step in the optimisation of the individual SDMs. The predictors considered were chosen on the basis of previous experience while developing the BoM SDM (Timbal and McAvaney, 2001; Timbal et al., 2003; Timbal, 2004), and evidences in the literature from other studies in similar areas. The optimum combination of predictors varies across regions, seasons and predictands (Table 2).

The optimal number of predictors is often three, apart from pan evaporation where most frequently only two predictors are used and for rainfall where four predictors are often required. The need for a large number of predictors for rainfall shows that it is a difficult predictand to capture from large-scale analogues. Some general patterns are emerging from the optimum combinations of predictors:

- Mean sea level pressure (MSLP) is the most frequently chosen predictor. It is used for all individual SDMs in the case of rainfall, T_{max} and dT_{min} but is picked up far less often for pan evaporation. This feature suggests that MSLP is a critical predictor for a synoptically driven technique such as the analogue approach.
- Thermal predictors are very important, especially for T_{max} and T_{min}. In general, T_{850} is the most important thermal predictor, although T_{min} is more important for dT_{min} and dT_{max}; thermal predictors rarely matter for rainfall.
- Moisture variables are also important predictors across all predictands with the notable exception of T_{max}. Specific humidity is almost always picked up apart from pan evaporation for which relative humidity is more skilful. Rainfall is often part of the optimised predictor's combination to downscale rainfall.
- Some measure of the air flow (either the zonal or meridional component of the wind) is often added to the optimised combination. It is an additional predictor to the de-facto combination of

synoptic-thermal-moisture. It is most useful for rainfall and then T_{max}, and least useful for dew-point temperature and pan evaporation. The zonal component is the most frequently used.

Variable	Season	SWEA	SEC	SMDB
Maximum Temperature **T_{max}**	Summer	MSLP & T_{850}	MSLP & T_{max}	MSLP & T_{max}
	Autumn	MSLP & T_{max}	MSLP & T_{max}	MSLP & T_{max}
	Winter	MSLP & T_{850} & T_{max} & U_{850}	MSLP & T_{max}	MSLP & T_{850} & T_{max} & U_{850}
	Spring	MSLP & T_{850}	MSLP & T_{850} & T_{max} & U_{850}	MSLP & T_{850} & U_{850}
Minimum Temperature **T_{min}**	Summer	MSLP & T_{850}	MSLP & T_{850} & Q_{850}	T_{850} & Q_{850}
	Autumn	MSLP & T_{850} & Q_{850}	MSLP & T_{850} & Q_{850}	T_{850} & Q_{850}
	Winter	MSLP & T_{850} & Q_{850}	MSLP & T_{850} & T_{min} & U_{850}	MSLP & T_{850} & Q_{850}
	Spring	MSLP & T_{850} & Q_{850}	MSLP & T_{850} & Q_{850}	MSLP & T_{850} & Q_{850}
Rainfall **PRCP**	Summer	MSLP & PRCP & T_{850}	MSLP & T_{max} & Q_{850} & U_{850}	MSLP & PRCP & V_{850}
	Autumn	MSLP & T_{max} & Q_{850} & U_{850}	MSLP & PRCP & Q_{850} & U_{850}	MSLP & PRCP & V_{850}
	Winter	MSLP & PRCP & V_{850}	MSLP & PRCP & U_{850}	MSLP & PRCP & V_{850}
	Spring	MSLP & PRCP	MSLP & PRCP & Q_{850} & U_{850}	MSLP & PRCP & V_{850}
Maximum dew-point Temperature **dT_{max}**	Summer	MSLP & Q_{925}	MSLP & Q_{925} & T_{min}	MSLP & Q_{850} & T_{min} & V_{850}
	Autumn	MSLP & Q_{925} & T_{min} & V_{850}	MSLP & Q_{925} & T_{min}	MSLP & Q_{850} & T_{min} & V_{850}
	Winter	MSLP & Q_{925} & T_{min}	MSLP & Q_{925} & T_{min}	T_{min}
	Spring	MSLP & Q_{925} & T_{min}	MSLP & Q_{925} & T_{min}	MSLP & Q_{850}
Minimum dew-point Temperature **dT_{min}**	Summer	MSLP & Q_{925} & T_{min}	MSLP & Q_{925} & T_{min}	MSLP & Q_{850} & T_{850}
	Autumn	MSLP & Q_{925} & T_{min}	MSLP & Q_{925} & T_{min}	MSLP & Q_{850} & T_{min} & U_{850}
	Winter	MSLP & Q_{925} & T_{min}	MSLP & Q_{925} & T_{min}	MSLP & Q_{850} & T_{min} & V_{850}
	Spring	MSLP & Q_{925} & T_{min}	MSLP & Q_{925} & T_{min}	MSLP & Q_{850} & T_{850}
Pan-Evaporation **P-Evap**	Summer	T_{max} & R_{925}	T_{max} & R_{925}	T_{max} & R_{850}
	Autumn	T_{max} & R_{925}	T_{max} & R_{925}	T_{max} & R_{850}
	Winter	T_{max} & R_{925}	MSLP & T_{max} & R_{925}	T_{max} & R_{925}
	Spring	T_{max} & R_{925}	T_{max} & R_{925} & U_{850}	T_{max} & R_{850}

Table 2: *Optimum combination of predictors for each calendar seasons and the six predictands in three regions: SWEA, SEC and SMD. The predictors are defined as follow: MSLP is the Mean Sea Level Pressure; T_{max} and T_{min} are the surface min and max temperature; PRCP is the total rainfall; Q is the specific humidity; R is the relative humidity; T is the temperature; U and V are the zonal and meridional wind components; and subscript numbers indicates the atmospheric level for the variable in hPa.*

The second step of the optimisation of individual SDMs was to set up some critical parameters of the analogue model. The SDM includes a large number of tuneable parameters; however previous studies have shown that only three parameters are critical and therefore only these three where systematically explored:

1. The size of the geographical domain used for the predictors (latitude and longitude); in general two domain sizes were tested; these domain' sizes are region dependent
2. The calendar window from which analogues are found. Three periods were tested; 15, 30 and 60 days prior to or after the date for which an analogue is searched for.
3. The way the daily anomalies are calculated using either three monthly means or a single seasonal average.

Once these two steps were completed, the optimised SDMs were validated their skills were systematically evaluated.

Skill of the SDM

The evaluation of the skill of the SDMs was done using a fully cross-validated approach to ensure that no spurious skill was taken into account. The model was first optimised on one half of the existing dataset and then applied to the other half (the length of these halves varies for each predictands according to the length of the available record). When applied to the validation part of the dataset, analogue are searched for in the development half of the dataset to ensure a fully cross-validation. Hence if the climate has recorded a shift during the two periods, the method has to be able to reproduce that shift, thus adding confidence in the ability of the technique to reproduce non-stationarity in the climate system now (useful for detection and attribution study) and in the future (useful for generating regional projections). However in this project, only the ability of the technique to reproduce the simultaneous observations was analysed; the ability of the method to reproduce observed changes is currently underway as part of the project 1.4.1. Here, the evaluation of the SDMs focused on the ability of the technique to reproduce the main characteristics of the observed series and that it is doing it for the right reasons.

A range of metrics was used. First the ability of the technique to reproduce the observed probability distribution functions (PDFs) was evaluated by looking at the first two moments of the PDFs: the mean and the variance. Further than the ability of the technique to reproduce the observed shape of the PDFs as defined by the first two moments of the series, it is important to ensure that the technique is skilful in reproducing day-to-day variability that is driven by large-scale synoptic changes. As indeed a random choice of analogue would reproduce perfectly the observed mean and variance but is not a skilful model. To do so, the Pearson correlation between daily observed and reconstructed series was calculated separately per region, per season and for each predictand. Each number is an average across all observations available in each region. Alongside the correlation coefficient, Root-Mean-Square errors (RMSEs) were also used to complement the evaluation of the skill of the SDMs to reproduce day-to-day variability. The motivation to use both correlation and RMSE is to be able to differentiate between cases where correlation is low but RMSEs are also low: indicative of an observed series with little variability and hence difficult to reproduce very well, and cases where correlation is low and RMS is large indicative of a less skilful SDM. Results are detailed in the appendix attached to this report.

Overall it was found that the analogue approach was successful across the SEACI domain, as results are fairly consistent across the three regions, the four seasons and the six predictands. It was found that the mean of the observed series is very well reproduced for all variables with the exception of rainfall, but the reconstructed series does under-estimate the observed variance in all cases. This underestimation of the variance varies from one predictand to another. In the case of rainfall, because the underestimation is very large and the daily PDFs do not have a near-normal distribution, the reduced variance leads to a dry bias. The variance reduction issues and subsequent dry bias can be addressed using a very simple (i.e. a single parametric coefficient applicable to all stations and all seasons) and robust (i.e. it only depends on the pool of observed rainfall occurrences and hence is applicable to the downscaling of climate models) inflation factor. In terms of ability to reproduce day-to-day variability, it was found that the analogue method was overall quite successful. The lowest skill was observed for rainfall, the best for daily temperature extremes. The best correlations tend to be achieved for most variables during the "transition seasons" autumn and spring, correlations in winter are often low but with low RMSEs (i.e. not less skill), in contrast, for all variables but daily temperature extremes, the model tends to have less skill (low correlation and high RMSEs) in summer.

Additional information

Acknowledgement

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Authors: Bertrand Timbal (Bureau of Meteorology)

Outputs from this project

Publications:

Timbal, B., E. Fernandez and Z. Li, 2008: Optimisation of a statistical downscaling model and development of a graphical user friendly interface to provide downscaled climate change projections on a continental scale. *Env. Mod. & Software*, (submitted).

Conference papers:

B. Timbal and Z. Li, 2007: "A user friendly interface to provide point specific climate change projections", *MOSDIM07*, Christchurch, December 2007.

Project Milestone Reporting Table

Milestone description[1]	Performance indicators[2]	Completion date[3]	Budget[4] for Milestone ($)	Progress[5]	Recommended changes to workplan[6]
1. Test statistical downscaling on humidity dataset	Quantify skill of this technique for moisture field	01/01/07	30 k$	Large-scale predictors have been tested.	RH is the only surface predictands not used.
2. Identify coherent climatic regions	SE Australia sub-domains defined	01/05/07	25 k$	3 sub-domains have been identified across the S.E.A.	None
3. Optimize choice of predictors	Define the optimal model in all cases	01/09/07	25 k$	All individual models have been optimised.	None. Work completed
4. Evaluate skill of the technique across the area of interest	A 6-page report compiling results from a range of metrics	01/01/08	25 k$	This work is now completed. The 6-page report is near completion and will be attached to the project final report	None.

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Appendix: Technical report on the evaluation of the technique (Milestone 4).

Methodology:

Following on the work done to select suitable stations for all surface predictands: maximal and minimal daily temperature (T_{max}, T_{min}), rainfall, pan-evaporation and maximal and minimal daily dew-point temperature (dT_{max}, dT_{min}) as part of project 1.1.1, statistical Downscaling Models (SDMs) were formed by first identifying coherent climatic regions (milestone 2 of this project) and optimizing the choice of predictors (milestone 3). This report summarizes the evaluation of the skill of individual SDMs across the South-East of Australia (SEA) for the six surface predictands (milestone 4).

The evaluation of the SDMs is done in a fully cross-validated manner. The model is first optimised on one half of the existing dataset and then applied to the other half. When applied to the validation part of the dataset, analogue are searched for in the development half of the dataset to ensure full cross-validation. Hence if the climate has recorded a shift during the two periods, the method has to be able to reproduce that shift, thus adding confidence in the ability of the technique to reproduce non-stationarity in the climate system now (useful for detection and attribution study) and in the future (useful for generating regional projections).

The evaluation was carried out using a range of metrics. First the ability of the technique to reproduce the observed probability distribution functions (PDFs) was evaluated by looking at the first two moments of the PDFs: the mean and the variance. Besides the ability of the technique to reproduce the observed shape of the PDFs as defined by the first two moments of the series, it is important to ensure that the technique is skilful in reproducing day-to-day variability that is driven by large-scale synoptic changes. Indeed, a random choice of analogue would reproduce perfectly the observed mean and variance but is not a skilful model. The Pearson correlation between daily observed and reconstructed series was calculated separately per region, per season and for each predictand. Each number is an average across all observations available in each region. Alongside the correlation coefficient, Root-Mean-Square Errors (RMSEs) were also used to complement the evaluation of the skill of the SDMs to reproduce day-to-day variability. The motivation to use both correlation and RMSE is to be able to differentiate between cases where correlation is low but RMSEs are also low: indicative of an observed series with little variability and hence difficult to reproduce very well, and cases where correlation is low and RMSE is large indicative of a less skilful SDM.

Temperature:

In the case of daily extreme temperature, the development period is 1958 to 1982 and the validation period is 1983 to 2006 (i.e. analogues to reproduce 1983 to 2006 are picked up from 1958 to 1982, a notably cooler period in many instances). The reproduction of the mean values for both predictands (Fig. 1) is very accurate. In each graph, points correspond to a single location for a single season with the observed mean value on the x-axis and the reconstructed mean along the y-axis. The number of points in each graph is equal to the total number of stations in one of the three climate regions times four seasons (224 in the case of temperature). Results for the mean are not far from a perfect match (especially for T_{max}), with points aligned with the diagonal.

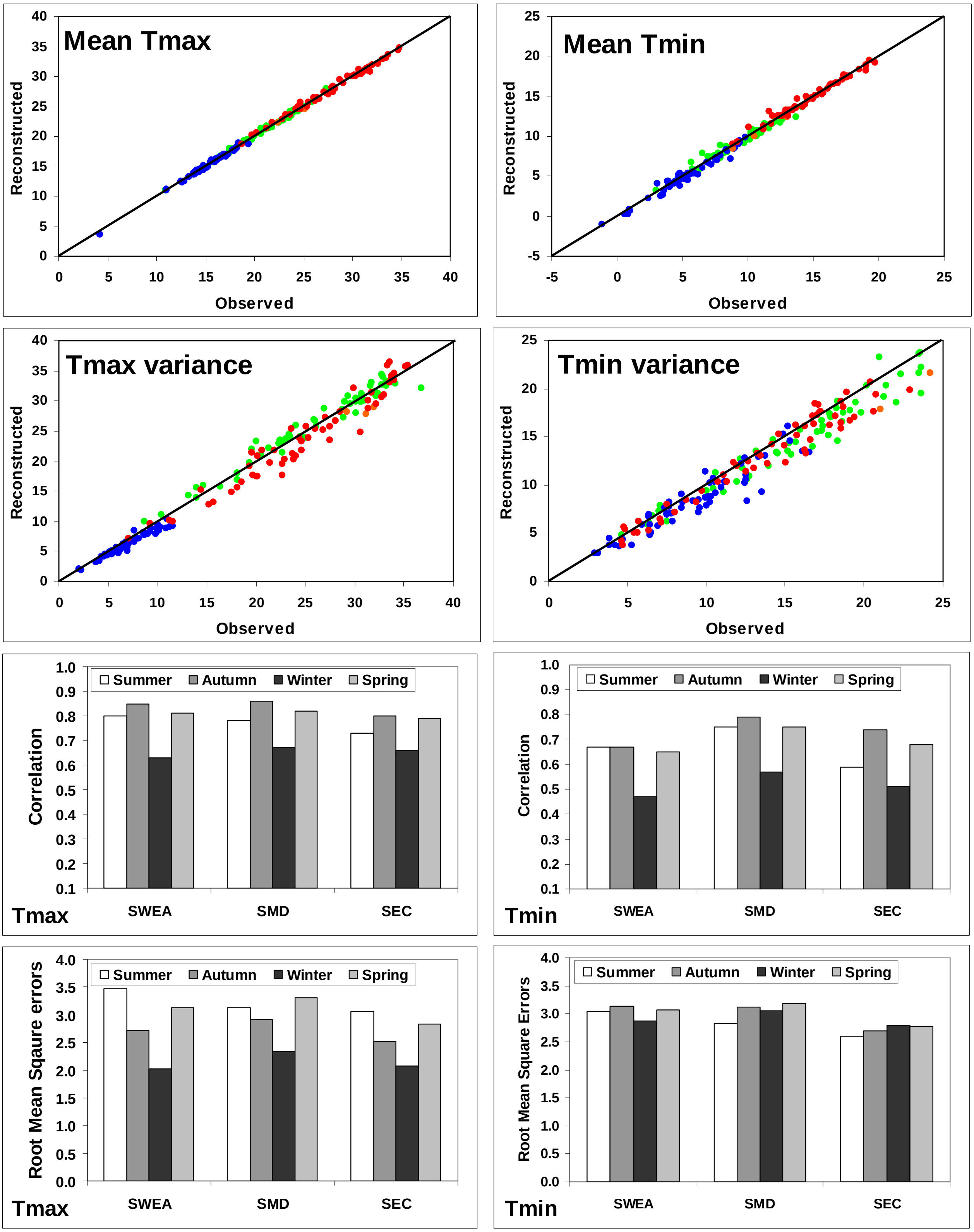

Fig 1: *Scatter plot of the reconstructed versus observed mean (top row) and variance (second row) and correlations (third row) and RMSEs (fourth row) between the two series for T_{max} (left) and T_{min} (right). On scatter plots, there is one point per station and per season, the colour-code refers to season: winter (blue), spring (green), summer (red) and autumn (orange). The diagonal is the line of perfect fit. Correlations and RMSEs are averaged across all stations per region (name on X-axis) and specified by season (coloured bars). Units for mean, variance and RMSE are ºC.*

Furthermore there is no evidence that the SDMs have more difficulty at reproducing mean observed values at either hand of the spectrum (large or small values).

Similarly results are shown for the reproduction of the standard deviation. The technique appears to have a tendency to underestimate the observed variance: points are aligned below the diagonal for most cases. This is particularly true in summer for T_{max} but obvious across all seasons for T_{min}. Average across all stations the reduction of variance ranges from 11.8% in winter to 0% in spring for T_{max} and 11.8% in winter and 5.3% in summer for T_{min}.

This variance underestimation is relatively small with the analogue approach (which does not require any linear assumption) compared to many other techniques (in particular linear techniques), but it remains an issue across all statistical downscaling technique (von Storch, 1999). For temperature, as daily values are not far from being normally distributed, the underestimation of the variance does not have a flow-on effect on the reproduction of the mean (unbiased as noted earlier).

Finally the ability of the SDM to skilfully reproduce day-to-day variability (i.e. the ability to reproduce the right PDFs for the right reasons) appears very successful based on correlations for both T_{max}, T_{min}. There is a marked seasonal cycle in correlation coefficients: lower values are observed in winter and highest values during autumn and spring. However in most instances, in particular for T_{max}, winter corresponds also to the lowest RMSEs. Therefore the lower correlation does not imply less skill but a season where day-to-day variability is less marked and hence harder to capture. On the contrary in autumn and spring the high correlation values are help by large day-to-day variability during the transient seasons. In the case of T_{min}, it is not obvious as RMSEs are fairly similar across all seasons and hence the lower correlations in winter suggest that the model is less skilful. Overall no particular region stands out as a climatic entity where the SDM skill in reproducing day-to-day variability is consistently lower or higher across all seasons. This result vindicates the fact that the model is applicable to the entire South-Eastern part of Australia where the climate by and large is driven by synoptic disturbances.

Rainfall:

Similar graphs were generated for rainfall (Fig. 2), as for temperature, the development period is 1958 to 1982 and the validation period is 1983 to 2006. The reproduction of the first two moments of the series (mean and variance) is less successful than for temperature (left plots in the first two rows of Fig. 2). The underestimation of the variance is much larger: ranging from 27% in autumn to 45% in summer. The consequence of the reduction of variance, in the case of rainfall, can be seen on the reproduction of the mean; points are located below the diagonal, indicating a bias toward drier values for reconstructed series. In the case of rainfall, the reproduction of the mean is dependent on the ability of the technique to reproduce the observed variance as rainfall is not normally distributed. For this reason, a correction factor to adjust the reconstructed rainfall series and enhance the variance and improve the reproduction of the mean was introduced in earlier applications of the analogue approach to rainfall series in Western Australia (Timbal et al., 2006).

The rationale for the applied correction is that the analogue reconstructed rainfall is affected by the size of the pool of analogues which becomes smaller in the case of rare large rainfall events. Therefore, the error in finding the best matching analogue increases and the chances are that the best analogue found would describe more frequent but less intense rainfall events thus underestimating the rainfall in the reconstructed series. It is assumed that the size of the pool depends on the ratio of rain days over dry days and that is valid across the range of climates encounter in SEA as it was the case in W.A.

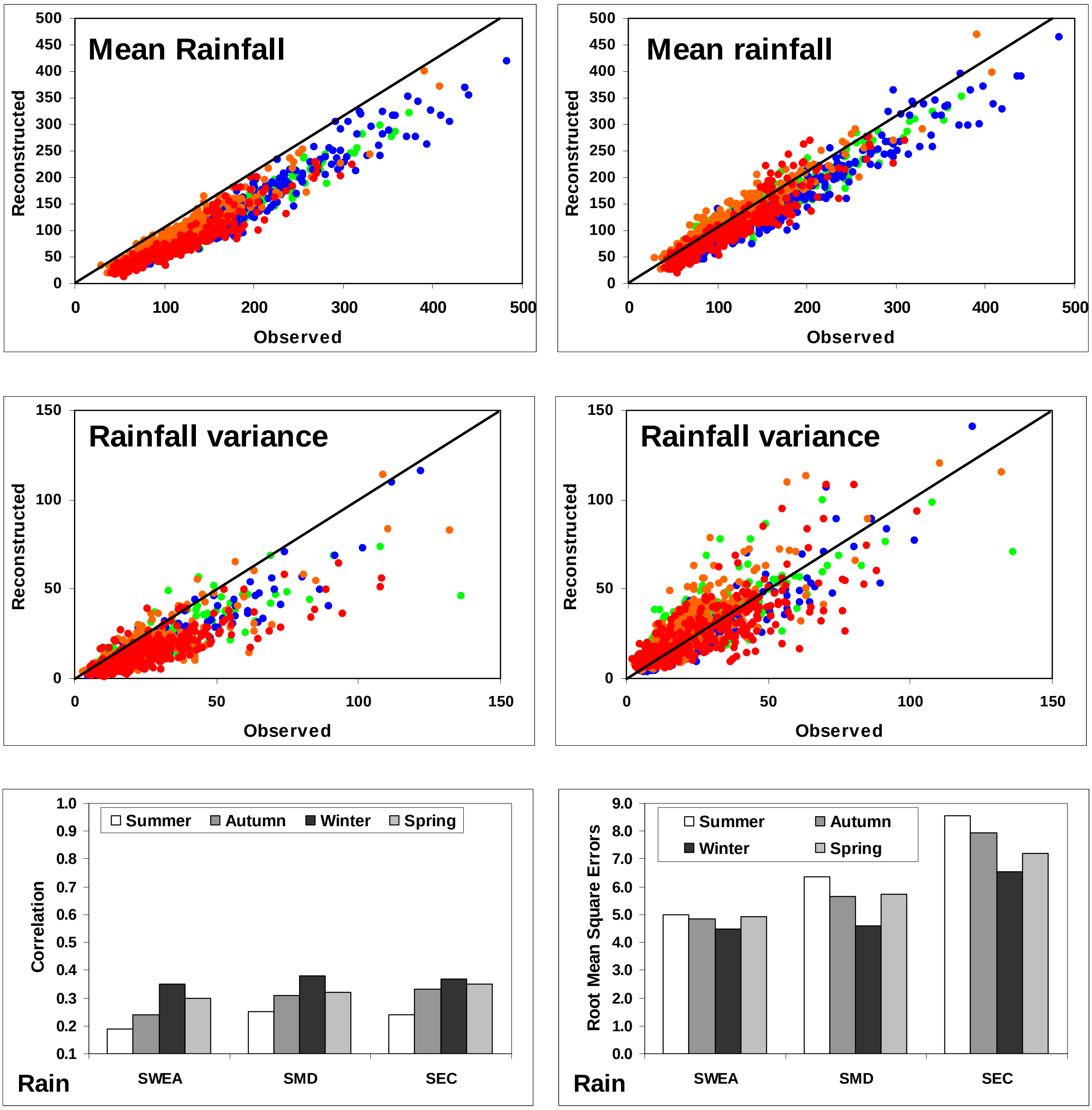

Fig 2: *As per Fig. 1 but for rainfall. The additional two scatter plot of the reconstructed versus observed mean and variance (in the right column) are for rainfall with an inflation factor applied to the reconstructed series (see main text for details). Units are mm.*

It was decided that the same very simple factor should be applied without further adjustment to limit some of the danger linked to artificially inflating the variance when using downscaling techniques (von Storch, 1999). The following single factor was used

$$C_{factor} = 1. + 0.10 \times \frac{N_{dry}}{N_{wet}} \quad \text{And} \quad C_{factor} \leq 1.5$$

Where N_{dry} and N_{wet} are the numbers of dry and wet (> 0.3mm) days observed for the season at an individual location. These numbers are station and season dependent. They are calculated on the available observations from which analogues are drawn and are therefore independent of the series being reconstructed. These ratios are equally applicable when developing the downscaling model (and hence evaluating their impact) or when downscaling climate simulations.

The impact of the inflation factor is clear (right plots in the first two rows of Fig. 2). It has dramatically reduced the variance bias and lead to an un-bias reproduction of the mean (as was the case for temperature) and un-biased reproduction of the variance (therefore better than for temperature). However, the spread of the reconstructed versus observed mean of the series is unchanged with the uncorrected series and is larger than with temperature.

For rainfall, correlations are by far lower than for temperature, although due to the very large sample considered (about 2000 days); all these correlations are significant at least at the 95% level, indicating some level of skill. Correlations peak in winter (up to 0.3 to 0.4) and are particularly low for the dry season: summer and autumn in the case of SWEA. These low correlations are confirmed by the high values for RMSEs. The largest errors are seen in summer and the smallest in winter thus confirming that the SDMs are more skilful for rainfall in winter.

Dew-point temperature:

Finally the skill of the model on newly formed high-quality dataset is evaluated, starting with dew-point temperature (Lucas, 2006): daily maximal (dT_{max}) and daily minimum (dT_{min}). In the case of daily extreme dew-point temperature, the development period is 1958 to 1982 and the validation period is 1983 to 2003 (as the high quality dataset has not been updated past that point).

Results are very similar than for temperature, the SDMs are able to reproduce the mean of the observed series very accurately (with slightly larger errors for dT_{min}). The underestimation of the variance is again visible: ranging between 11.6% in summer and 4.4% in autumn for dT_{max}, and from 16.7% in winter and 7.7% in spring for dT_{min}. As for temperature, daily values of dew-point temperature are not far from being normally distributed, and hence the underestimation of the variance does not have a flow-on effect on the reproduction of the mean.

Correlations between reconstructed and daily series for dT_{max} have a lot in common with results for temperature, albeit with correlation being overall lower. Lowest correlation are in winter but corresponds to low RMSEs as well, hence not suggesting less skilful SDMs. Highest correlation are seen during the “transition season” autumn and spring and largest RMSEs tend to be in summer. In the case of dT_{min} results are very homogeneous across seasons and regions. The exception being SMD during the spring and summer when RMSEs are much larger and correlation are rather low thus suggesting that the model is less skilful during the warmer seasons in this region.

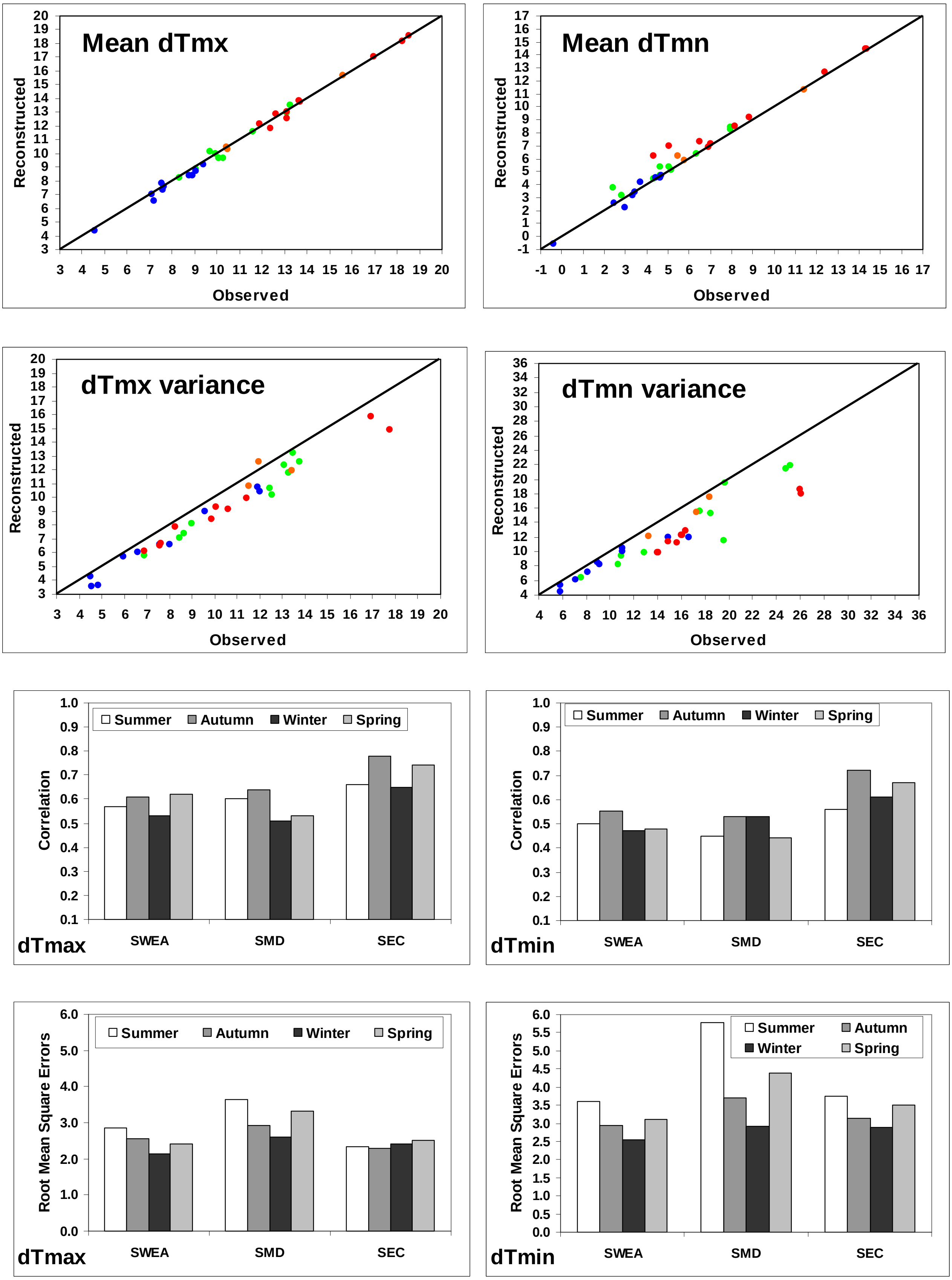

Fig 3: *As per Fig. 1 but for daily maximum dew point temperature (left) and daily minimum dew point temperature (right). Units for mean, variance and RMSE are ºC.*

Pan-evaporation:

Finally in the case of pan-evaporation, for which the high quality dataset span a shorter period (Jovanovic et al., 2008), the development period is 1975 to 1988 and the validation period is 1989 to 2003 (as the high quality dataset has not been updated past that point).

As for the other variables, the mean of the reconstructed series is very accurate although some errors up to 1 $mm.day^{-1}$ are noticeable during the warmer seasons (spring and summer). Errors on the variance can be quite large, up to 3 $mm.day^{-1}$ in some instances, but there is a slightly lesser bias toward a reduction of the variance. The mean variance bias is between 13.7% in winter and only 1.6% in spring.

The skill of the SDMs in reproducing day-to-day variability varies a lot form one season to another according to the correlation: it is high for the transitions seasons and low in winter (especially in SMD and SWEA) and in summer (especially in SEC). However the RMSEs suggest that the low correlations in winter are partly due to very small day to day variability thus giving very small RMSEs. On the contrary in summer, the low correlation and high RMSEs suggest that the SDMs have less skill.

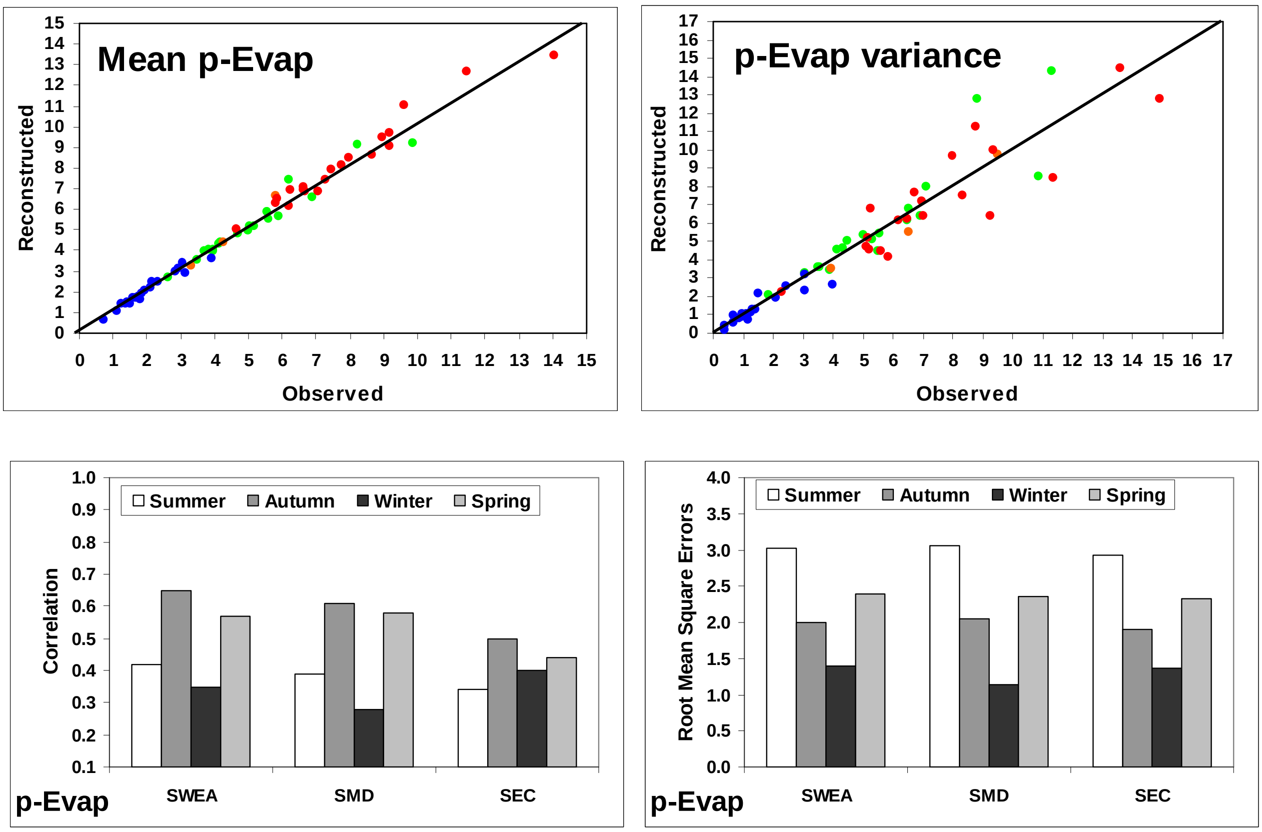

Fig 4: *As per Fig. 1 but for pan-Evaporation. Units for mean, variance and RMSE are mm.day*$^{-1}$.

Conclusions:

Overall the evaluation of the skill of the SDMs has shown that:

- The results are fairly consistent across the three regions thus confirming that the analogue approach is a suitable downscaling method for mid-latitude temperate climate;
- The reproduction of the mean of the observed series (in a fully cross-validated sense) is very accurate with the exception of rainfall;
- For all variables, the reconstructed series does under-estimate the observed variance, this underestimation varies from one predictand to another and is largest for rainfall;
- In the case of rainfall, because the daily PDFs is not near normally distributed the reduced variance leads to a dry bias, this dry bias can be reduced with a very simple and robust inflation factor;
- Best skills tend to be achieved for most variables during the “transition seasons” autumn and spring;
- Correlations in winter are often low but this is often because the day-to-day variability in winter is low rather than because the model is less skilful; and
- In contrast, for all variables but daily temperature extremes, the model tends to have less skill (low correlation and high RMSEs) in summer.

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