Statistical downscaling of general circulation model outputs to evaporation, minimum temperature and maximum temperature using a key-predictand and key-station approach

D. A. Sachindra, F. Huang, A. F. Barton and B. J. C. Perera

ABSTRACT

A key-predictand and key-station approach was employed in downscaling general circulation model outputs to monthly evaporation, minimum temperature ($T_{\text{min}}$) and maximum temperature ($T_{\text{max}}$) at five observation stations concurrently. $T_{\text{max}}$ was highly correlated (magnitudes above 0.80 at $p \leq 0.05$) with evaporation and $T_{\text{min}}$ at each individual station, hence $T_{\text{max}}$ was identified as the key predictand. One station was selected as the key station, as $T_{\text{max}}$ at that station showed high correlations with evaporation, $T_{\text{min}}$ and $T_{\text{max}}$ at all stations. Linear regression relationships were developed between the key predictand at the key station and evaporation, $T_{\text{min}}$ and $T_{\text{max}}$ at all stations using observations. A downscaling model was developed at the key station for $T_{\text{max}}$. Then, outputs of this downscaling model at the key station were introduced to the linear regression relationships to produce projections of monthly evaporation, $T_{\text{min}}$ and $T_{\text{max}}$ at all stations. This key-predictand and key-station approach was proved to be effective as the statistics of the predictands simulated by this approach were in close agreement with those of observations. This simple multi-station multivariate downscaling approach enabled the preservation of the cross-correlation structures of each individual predictand among the stations and also the cross-correlation structures between different predictands at individual stations.

Key words | downscaling, general circulation model, key predictand, key station

INTRODUCTION

General circulation models (GCMs) are considered as the most reliable tools available for the projection of global climate into the future (Anandhi et al. 2008). These GCMs are based on the physics of the atmosphere and they project the climate hundreds of years into the future considering the greenhouse gas (GHG) concentrations in the atmosphere. The resolution of the outputs of modern GCMs is still in the order of a few hundred kilometres (Tripathi et al. 2006). This coarse spatial resolution of GCM outputs hinders their direct application at the catchment scale. This is because the climate information needed by most of the catchment scale studies is much finer in spatial resolution than that of GCM outputs. As a solution to this resolution mismatch, downscaling techniques have been developed. They relate the coarse resolution GCM outputs to the catchment scale hydroclimatic variables. There are two classes of downscaling techniques in use: (1) dynamic downscaling and (2) statistical downscaling. In dynamic downscaling, a finer resolution regional climate model is nested in a coarse resolution GCM (Murphy 1998). On the other hand, in statistical downscaling, empirical relationships between the GCM outputs and the catchment scale hydroclimatic variables are determined (Hay & Clark 2003). Reviews on dynamic and statistical downscaling techniques can be found in Fowler et al. (2007), Maraun et al. (2010) and Sachindra et al. (2014c).
Statistical downscaling exercises are performed at individual stations (e.g. Tripathi et al. 2006) and also at multiple stations simultaneously (e.g. Jeong et al. 2013a, b). When downscaling is performed at individual stations, a separate downscaling model is developed at each station. In such a case, no explicit attempt is made to maintain the spatial correlations (cross-correlations) seen among the observations of stations, in the outputs of the downscaling models. When downscaling is performed at multiple stations simultaneously, explicit measures are made to preserve the spatial correlation structure among the stations. This enables the realistic representation of spatial variations of the climatic variable of interest, over the study area. Khalili et al. (2011) found that neglecting the spatial correlation structure among precipitation and temperature data generated at multiple stations may result in large under-predictions of high streamflows estimated using a hydrologic model fed with those precipitation and temperature data. Cannon (2008) stated that maintaining the correlations among the outputs of downscaling models developed at precipitation stations in a certain study area is critical as spatial variations of precipitation can significantly influence the streamflow. Furthermore, Jeong et al. (2013a) commented that projections of precipitation produced at multiple stations considering the spatial coherence is quite important in the management of water resources. However, it should be noted that, under changing climate the observed spatial structures between the stations. Also when downscaling is performed at multiple stations concurrently, the accuracy at each individual station may tend to decrease as spatial correlations among a number of stations have to be maintained in parallel.

A weather generation technique was used by Wilks (1999) to generate daily precipitation, minimum temperature, maximum temperature and solar radiation simultaneously at 62 stations over the western USA. The conditional resampling method was employed by Wilby et al. (2003) in order to downscale daily precipitation from GCM outputs to multiple locations in the UK. Mehrotra et al. (2006) used parametric (hidden Markov model) and non-parametric (k-nearest neighbour) weather generation techniques for the generation of precipitation occurrences at multiple stations simultaneously. It was concluded that the parametric multi-station weather generation techniques are associated with a large number of parameters in comparison to non-parametric weather generators. The concept of spatial autocorrelation (degree of dependence of observations over space) was used in a weather generator by Khalili et al. (2007) for the generation of daily precipitation at multiple stations. The same concept was employed in the generation of daily maximum temperature, minimum temperature and solar radiation at multiple stations concurrently by Khalili et al. (2009). Again Khalili et al. (2011) used the concept of spatial autocorrelation for the generation of daily precipitation and temperature at multiple stations concurrently (considering each predictand separately) over a catchment in Canada, which were then used in a hydrologic model to simulate streamflow in the catchment. Khalili et al. (2013) used a linear regression technique for linking the GCM outputs to catchment scale maximum temperature and minimum temperature and then the spatial dependence structures among the stations for the two predictands were determined using a stochastic technique. It was found that this multi-station multivariate downscaling methodology was able to reproduce the spatial and temporal characteristics of maximum temperature and minimum temperature with good accuracy. Jeong et al. (2012) applied the multivariate multi-linear regression (MMLR) technique for downscaling GCM outputs to daily maximum temperature and daily minimum temperature concurrently at nine stations in Canada. In that study it was found that the addition of spatially correlated random noise (randomization process) between the predictands and the stations to the deterministic time series of the predictands produced by the MMLR technique could aid in correctly reproducing the cross-correlation structures of predictands between the stations and the cross-correlation structures between the two predictands at individual stations. The MMLR technique combined with a stochastic weather generation technique was used by Jeong et al. (2013b) for downscaling reanalysis outputs to daily precipitation, simultaneously at nine observation stations in
Canada. In that study, it was found that the use of the stochastic weather generation technique (along with the regression technique) enhanced the capabilities of the downscaling model in capturing the spatial and temporal characteristics of precipitation. Liu et al. (2009) developed the MODAWEC (MONTHLY TO DAILY WEATHER CONVERTER) model, which is a parametric weather generator for generating daily precipitation, maximum and minimum temperature using their corresponding monthly values, while preserving the monthly totals and averages. The MODAWEC weather generator can be used for downscaling of daily climatic variables from monthly GCM outputs. The applications of the MODAWEC weather generator are found in Liu & Yang (2010) and Liu et al. (2013). More applications of multi-station weather generation techniques are found in the studies by Qian et al. (2002), Kottegoda et al. (2003), Apipattanavis et al. (2007) and Bárdossy & Pegram (2009).

The majority of the existing multi-station and multi-station multivariate downscaling techniques are quite complex in nature. Hence there is a need for simple yet effective multi-station and multi-station multivariate downscaling techniques (e.g. Maraun et al. 2010). Unlike the complex multi-station downscaling techniques used in the previous studies, in the present study a relatively simple yet effective multi-station multivariate downscaling methodology was investigated. In the present study, a key-predictand and key-station approach was used for simultaneously downsampling GCM outputs to monthly evaporation, minimum temperature and maximum temperature at several observation stations. Using this key-predictand and key-station approach the cross-correlation structures for each predictand among the stations and also the cross-correlation structures among different predictands at individual stations can be preserved. Hence the key-predictand and key-station approach allows the plausible representation of the spatial variations of each predictand and also aids in maintaining realistic representation of the relationships among different predictands considered in a downscaling exercise. Furthermore, since downscaling models are developed only at the key stations for the key predictands, the predictor selection, calibration and validation of the downscaling models and the bias-correction have to be performed only for a limited number of predictands at a limited number of stations.

However, it should be noted that for the effective implementation of the key-predictand and key-station approach, the predictands of interest should be highly correlated (preferably magnitudes above 0.80 at $p \leq 0.05$) with each other over space. If these spatial correlations are low, the overall effectiveness of this approach becomes limited. Details of the key-predictand and key-station approach employed in this study are provided later in the paper.

Evaporation is one of the many processes responsible for the loss of water from a catchment. Temperature variations are directly influential on the changes in the evaporation, snow melt, etc. (King et al. 2014). Therefore, evaporation, minimum temperature and maximum temperature were considered as the catchment scale predictands in this study. For the demonstration of the methodology, five observation stations located in the operational area of the Grampians Wimmera Mallee Water Corporation (GWMWater) in north western Victoria, Australia were considered in this study. This region contains several large water supply reservoirs which supply water to a large number of domestic and industrial users. Also this area is quite sensitive to severe droughts (Barton et al. 2011). Hence, the determination of dependable point scale climatic information pertaining to likely future climate over the study area was identified as an important task.

### STUDY AREA AND DATA

The study area is located in the southern region of the operational area of the GWMWater (GWMWater 2013). The operational area (62,000 km$^2$) of GWMWater is located in the north western part of Victoria, Australia and is shown in Figure 1. The study area is mountainous and does not have a clear dry season (Bureau of Meteorology 2013) in comparison with the northern region of the operational area of the GWMWater, which is relatively flatter and persistently dry. This study area contains some important water supply reservoirs such as Lake Taylor, Lake Lonsdale, Lake Bellfield and Rockland Reservoir, several rivers such as Wimmera River and Glenelg River and some agricultural production areas. Hence the study of impact of climate change over this area was identified as a timely need.
For the demonstration of the methodology five observation stations were considered in this study and they are shown with their latitudes and longitudes in Table 1 (refer to Figure 1 for relative locations of stations). Over the period 1950–2010, the observations of monthly evaporation, maximum temperature and minimum temperature at the five stations considered in this study displayed high positive correlations with those at other stations (Ouyen Post Office, Longerenong, Halls Gap Post Office, Birchip Post Office, Great Western, Swan hill Post Office, Rainbow, Wartook Reservoir, Hamilton Airport, Stawell, Eversley, Ararat Prison) located across the operational area of GWMWater. Therefore, it was assumed that the likely changes in the future climate at the other stations located in the operational area of GWMWater will be consistent with those at the five stations considered in this study.

Observations of daily evaporation, maximum temperature and minimum temperature for the five observation stations, were obtained from the SILO database of Queensland Climate Change Centre of Excellence (QCCCE 2013) for the period 1950–2010. These daily observations were added to derive the corresponding monthly observations at each station. Monthly observations were used for the computation of correlations between the predictands at stations in identifying key predictands and key stations.

Table 1 | Stations considered in this study

<table>
<thead>
<tr>
<th>Name of the station</th>
<th>Station ID</th>
<th>Latitude</th>
<th>Longitude</th>
</tr>
</thead>
<tbody>
<tr>
<td>Polkemmet</td>
<td>79023</td>
<td>–36.66</td>
<td>142.07</td>
</tr>
<tr>
<td>Lake Lonsdale</td>
<td>79026</td>
<td>–37.03</td>
<td>142.58</td>
</tr>
<tr>
<td>Moyston Post Office</td>
<td>79034</td>
<td>–37.30</td>
<td>142.77</td>
</tr>
<tr>
<td>Tottington</td>
<td>79079</td>
<td>–36.79</td>
<td>143.12</td>
</tr>
<tr>
<td>Balmoral Post Office</td>
<td>89003</td>
<td>–37.25</td>
<td>141.84</td>
</tr>
</tbody>
</table>

Station ID is as defined by the Bureau of Meteorology Australia at http://www.bom.gov.au/climate/data/stations/.
Also these observations were used in calibration and validation of the downscaling models developed at the key stations. Furthermore, the observations were used as the reference data set for the correction of bias in the outputs of the downscaling models.

National Centers for Environmental Prediction/National Center for Atmospheric Research (NCEP/NCAR) reanalysis outputs were obtained from the physical sciences division of the National Oceanic and Atmospheric Administration/Earth System Research Laboratory (NOAA/ESRL) (NOAA/ESRL 2013), for providing inputs to the downscaling models in their calibration and validation phases. To reproduce the past observations of key predictands using the downscaling models, the 20th century climate experiment (20C3M) outputs of ECHAM5 (a GCM) were extracted from the Programme for Climate Model Diagnosis and Inter-comparison (PCMDI) (PCMDI 2013) over the period 1950–1999. Also ECHAM5 outputs pertaining to the A2 GHG emission scenario were obtained for the period 2000–2099, from PCMDI, for the projection of catchment scale climate into the future.

Smith & Chandler (2009) stated that a few GCMs including ECHAM5 are capable of correctly simulating the precipitation over Australia and also able to produce credible predictions of El Niño Southern Oscillation (ENSO). They also argued that, a GCM which can correctly simulate precipitation should be able to simulate other climatic variables with a good degree of accuracy. Therefore, for the present study, the outputs of ECHAM5 were used. The A2 GHG emission scenario of the Intergovernmental Panel on Climate Change was used in this study as it refers to relatively higher amounts of GHGs in the atmosphere in the future. Therefore, the projections produced based on the A2 GHG emission scenario will refer to high levels of impact on the environment.

**Identification of key predictands and groups**

In this paper, a key predictand refers to a climatic variable (e.g. evaporation, temperature) which is highly correlated (magnitude above 0.80 at $p \leq 0.05$) with other climatic variables of interest at each individual observation station, in a group of observation stations, located in a certain study area. If the study area contains only one observation station, a predictand which is highly correlated with other predictands at that station becomes the key predictand.

As a simple example consider the three predictands $P_1$, $P_2$ and $P_3$ at the five observation stations $S_{1}, S_{2}, S_{3}, S_{4}$ and $S_{5}$ located in a certain study area. For the identification of key predictands, initially, the Pearson correlations (Pearson 1895) among the observations of different predictands were computed for each individual observation station (intra-station correlations), considering all calendar months together. Then at each observation station, the predictand combinations (e.g. $P_1$ and $P_2$; referred later in this paragraph as $P_1 - P_2$) which showed high correlations (magnitude above 0.80 at $p \leq 0.05$) were identified as shown in Figure 3. Note that in Figure 3, high correlations were denoted with a ✓ and relatively low correlations were indicated with a ×. Thereafter, groups of stations were identified based on the highly correlated combinations of predictands common to the stations. For example, as shown in Figure 3, at stations $S_{1}, S_{2}$ and $S_{5}$ predictand combinations $P_1 - P_2$ and $P_2 - P_3$ showed high correlations. Therefore stations $S_{1}, S_{2}$ and $S_{5}$ were considered under group 1. At these stations predictand $P_2$ was common to both predictand combinations which showed high correlations. Hence predictand $P_2$ was identified as the key predictand for group 1. At stations $S_{3}$ and $S_{4}$ predictand combinations $P_1 - P_3$ and $P_2 - P_3$ showed high correlations. Therefore stations $S_{3}$ and $S_{4}$ were considered as group 2 (see Figure 3). Since predictand $P_3$ was common to both $P_1 - P_3$ and $P_2 - P_3$ predictand combinations, it was identified as the key predictand for group 2. In the same manner, this procedure can be extended to $n \ (\leq Z^+) \ \text{number of stations and } m \ (\leq Z^+) \ \text{number of predictands}$ for the identification of key predictands and groups of observation stations.

Note that, at times, there can be one single key predictand over the entire study area, as this predictand shows high correlations with all other predictands, at all stations.
Figure 2 | Steps involved in application of the key-predictand and key-station approach.
Also the maximum number of key predictands is always equal to the total number of predictands considered in the study. The maximum number of groups is also equal to the total number of predictands, as each group is governed by a key predictand.

**Identification of key stations and clusters**

Once the key predictands were identified, as the next step, key stations were determined over the study area. In this paper, a key station is an observation station where a key predictand (refer to previous section) is highly correlated (magnitude above 0.80 at \( p \leq 0.05 \)) with all predictands (this also includes the key predictand) in a cluster of observation stations located within a group of observation stations governed by that key predictand. The key station and the other stations which showed high correlations between the key predictand and all predictands were defined as a cluster of stations. These other stations in a cluster were referred to as the member stations. Note that a group of stations can have one or more clusters and each cluster is governed by a key station.

In order to determine the key stations, the correlations between the key predictands and all predictands of interest were computed at all stations in each group of stations, identified in the previous section. For this purpose, at each station, data of each predictand for all calendar months together were considered. The above procedure yielded correlation matrices between each key predictand and all predictands of interest in each group. In other words, one correlation matrix for each key predictand and each of the predictands of interest was computed. Then for each of these correlation matrices, a threshold with a magnitude of 0.80 was imposed. In a group, a certain station in which the key predictand showed the highest number of high correlations with all predictands of interest was identified as the first key station. Note that, when a certain key predictand at several stations shows the highest number of high correlations with all predictands of interest, any such station can be considered as a key station. The key station and the other stations which showed high correlations between the key predictand and all predictands were defined as a cluster of stations. Then the same procedure was repeated on the rest of the stations in the group. This procedure was continued until all stations in all groups were assigned to clusters.

As an example, in Figure 4 (same stations and predictands as in Figure 3), in group 1, if the key predictand \( P_2 \) at station \( St_1 \) showed high correlations with predictands \( P_1, P_2 \) and \( P_3 \) (all predictands of interest) at station \( St_2 \) and relatively low correlations with those predictands at
station $S_{t_3}$, then station $S_{t_1}$ becomes the key station of cluster 1 and station $S_{t_2}$ becomes a member station of that cluster. In such a case, station $S_{t_3}$ becomes the second key station in group 1 since it is the only remaining station in the group. Likewise, in group 2, if key predictand $P_3$ at station $S_{t_3}$ was highly correlated with predictands $P_1$, $P_2$ and $P_3$ (all predictands of interest) at station $S_{t_4}$, then station $S_{t_3}$ becomes the key station and station $S_{t_4}$ becomes a member station of cluster 2.

Intra- and inter-station regression relationships in clusters

Once the key predictands and key stations were identified, simple linear regression equations were built between the key predictands at key stations and other predictands at the key stations in all clusters using observations. These regression equations are referred to as the intra-station regression relationships in this paper. Also simple linear regression equations were developed between the key predictands at key stations and all predictands at the member stations in all clusters using observations. In this paper, these regression equations are called the inter-station regression relationships.

All simple linear regression relationships (intra- and inter-station) between the predictands were computed for each calendar month separately. This was done in order to better capture the seasonal variations in the relationships between the predictands. The first two-thirds of the observations of predictands were used for the calibration of intra- and inter-station regression relationships, while the rest of the observations were used for the validation of these relationships (derived in the calibration). In the calibration of the intra- and inter-station regression relationships, the optimum values of the coefficients and the constants of the equations were determined by minimizing the sum of squared errors between the observations and the outputs of these regression relationships.

Atmospheric domain and predictor selection

Once intra- and inter-station regression relationships were determined in each cluster, an atmospheric domain was defined over the study area. The atmospheric domain enables the inclusion of the influences of the atmospheric circulations on the catchment scale climate which is modelled by the downscaling models. The same atmospheric domain was used for the development of downscaling models at all key stations for all key predictands.

The probable predictors for the study were selected for each key predictand separately, from the past literature and based on principles of hydrology. The probable predictors were the likely predictors to influence a certain key predictand at the catchment scale. The pool of probable predictors varies from one key station to another. The potential predictors are subsets of probable predictors which vary seasonally and also from one key station to another. These potential predictors are the most influential predictors on a certain key predictand at a key station.

In this study, the correlations between the reanalysis data (e.g. NCEP/NCAR) of probable predictors and the observations of the key predictands at the key stations were used as the basis for the extraction of potential predictors, from the pool of probable predictors. The reanalysis data pertaining to the probable predictors, and the observations of the key predictands at key stations were split into 20 year time slices (in this study 1950–1969, 1970–1989 and 1990–2010), in chronological order. Then, for each calendar month, the Pearson correlation coefficients between the probable predictors and the key predictand at each key station were computed for each time slice and the whole period of the study (in this study 1950–2010), at all grid points in the atmospheric domain. The probable predictors which showed the best correlations ($p \leq 0.05$) with a key predictand at a key station, consistently, in all time slices and the whole period of the study were extracted as the potential predictors for that key predictand at that key station. The extraction of potential predictors was practised for each calendar month separately as it can yield sets of potential predictors which can reflect the seasonal variations of the atmospheric conditions. Sachindra et al. (2013, 2014a) successfully used the above procedure, for the selection of potential predictors in the development of models used for statistically downscaling NCEP/NCAR reanalysis outputs to monthly streamflows and monthly precipitation.
Development of downscaling models for key predictands at key stations

For each key predictand at each key station, downscaling models were then developed (calibrated and validated). The first two-thirds of the reanalysis data pertaining to the potential predictors and the observations of the key predictands at key stations were used for the calibration of the downscaling models. The rest of the data were used for the validation of these models. The reanalysis data pertaining to the calibration and validation phases of the downscaling models were standardized using the means and the standard deviations of those corresponding to the calibration phase, for each calendar month separately. The means and the standard deviations of the reanalysis data pertaining to the calibration period of the downscaling models were considered as fixed components of them.

In calibration of a downscaling model for a key predictand at a key station (in a cluster), first the standardized data of the potential predictor which displayed the best correlation with the observations of the key predictand of interest over the whole period of the study was introduced to the downscaling model. Then by minimizing the sum of squared errors between the model outputs and the observations, the optimum values of the constant and the coefficient of the linear regression equation were determined. The performances of the downscaling model in calibration were also monitored using the Nash-Sutcliffe efficiency (NSE) (Nash & Sutcliffe 1970). Thereafter the reanalysis data of that predictand pertaining to the validation period were introduced to the downscaling model while keeping the optimum values of the constant and the coefficient of the linear regression equation determined in calibration fixed. During the validation, the performance of the downscaling model was measured using the NSE. Then the next best potential predictors based on their correlations with the key predictand of interest over the whole period of the study were added to the downscaling model at the key station of interest, one at a time. The downscaling model was calibrated and validated, following the addition of each predictand. It produced multi-linear regression equations between the key predictand and the potential predictors introduced to the downscaling model. This procedure was performed until the model performance in validation reached a maximum in each calendar month. This procedure yielded the best set of potential predictors and the optimum downscaling model for each calendar month. In this manner, downscaling models were developed for each key predictand at each key station in each cluster in each group. The performances of the downscaling models built for each key predictand at each key station were assessed numerically by comparing the statistics of the model outputs with those of observations. Also the model outputs were graphically compared with the observations using scatter plots.

Reproduction of past observations of key predictands and bias-correction

Once the downscaling models were developed for the key predictand at the key station in each cluster in each group, the 20C3M outputs of the GCM (in this study ECHAM5) were standardized with the means and the standard deviation of the reanalysis outputs corresponding to the calibration period. This procedure was practised for each calendar month separately. Then, the past observations of the key predictands at the key stations were simulated, by introducing these standardized 20C3M outputs of the GCM to the downscaling models developed in the previous section. This analysis enabled the assessment of the performances of the downscaling models (developed with reanalysis data) in reproducing the past climate with the 20C3M outputs of the GCM. This analysis was important as these downscaling models which were developed with better quality reanalysis outputs were meant to be used with GCM outputs which have a higher degree of uncertainty, for the projection of catchment scale climate into the future.

The bias contained in GCM outputs can cause downscaling models to produce erroneous projections into the future. According to Salvi et al. (2011), bias is the mismatch between the GCM outputs and the observations. Ojha et al. (2013) emphasized the importance of bias-correction in downscaling. Hence, it was realized that either the bias in the GCM outputs (which are used as inputs to the downscaling model) or the bias in the outputs of the downscaling models run with the GCM outputs should be corrected prior to any use (Sachindra et al. 2014b). In the current study, the monthly bias-correction (refer to Johnson & Sharma (2012)
for theory) was used on the outputs of the downscaling models produced when they were run with the 20C3M outputs of the GCM. The monthly bias-correction assumes that the bias in the means and the standard deviations of the outputs of the downscaling models produced for the past will remain the same in future.

In the application of the monthly bias-correction, outputs of the downscaling models pertaining to the calibration period produced with the 20C3M outputs of the GCM were standardized with their means and standard deviations corresponding to the same period. Then these standardized outputs of the downscaling models were rescaled using the means and the standard deviations of the observations relevant to the calibration period of the downscaling model. In the validation of the monthly bias-correction, the outputs of the downscaling models produced over the validation period with the 20C3M outputs of the GCM were standardized with the means and the standard deviations of the outputs of the downscaling models produced over the calibration period with the 20C3M outputs of the GCM. Then these standardized outputs of the downscaling models were rescaled using the means and the standard deviations of the observations pertaining to the calibration period of the downscaling model. The monthly bias-correction was applied and validated for each calendar month separately.

**Development of downscaling models at a key station and a member station for a predictand not identified as a key predictand**

A downscaling model was developed at a key station (of a cluster) for downscaling reanalysis outputs to a predictand which was not identified as a key predictand. This was performed to assess the quality of the outputs produced by the intra-station regression relationships against the outputs of the downscaling model developed at that key station for that predictand which was not identified as a key predictand. In order to assess the quality of the outputs produced by the inter-station regression relationships, a downscaling model was built at a member station (of a cluster) for downscaling reanalysis outputs to a predictand which was not identified as a key predictand. For the development of these two downscaling models, the same procedure that was practised in building downscaling models for key predictands at key stations was adopted. The calibration and validation of these downscaling models were performed over the same periods as those of the downscaling models developed for key predictands at key stations in each cluster. The outputs of the intra-station and inter-station regression relationships were compared with those of downscaling models, both numerically and graphically.

**Projections into the future**

For producing projections of catchment scale climate into the future, the outputs of a GCM (in this study ECHAM5) pertaining to the future climate were obtained. Then these GCM outputs were standardized using the means and the standard deviations of the reanalysis outputs relevant to the calibration period of the downscaling models, for each calendar month. Thereafter these standardized GCM outputs were introduced to the downscaling models which were developed at key stations for key predictands. This way, at the key stations, the projections of the key predictands were produced into the future. The projections of the key predictands produced at key stations were then bias-corrected using the monthly bias-correction following the procedure employed in the validation of the bias-correction which was detailed in the section entitled ‘Reproduction of past observations of key predictands and bias-correction’. Then these bias-corrected projections were introduced to the intra- and inter-station regression relationships for the projection of catchment scale climate into the future at all stations in each cluster in each group.

**APPLICATION**

The generic methodology detailed previously was used to downscale monthly GCM outputs to monthly evaporation, minimum temperature and maximum temperature at the five observation stations (see Table 1) located in the southern region of the operational area of GWMWater, in north western Victoria, Australia (see Figure 1).
Identification of key predictands

For the identification of the key predictands, the correlations among the three predictands, evaporation, minimum temperature and maximum temperature, were computed at each individual station using the monthly observations of these predictands of the period 1950–2010. Table 2 shows these correlations.

According to Table 2, at all stations all predictand combinations (e.g. evaporation – maximum temperature) showed correlations above 0.80 (p ≤ 0.05). Therefore it was realized that there are strong linear relationships between evaporation, minimum temperature and maximum temperature at all stations. Then at each individual station, the predictand which showed high correlations with all other predictands was identified. It was seen that, at all stations, maximum temperature showed the highest correlations with the other two predictands (evaporation, minimum temperature). Hence, the maximum temperature was identified as the only key predictand and all five stations were included in one group governed by this key predictand. Furthermore, evaporation displayed consistently higher correlations with maximum temperature than with minimum temperature. This indicated that maximum temperature is more influential than minimum temperature on evaporation.

Identification of key stations and clusters

Since maximum temperature was identified as the only key predictand, the correlations between the maximum temperature and all predictands (i.e. evaporation, minimum temperature and maximum temperature) over the period 1950–2010 were computed at all stations using observations.

Table 3 shows the correlations between the maximum temperature and all predictands at all stations.

According to Table 3, it was seen that the observations of maximum temperature at all stations were highly correlated (p ≤ 0.05) with those of evaporation, minimum temperature and maximum temperature at all stations over the period 1950–2010. Therefore any station was seen as a potential key station and also all five observation stations were considered in one cluster. In this study, the observation station at Lake Lonsdale (79026) was selected as the only key station. Hence, stations at Polkemmet (79023), Moyston Post Office (79034), Tottington (79079) and Balmoral Post Office (89003) were identified as the member stations of the only cluster defined in this study. Note that in this study, both the group and the cluster referred to the same set of stations as there was only one cluster located within the only group identified. Figure 1 shows the locations of the key station and the member stations identified in this study along with some of the water resources (lakes and rivers) in the region.

Intra- and inter-station regression relationships

Following the procedure stated in the ‘Generic methodology’ section, intra- and inter-station regression relationships were developed (calibrated and validated). The calibration and validation of the intra- and inter-station regression relationships were performed over the periods 1950–1989 and 1990–2010, respectively.

The intra-station regression relationships were developed at the key station 79026, between the maximum temperature (key predictand) and evaporation, and also between the maximum temperature and minimum temperature. The inter-station regression relationships were developed between the maximum temperature at the key station 79026 and evaporation, minimum temperature and maximum temperature at each member station of the cluster.

Table 4 shows the statistics of the monthly evaporation at all stations reproduced by the intra- and inter-station regression relationships built between the maximum temperature and evaporation. According to Table 4, the intra- and inter-station regression relationships were able to reproduce the average and the standard deviation of monthly

Table 2 | Correlations among evaporation, minimum temperature and maximum temperature at each individual station

<table>
<thead>
<tr>
<th>Station</th>
<th>79023</th>
<th>79026</th>
<th>79034</th>
<th>79079</th>
<th>89003</th>
</tr>
</thead>
<tbody>
<tr>
<td>Evaporation-Tmax</td>
<td>0.953</td>
<td>0.951</td>
<td>0.952</td>
<td>0.951</td>
<td>0.949</td>
</tr>
<tr>
<td>Evaporation-Tmin</td>
<td>0.876</td>
<td>0.878</td>
<td>0.864</td>
<td>0.879</td>
<td>0.861</td>
</tr>
<tr>
<td>Tmax-Tmin</td>
<td>0.929</td>
<td>0.949</td>
<td>0.944</td>
<td>0.955</td>
<td>0.939</td>
</tr>
</tbody>
</table>

Tmax – monthly maximum temperature, Tmin – monthly minimum temperature.
### Table 3  
Correlations between observations of key predictand and all predictands

<table>
<thead>
<tr>
<th>Key predictand</th>
<th>Other predictand</th>
<th>Station 79023</th>
<th>79026</th>
<th>79034</th>
<th>79079</th>
<th>89003</th>
</tr>
</thead>
<tbody>
<tr>
<td>$T_{\text{max}}$</td>
<td>Evaporation</td>
<td>0.953</td>
<td>0.953</td>
<td>0.955</td>
<td>0.948</td>
<td>0.955</td>
</tr>
<tr>
<td>$T_{\text{max}}$</td>
<td>$T_{\text{min}}$</td>
<td>0.929</td>
<td>0.945</td>
<td>0.936</td>
<td>0.954</td>
<td>0.928</td>
</tr>
<tr>
<td>$T_{\text{max}}$</td>
<td>$T_{\text{max}}$</td>
<td>1.000</td>
<td>0.998</td>
<td>0.996</td>
<td>0.998</td>
<td>0.996</td>
</tr>
</tbody>
</table>

$r_{\text{max}}$ – monthly maximum temperature, $T_{\text{min}}$ – monthly minimum temperature.

### Table 4  
Statistics of evaporation reproduced by intra- and inter-station regression relationships of all stations between maximum temperature and evaporation

<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Season</strong></td>
<td><strong>Average</strong></td>
</tr>
<tr>
<td></td>
<td>Obs</td>
</tr>
<tr>
<td><strong>Summer</strong></td>
<td></td>
</tr>
<tr>
<td>79023</td>
<td>232.9</td>
</tr>
<tr>
<td>79026</td>
<td>211.0</td>
</tr>
<tr>
<td>79034</td>
<td>198.7</td>
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<tr>
<td>79079</td>
<td>216.3</td>
</tr>
<tr>
<td>89003</td>
<td>205.2</td>
</tr>
<tr>
<td><strong>Autumn</strong></td>
<td></td>
</tr>
<tr>
<td>79023</td>
<td>107.9</td>
</tr>
<tr>
<td>79026</td>
<td>97.5</td>
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<tr>
<td>79034</td>
<td>90.9</td>
</tr>
<tr>
<td>79079</td>
<td>96.6</td>
</tr>
<tr>
<td>89003</td>
<td>96.5</td>
</tr>
<tr>
<td><strong>Winter</strong></td>
<td></td>
</tr>
<tr>
<td>79023</td>
<td>47.7</td>
</tr>
<tr>
<td>79026</td>
<td>40.9</td>
</tr>
<tr>
<td>79034</td>
<td>37.6</td>
</tr>
<tr>
<td>79079</td>
<td>39.0</td>
</tr>
<tr>
<td>89003</td>
<td>44.1</td>
</tr>
<tr>
<td><strong>Spring</strong></td>
<td></td>
</tr>
<tr>
<td>79023</td>
<td>131.2</td>
</tr>
<tr>
<td>79026</td>
<td>115.3</td>
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<td>79034</td>
<td>108.9</td>
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<tr>
<td>79079</td>
<td>118.7</td>
</tr>
<tr>
<td>89003</td>
<td>114.7</td>
</tr>
</tbody>
</table>

Average – average of monthly evaporation in mm, Std – standard deviation of monthly evaporation in mm, Max – maximum of monthly evaporation in mm, Obs – observed, Reg – intra- or inter-station regression relationships, NSE – Nash-Sutcliffe efficiency.
evaporation with good accuracy in all seasons during the calibration period 1950–1989 and the validation period 1990–2010 at all stations. In all seasons, the intra- and inter-station regression relationships were able to reproduce the maximum of monthly evaporation at the majority of stations in both calibration and validation periods with considerable accuracy despite some under- and over-estimations. It was realized that these relationships built between the maximum temperature and evaporation were effective in translating maximum temperature to evaporation.

It was found that, the intra- and inter-station regression relationships built between the maximum temperature at key station 79026 and minimum temperature at all stations are quite robust in all seasons in capturing the average of minimum temperature. However in winter, these relationships were relatively weaker at all stations, and they under-estimated the standard deviation of the minimum temperature and the minimum of the minimum temperature was over-estimated.

It was proved that the inter-station regression relationships were able to reproduce the statistics of the maximum temperature at all member stations in all seasons with a high degree of accuracy. Hence it was realized that the inter-station regression relationships built between the maximum temperature at key station 79026 and that of member stations are quite reliable.

Atmospheric domain and predictor selection

An atmospheric domain consisting of seven grid points in the longitudinal direction and six grid points in the latitudinal direction was defined over the study area. This atmospheric domain is shown in Figure 5. In this atmospheric domain, grid points were 2.5° apart from each other in both longitudinal and latitudinal directions. This grid resolution was maintained across the atmospheric domain in order to comply with the spatial resolution of the NCEP/NCAR reanalysis outputs. All GCM outputs used in this study were interpolated to the grid shown in Figure 5, using the inverse distance weighted method.

Timbal et al. (2009) used the method of meteorological analogues for downscaling NCEP/NCAR reanalysis data to daily precipitation, pan evaporation, minimum temperature, maximum temperature and dew point temperature over six regions in the southern half of Australia. The present study area is also located in the southern half of Australia. Hence the predictors used by Timbal et al. (2009) were included in the pool of probable predictors.
used in the present study. The pool of probable predictors used in this study included the geopotential heights at 200, 500, 700, 850 and 1,000 hPa pressure levels, relative humidity at 700, 850, 925 and 1,000 hPa pressure levels, specific humidity at 500, 850 and 1,000 hPa pressure levels, air temperature at 500, 850 and 1,000 hPa pressure levels, surface air temperature, surface skin temperature, surface air pressure, mean sea level pressure, and zonal and meridional wind speeds at 850 hPa pressure level. Following the procedure detailed in the ‘Generic methodology’ section, potential predictors for maximum temperature at key station 79026 were extracted for each calendar month from the pool of probable predictors.

**Development of a downscaling model for monthly maximum temperature at key station 79026**

For the development of the downscaling model for monthly maximum temperature at the key station 79026, the observations of monthly maximum temperature and the NCEP/NCAR reanalysis outputs pertaining to the potential predictors were split into two chronological groups: 1950–1989 and 1990–2010. The first group of data was used in the calibration of the downscaling model and the second group was used in the validation. Following the procedure detailed in the ‘Generic methodology’ section, downscaling models were developed for each calendar month. Hence, the final sets of potential predictors and the best downscaling models for each calendar month were identified. When the key-predictand and key-station approach is employed in a downscaling exercise the downscaling models are developed only for the key predictands at the key stations. Therefore the selection of probable predictors and the correction of bias have to be performed only for a few predictands at a few stations.

Table 5 displays the final sets of potential predictors used in the development of the downscaling model for monthly maximum temperature at the key station 79026. According to Table 5, it was seen that in the majority of calendar months, air temperature at earth surface and also air temperature at various pressure levels in the atmosphere are among the potential predictors. This indicated the high degree of influence of air temperature fields on the monthly maximum temperature at the catchment scale. Other than air temperature, relative and specific humidity fields were also seen among the final sets of potential predictors used in the development of the downscaling model for monthly maximum temperature at the key station 79026.

---

<table>
<thead>
<tr>
<th>Month</th>
<th>Potential variables used for downscaling model with grid locations</th>
</tr>
</thead>
</table>
| January | 1,000 hPa air temperature \{5,1\}  
200 hPa relative humidity \{3,6\},\{3,7\}  
1,000 hPa specific humidity \{5,1\},\{6,2\} |
| February | 850 hPa zonal wind \{(1,1),\(2,1\),\(2,2\)\}  
500 hPa relative humidity \{(4,7),\{5,6\},\{5,7\}\}  
500 hPa specific humidity \{(1,3)\} |
| March | Surface air temperature \{(2,2)\} |
| April | 850 hPa air temperature \{(1,4),\(1,5\)\}  
850 hPa relative humidity \{(5,2),\{5,3\},\{5,4\},\{6,4\},\{6,5\}\}  
700 hPa relative humidity \{(6,5)\}  
850 hPa specific humidity \{(5,1),\{6,2\},\{6,3\}\} |
| May | 1,000 hPa relative humidity \{(2,1),\{3,1\}\}  
925 hPa relative humidity \{(1,1),\{2,1\},\{2,2\},\{3,1\},\{3,2\}\}  
500 hPa relative humidity \{(5,6)\} |
| June | Surface air temperature \{(6,2)\} |
| July | Surface air temperature \{(4,7),\{5,6\}\} |
| August | Surface air temperature \{(3,3),\{4,3\}\} |
| September | Surface air temperature \{(3,5),\{4,3\}\}  
850 hPa air temperature \{(4,5)\} |
| October | Surface air temperature \{(5,1),\{5,2\},\{5,3\},\{5,4\},\{6,1\},\{6,2\}\} |
| November | 850 hPa relative humidity \{(6,5)\}  
500 hPa specific humidity \{(6,1),\{6,2\}\} |
| December | Surface air temperature \{(2,1),\{3,1\},\{4,2\},\{4,3\},\{4,4\}\}  
500 hPa relative humidity \{(4,1),\{4,2\}\}  
500 hPa specific humidity \{(3,1),\{3,2\}\} |

hPa – Atmospheric pressure in hectopascal; and the locations are given within brackets (see Figure 5).
Table 6 shows the statistics of the observed monthly maximum temperature and those of model reproduced monthly maximum temperature for the calibration and validation periods of the downscaling model at key station 79026. As seen in Table 6, the average, the standard deviation and the maximum of the monthly maximum temperature were reproduced by the downscaling model during both calibration and validation periods in all seasons with a good degree of accuracy. Hence, it was realized that this downscaling model is capable of properly reproducing the statistics of observed monthly maximum temperature with the NCEP/NCAR reanalysis outputs.

Figure 6 shows the scatter plots for the calibration (1950–1989) and validation (1990–2010) periods of the downscaling model developed at the key station 79026 for monthly maximum temperature. Owing to the limited scatter seen in Figure 6, it was realized that there is a very good agreement between the observations of monthly maximum temperature and the monthly maximum temperature reproduced by the downscaling model, in both calibration (NSE = 0.97) and validation (NSE = 0.96) periods. However,
the scatter of the monthly maximum temperature tended to increase slightly with the increase in its magnitude during both calibration and validation periods. This indicated that the accuracy of relatively high values of monthly maximum temperature are less accurate compared to relatively low and medium values of monthly maximum temperature simulated by the downscaling model.

Reproduction of past observations of maximum temperature and bias-correction

Following the procedure detailed in the ‘Generic methodology’ section, the monthly bias-correction (Johnson & Sharma 2012) was applied over the period 1950–1989 and it was validated for the period 1990–1999. The statistics of the monthly maximum precipitation reproduced by the downscaling model with the 20C3M outputs of ECHAM5, before and after bias-correction for both application and validation periods are shown in Table 7.

According to Table 7, it was seen that the mismatches between the average, the standard deviation and the maximum of observed monthly maximum temperature and those reproduced by the downscaling model at key station 79026 when it was run with the 20C3M outputs of ECHAM5 were successfully corrected by the monthly bias-correction in both application and validation periods. Following the bias-correction, the NSEs in all seasons in both the calibration and validation periods showed an increase. This indicated that the scatter of the maximum monthly temperature reproduced by the downscaling model reduced after the bias-correction in all seasons in both calibration and validation periods. Figure 7 shows the scatter plots for the monthly maximum temperature reproduced by the downscaling model with the 20C3M outputs of ECHAM5, before and after the application of the monthly bias-correction. It was observed that the scatter of the monthly maximum temperature reproduced by the downscaling model reduced after the bias-correction.

In the application of the monthly bias-correction, explicit measures are taken only for the correction of the monthly mean and the monthly standard deviation of the variable of interest. However, it was realized that when the scatter of the variable prior to the application of the monthly bias-correction is limited (refer to Figure 7(a)), the monthly bias-correction can reduce the scatter (refer to Figure 7(b)) and improve the time series of the variable. Sachindra et al. (2014b) found that when the scatter of the variable prior to the application of the monthly bias-correction is very large the monthly bias-correction fails to reduce the scatter of the variable.

Table 7 | Statistics of maximum temperature reproduced by downscaling model at key station 79026, with 20C3M outputs of ECHAM5, before and after bias-correction

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Summer</td>
<td>Autumn</td>
</tr>
<tr>
<td>Observed</td>
<td>Avg</td>
<td>27.4</td>
<td>20.5</td>
</tr>
<tr>
<td>Before B-C</td>
<td></td>
<td>30.9</td>
<td>18.3</td>
</tr>
<tr>
<td>After B-C</td>
<td></td>
<td>27.4</td>
<td>20.5</td>
</tr>
<tr>
<td>Observed</td>
<td>Std</td>
<td>2.2</td>
<td>4.0</td>
</tr>
<tr>
<td>Before B-C</td>
<td></td>
<td>6.1</td>
<td>2.5</td>
</tr>
<tr>
<td>After B-C</td>
<td></td>
<td>2.2</td>
<td>4.0</td>
</tr>
<tr>
<td>Observed</td>
<td>Max</td>
<td>32.6</td>
<td>27.3</td>
</tr>
<tr>
<td>Before B-C</td>
<td></td>
<td>46.2</td>
<td>24.7</td>
</tr>
<tr>
<td>After B-C</td>
<td></td>
<td>31.9</td>
<td>27.5</td>
</tr>
<tr>
<td>Before B-C</td>
<td>NSE</td>
<td>−13.71</td>
<td>−0.07</td>
</tr>
<tr>
<td>After B-C</td>
<td></td>
<td>−0.37</td>
<td>0.79</td>
</tr>
</tbody>
</table>

Development of downscaling models at key station 79026 and member station 79023 for evaporation

For the purpose of comparing the quality of the outputs of an intra-station regression relationship with the outputs of the downscaling model at the key station, a downscaling model was built at the key station 79026 for evaporation which was not selected as a key predictand. This downscaling model was calibrated and validated over the periods 1950–1989 and 1990–2010, respectively, following the same procedure used in the development of a downscaling model for a key predictand.

It was found that the average, the standard deviation and the maximum of monthly evaporation reproduced by the above downscaling model at the key station 79026 were in close agreement with those of observations and those produced by the intra-station regression relationship at this station. It was assumed that the other intra-station regression relationship between the maximum temperature and the minimum temperature at key station 79026 can

Figure 7  | Scatter of the monthly maximum temperature reproduced by the downscaling model at key station 79026 with the 20C3M outputs of ECHAM5, before and after the application of the monthly bias-correction. (a) Before bias-correction; (b) After bias-correction.

Figure 8  | Evaporation reproduced by intra-station regression relationship against evaporation reproduced by downscaling model developed at station 79026. (a) Calibration (1950–1989); (b) validation (1990–2010).
also properly capture the statistics of observations of minimum temperature. Furthermore, it was realized that when the correlations between the observations of the key predictand and other predictands at a key station (in a cluster) are high, instead of developing downscaling models for each of the other predictands (at that key station) the intra-station regression relationships can be used effectively for the determination of the values of the other predictands.

**Figure 8** shows the scatter plots for the monthly evaporation simulated by the intra-station regression relationship against the monthly evaporation simulated by the downscaling model developed at key station 79026. According to the small scatter seen in **Figure 8**, it was further realized that the time series of monthly evaporation reproduced by the intra-station regression relationship and that reproduced by the downscaling model developed at key station 79026 are in good agreement with each other.

In order to compare the quality of the outputs of an inter-station regression relationship against the outputs of a downscaling model, a downscaling model was built at member station 79023 (Polkemmet) for evaporation which was not selected as a key predictand. This downscaling model was also calibrated and validated over the periods 1950–1989 and 1990–2010, respectively, following the same procedure used in the development of a downscaling model for a key predictand.

It was found that the average, the standard deviation and the maximum of the monthly evaporation at station 79023 estimated by the above downscaling model were in close agreement with those of observations and those produced by the inter-station regression relationships. The scatter of the evaporation simulated by the inter-station regression relationship between the maximum temperature at key station 79026 and evaporation at member station 79023 against the evaporation simulated by the downscaling model developed at station 79023 was also quite limited (not shown).

Following the above findings, it was assumed that the statistics and the time series of the outputs of all inter-station regression relationships developed in this study can closely represent those of the outputs of downscaling models. It was realized that when the correlations between the observations of a key predictand at a key station and all predictands at member stations (in a cluster) are high, instead of developing separate downscaling models for each predictand at each station, inter-station regression relationships can be used effectively for the determination of the values of all predictands at member stations.

**Projections of evaporation, minimum temperature and maximum temperature into the future**

Following the procedure detailed in the ‘Generic methodology’ section, projections of monthly evaporation, minimum temperature and maximum temperature were produced into the future using the outputs of ECHAM5 pertaining to the A2 GHG emission scenario for the period 2000–2099. **Table 8** shows the percentage changes in the monthly evaporation, minimum temperature and maximum temperature in the period 2000–2099 at all stations with respect to the observations of the period 1950–1989.

According to **Table 8**, it was seen that at each station in all seasons the changes in the average, the standard deviation and the maximum of monthly evaporation are equal to those of the monthly maximum temperature. This showed the uniform relationship between the maximum temperature and evaporation. However, the changes in the statistics of monthly minimum temperature did not display clear uniform association with either monthly evaporation or monthly maximum temperature. As shown in **Table 8**, in all seasons at all stations the averages of monthly evaporation and monthly maximum temperature in the period 2000–2099 indicated a rise in comparison with observations of the period 1950–1989. This indicated that in the future, the loss of water into the atmosphere due to evaporation will tend to increase with the rising GHG concentrations in the atmosphere over the study area. Except in winter, at all stations the standard deviations of GHG concentrations in the atmosphere over the study area. The maximum of monthly evaporation and the maximum of monthly maximum temperature also displayed a rise at all stations in summer, autumn and spring during the period 2000–2099.

The average of the minimum temperature showed a rise at all stations except in spring. Except in winter, at the
majority of stations the standard deviation of the minimum temperature also showed an increase indicating more fluctuations in the minimum temperature in future. The minimum of the minimum temperature indicated an increase in all seasons in the period 2000–2099; however, these predictions are less reliable as intra- and inter-station regression relationships consistently over-estimated the minimum of the minimum temperature during their calibration and validation phases.

It was concluded that in the future the evaporation, minimum and maximum temperature will tend to increase across the study area and hence the future climate in the study area will be dryer and warmer. Furthermore, the fluctuations in these predictands are also likely to increase with the rising GHGs.

According to median estimates obtained from the raw outputs of a number of GCMs, the Victorian Government Department of Sustainability and Environment (2008) found that the average of temperature and evaporation over the present study area are likely to increase under B1 (low emissions), A1B (medium emissions) and A1F1 (high emissions) emission scenarios, in all seasons. It was realized that the findings of the present research are in close agreement with those of the Victorian Government Department of Sustainability and Environment (2008).

However, unlike that previous study which directly used the raw outputs of GCMs for the determination of future climate in this study area, in this study using a statistical downscaling methodology the raw outputs of a GCM were translated to point specific climatic information pertaining to the future. This was performed while maintaining the spatial correlation structures of each individual predictand among the stations and also the correlation structures between different predictands at individual stations. The observations of monthly evaporation, maximum temperature and minimum temperature at all observation stations (including the stations not considered in this study) located in the operational area of GWMWater showed high positive correlations with each other. Hence it can be assumed that the patterns of changes in evaporation, maximum temperature and minimum temperature determined for the five observation stations considered in this study are also valid for those at the other stations in the operational area of GWMWater.
Furthermore, it was realized that the key-predictand and key-station approach can also be applied to an area of any extent with any number of stations and any number of predictands effectively, provided that there are high correlations among stations (in a cluster) for each individual predictand and high correlations among different predictands at each individual station in the clusters.

**SUMMARY AND CONCLUSIONS**

Statistical downscaling of GCM outputs to monthly evaporation, minimum temperature and maximum temperature was performed using a key-predictand and key-station approach at five observation stations located in north-western Victoria, Australia. For the effective application of the key-predictand and key-station approach, high correlations (magnitudes above 0.80 at \( p \leq 0.05 \)) should prevail between the observations of each individual predictand among the stations and also among different predictands at each individual station. In this study, high correlations between monthly evaporation, minimum temperature and maximum temperature were seen over the period 1950–2010 at each individual station and among the five stations for each individual predictand. Hence the key-predictand and key-station approach was effectively employed. Owing to the good agreement seen between the outputs of intra- and inter-station regression relationships and those of downscaling models developed at a key station and a member station respectively, the effectiveness of the key-predictand and key-station approach was realized.

The following conclusions were drawn from this study:

1. The correlations between the evaporation and the maximum temperature were consistently higher than those between the evaporation and the minimum temperature at each individual station. Therefore it was realized that the maximum temperature is more influential than the minimum temperature on evaporation.

2. The key-predictand and key-station approach was proved to be a simple yet effective methodology for downscaling GCM outputs to multiple predictands at multiple stations simultaneously. It not only aids in maintaining the cross-correlation structures among the observation stations for each individual predictand but also enables the preservation of the cross-correlation structures among different predictands at each individual observation station. Therefore the plausible representation of spatial variations of individual predictands among observation stations and also the realistic relationships between different predictands can be maintained in the projections produced by the downscaling models into the future.

3. However, for the effective implementation of the key-predictand and key-station approach the presence of high correlations (magnitudes above 0.80 at \( p \leq 0.05 \)) among the observation stations (in a cluster) for each individual predictand and high correlations among different predictands at each individual observation station are prerequisites.

4. In the application of the key-predictand and key-station approach, downscaling models are only developed for the key predictands at key stations. Therefore unlike downscaling at each individual station separately, in this approach the selection of potential predictors and the correction of bias have to be performed only at several stations for several predictands.

5. Although the monthly bias-correction employs explicit measures to correct only the monthly mean and the standard deviation of a climatic variable (e.g. output of a GCM or downscaling model), when the bias is limited, monthly bias-correction is also capable of improving the time series of the climatic variable.

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