A Comparison of Australian Open Water Body Evaporation Trends for Current and Future Climates Estimated from Class A Evaporation Pans and General Circulation Models

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ABSTRACT

Trends of decreasing pan evaporation around the world have renewed interest in evaporation and its behavior in a warming world. Observed pan evaporation around Australia has been modeled to attribute changes in its constituent variables. It is found that wind speed decreases have generally led to decreases in pan evaporation. Trends were also calculated from reanalysis and general circulation model (GCM) outputs. The reanalysis reflected the general pattern and magnitude of the observed station trends across Australia. However, unlike the station trends, the reanalysis trends are mainly driven by vapor pressure deficit changes than wind speed changes. Some of the GCMs modeled the trends well, but most showed an average positive trend for Australia. Half the GCMs analyzed show increasing wind speed trends, and most show larger changes in vapor pressure deficit than would be expected based on the station data. Future changes to open water body evaporation have also been assessed using projections for two emission scenarios. Averaged across Australia, the models show a 5% increase in open water body evaporation by 2070 compared to 1990 levels. There is considerable variability in the model projections, particularly for the aerodynamic component of evaporation. Assumptions of increases in evaporation in a warming world need to be considered in light of the variability in the parameters that affect evaporation.

1. Introduction

Loss of water through evaporation is a major consideration in the design and management of water supply reservoirs. Because of the large surface area of most water supply reservoirs, there is little that can be done to reduce these losses, which makes it even more important to accurately predict evaporation losses from a system. Concerns about the impacts of climate change on the security of water supplies have led to renewed interest in evaporation processes.

It has generally been expected that potential evaporation will increase in the future because of increasing temperatures from global warming and an intensifying hydrologic cycle (Huntington 2006). However, despite increasing temperatures over recent decades, pan evaporation has been decreasing in many places around the world in the last 40–50 years (e.g., Brutsaert 2006; Roderick and Farquhar 2004; Lawrimore and Peterson 2000).

The pan evaporation trends prompt several questions; first, can we model the twentieth-century trends in Australia using either observed climatological data or outputs from general circulation models (GCMs) and in doing so understand the drivers of the trends? And second, if pan evaporation in the current climate has been decreasing even with increasing temperatures, what will happen in the future?

In this paper, we analyze observed pan evaporation records in Australia at 27 locations, with a view to understanding what has led to the trends and evaluate the projections of these trends for future climates. Trends are analyzed using observed climatological data as inputs to the PenPan model of a class A evaporation pan (Rotstayn et al. 2006). After establishing that the model can reproduce the observed trends adequately, we see if the GCMs and a reanalysis dataset also can reproduce the observed pan evaporation trends using the model. We analyze why they get the trends right or wrong and then examine future estimates of open water body
evaporation, with the aim of identifying the types of uncertainties inherent in any such projections.

2. Pan evaporation trends

Evaporation is difficult to measure directly, and therefore many theoretical and empirical approaches have been developed. Some of the commonly used techniques include the Penman equation (Penman 1948), the Priestley–Taylor equation (Priestley and Taylor 1972), and energy balance methods. The eddy correlation or covariance method estimates evaporation directly by measuring water vapor fluxes. However, the method is generally only used in experimental settings because of the cost of the instrumentation (Brutsaert 2005).

In contrast to the eddy correlation method, evaporation pans are a common method of measuring apparent potential evaporation because they are simple to use and affordable (Roderick et al. 2009a). It is assumed the observed pan evaporation is proportional to the potential evaporation, with the proportionality constant referred to as the pan coefficient. For open water bodies, as long as the body is not so deep that heat storage becomes significant, monthly estimates of potential evaporation using pans with a pan coefficient applied “should be within ±10% in most climates” (Shuttleworth 1993). Because the focus of this paper is on pan and open water body evaporation, for simplicity we use the term “evaporation” throughout, rather than also using “evapotranspiration.” It is important to note that in some situations, transpiration will contribute significantly to the total water transfer to the atmosphere.

As mentioned earlier, many studies completed in the last 10 years have shown trends of decreasing pan evaporation. A summary of some of the worldwide trends is presented in Table 1. Lawrimore and Peterson (2000) related average regional warm-season pan evaporation trends to warm-season precipitation trends. Pan evaporation trends were found to range from approximately −1.5 to −2 mm yr⁻² over much of the United States, with the exception of the southeast, which recorded increases of approximately 0.6 mm yr⁻². Golubev et al. (2001) examined trends in the former Union of Soviet Socialist Republics (USSR) as well as the continental United States. For the USSR, decreasing pan evaporation was found in all locations, except for a small, not significant, increase in Central Asia and Kazakhstan. Liu et al. (2004) found that the averaged pan evaporation for China decreased by 2.9 mm yr⁻², with individual regions recording decreases of up to 9 mm yr⁻². In summary, although some individual stations have recorded increasing pan evaporation, the majority of stations have generally shown decreasing trends, such that when all the individual station trends are averaged at a regional and/or national scale, the overall trend is negative (i.e., one of decreasing pan evaporation).

Looking at Australia specifically, all four previous studies, as shown in Table 1, have found that the pan evaporation averaged over the country has decreased, although the size and significance of the trends was different in each study. The significance of the average decreasing trends across the country depends on the period and method of trend analysis. Roderick and Farquhar (2004) found a statistically significant decreasing trend of approximately 3 mm yr⁻² for the periods 1970–2002 and 1975–2002; however, when the latter analysis was extended to 1975–2004 (Roderick et al. 2007), the trend, although still negative, was not significant at the 90% level—a result confirmed by the work of Kirono and Jones (2007). Jovanovic et al. (2007) found that the negative trend of −2.5 mm yr⁻² for average Australian annual evaporation for 1970 to 2005 is not significant, despite individual stations and some geographic regions showing decreases significant at the 95% level. It is important to note that the uncertainty limits from their study are not directly comparable to the other studies listed earlier, as they are based on the trend of a time series of Australian average evaporation, rather than the average of trends from individual stations.

In Brutsaert and Parlange (1998), the pan evaporation trends are explained with reference to the complementary

<table>
<thead>
<tr>
<th>Location</th>
<th>Annual trend (mm yr⁻¹), period of analysis, and reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Australia</td>
<td>−2.5 ± 5.1, 1970–2005, Jovanovic et al. (2007)</td>
</tr>
<tr>
<td>Australia</td>
<td>−0.7 ± 1.6, 1970–2004, Kirono and Jones (2007)</td>
</tr>
<tr>
<td>New Zealand</td>
<td>−2.1, varying periods, Roderick and Farquhar (2005)</td>
</tr>
<tr>
<td>USA</td>
<td>−2–0.7, 1948–98, Lawrimore and Peterson (2000)</td>
</tr>
<tr>
<td>USSR</td>
<td>−4–0.1, 1950–90, After Golubev et al. (2001)</td>
</tr>
</tbody>
</table>

* As discussed in section 2, the trend and uncertainty from Jovanovic et al. (2007) is based on Australian average evaporation rather than the average of trends from individual stations; the uncertainty is therefore not comparable to other studies which have used the latter methodology.
principle of evaporation, which was first described by Bouchet (1963). The complementary principle can be summarized by (1), which shows that the apparent potential evaporation recorded by the evaporation pan \( E_{\text{PAN}} \), and actual evaporation \( E_A \) can be related to the potential evaporation \( E_{\text{PO}} \), the evaporation rate over a large uniform land surface when water is not limited (Kahler and Brutsaert 2006). It is important to note that the complementary principle applies at the landscape or regional scale, rather than the point scale of pan evaporation considered thus far. The constants \( b \) and \( C_P \), the pan coefficient, account for the additional energy an evaporation pan receives compared to its surrounding environment.

\[
(1 + b)E_{\text{PO}} = bE_A + C_P E_{\text{PAN}}.
\]

It was argued by Brutsaert and Parlange (1998) that the decreases in pan evaporation at the station level are a consequence of increases in \( E_A \) over larger regions. Golubev et al. (2001) compared actual evaporation and pan evaporation and also found that actual evaporation had increased despite decreasing pan evaporation for regions with a high index of dryness (ratio of potential evaporation to precipitation). Increases in actual evaporation will occur in moisture-limited locations that experience increasing precipitation or increased moisture supply, for example, expansion of irrigation regions. Chattopadhyay and Hulme (1997) used stepwise regression to analyze historic pan evaporation trends in India, finding that increases in relative humidity were the most strongly associated with the decreasing pan evaporation trends. Roderick et al. (2009b) suggest that this may be due to widespread irrigation, leading to increased actual evaporation from the landscape and via the complementary principle and decreased pan evaporation. For other regions, in the absence of changes to moisture supply, which will change \( E_A \) and hence \( E_{\text{PAN}} \), we must look at alternative reasons for the pan evaporation trends.

Solar radiation changes have been examined as a possible driver of the pan evaporation trends. Solar radiation changes may be due to cloud cover changes or changes to the concentrations of aerosols in the atmosphere. Norris and Wild (2007) found that cloud cover changes could not fully account for trends in solar radiation in the Northern Hemisphere between 1965 and 2004. Instead, the authors offer as the most likely explanation that changes in the concentrations of anthropogenic aerosols led to a period of “global dimming” during the 1970s to the mid-1980s, followed by a period of “solar brightening” from the mid-1980s. Wild et al. (2009) extend previous studies of global dimming to data from after 2000. They find that the brightening continued over much of Europe, the United States, and East Asia, with a leveling off of brightening in Japan and Antarctica. Liu et al. (2004) attribute the pan evaporation trends in China to decreasing solar radiation, which, in the absence of cloud cover changes, is believed to be caused by increasing aerosol concentrations. Wild et al. (2009) found that dimming continues in China into the twenty-first century. Roderick et al. (2007) found that decreases in solar radiation in northern Australia contributed to the pan evaporation decreases. It has been hypothesized that these solar radiation decreases are due to increased cloudiness and rainfall resulting from changes to monsoonal winds caused by Asian anthropogenic aerosols (Rotstain et al. 2007).

Recent studies in Australia (Rayner 2007; Roderick et al. 2007) have also found that wind speed changes have contributed to decreases in pan evaporation. Potential reasons for changes in wind run are unclear, and they may be due to large-scale climatological changes or alterations to the environment surrounding a particular evaporation pan (Rayner 2007). McVicar et al. (2008) found decreasing wind run trends for the period 1975–2006 over almost 90% of Australia, concluding that this high degree of spatial coherence indicates regional processes dominate the changes.

There are numerous studies evaluating the performance of GCMs in reproducing the observed climate of the twentieth century—for example, Meehl et al. (2007), Murphy et al. (2004), and Perkins et al. 2007—particularly with respect to temperature trends. In addition, the Intergovernmental Panel on Climate Change’s (IPCC) assessment reports (e.g., Meehl et al. 2007) provide detailed information regarding expected temperature increases resulting from different greenhouse gas emission scenarios. For Australia specifically, the best estimates of temperature increases by 2070 are 1.5°C–2.5°C for the Special Report on Emissions Scenarios (SRES) B1 emission scenario and 2°C–4°C in the A2 scenario (CSIRO and BOM 2007). However, only a few studies have examined future projections of evaporation using the outputs of GCMs. McKenney and Rosenberg (1993) compared eight alternative methods of estimating potential evaporation for five sites in the central United States. They noted that many previous studies had only considered temperature-based estimates of evaporation, and they point out that changes in other climatic variables may have important impacts on evaporation in the future but conclude that the future estimates are sensitive to both the GCM and evaporation equation used. Chattopadhyay and Hulme (1997) used six GCMs to provide estimates of percentage changes in potential evaporation per degree Celsius of warming. Projected potential evaporation increases in...
India in the future result from decreased relative humidity and increases in solar radiation (from decreasing cloudiness). The Commonwealth Scientific Industrial Research Organisation (CSIRO) and the Australian Bureau of Meteorology (BOM; CSIRO and BOM 2007) assess future potential evapotranspiration across Australia using 14 GCMs and six emission scenarios. The potential evapotranspiration is estimated using the complementary relationship areal evaporation (CRAE) model (Morton 1983). The best estimates for potential evapotranspiration increases in 2070 are 6% in the south and west of Australia and 10% in the north and east.

We now model the observed pan evaporation trends for Australia using the PenPan model. We then use the PenPan model with the outputs from reanalysis data and a suite of GCMs to ascertain if they correctly represent the observed pan evaporation trends. Lastly, we use GCM projections to estimate open water body evaporation for three periods in the future: 2030, 2050, and 2070.

3. Pan and open water body evaporation estimates

We now present details of the equations used for the analysis of pan evaporation and open water body evaporation. Data sources for the station data and GCMs are then described.

a. Methodology

1) OPEN WATER BODY AND PAN EVAPORATION EQUATIONS

The Penman combination approach is often used for estimating open water body evaporation, and Shuttleworth (1993) recommends it for this purpose. The Penman equation for open water body evaporation (Brutsaert 1982) is shown in Eq. (2):

$$E_W = \frac{\Delta}{\Delta + \gamma \rho \mathcal{L}_v} Q_N + \frac{\gamma}{\Delta + \gamma} f(u)(e_s - e_u), \quad (2)$$

where $E_W$ is open water body evaporation (mm day$^{-1}$), $\Delta$ is the gradient of the saturated vapor pressure function (Pa K$^{-1}$), $\gamma$ is the psychrometric constant (Pa K$^{-1}$), $\rho$ is the density of water (kg m$^{-3}$), $\mathcal{L}_v$ is the latent heat of vaporization (J kg$^{-1}$), $e_s$ is the saturated vapor pressure (kPa), and $e_u$ is the actual vapor pressure (kPa). Here, $Q_N$ is the available energy flux (W m$^{-2}$). For calculations at daily or longer periods, the ground conductance of heat from an open water body is relatively small and can be neglected (Shuttleworth 1993), and we can approximate the available energy as the net (all wave) radiation $R_N$.

The original Penman wind function $f(u)$, with wind speed ($u$) in units of meters per second, has been used as recommended by Brutsaert (1982) and is shown in Eq. (3), with constants based on metric units for the variables (Shuttleworth 1993):

$$f(u) = \frac{6.43}{1 \times 10^3 \mathcal{L}_v} \times (1 + 0.536u). \quad (3)$$

The Penman equation cannot be used to directly estimate the evaporation from a class A pan, as we need to account for the additional energy available at the pan due to the exposed base and sides. Several variations of the Penman equation have been developed to model evaporation pans (e.g., Thom et al. 1981; Linacre 1994; Rotstayn et al. 2006). The PenPan model (Rotstayn et al. 2006) has been used in the present study, as it has previously demonstrated model Australian class A pans successfully (Roderick et al. 2007). The equation for the PenPan model is shown in (4):

$$E_{\text{PAN}} = \frac{\Delta}{\Delta + a \gamma} \frac{R_{\text{NPAN}}}{\rho \mathcal{L}_v} + \frac{a \gamma}{\Delta + a \gamma} f_{\text{PAN}}(u)(e_s - e_u). \quad (4)$$

where $E_{\text{PAN}}$ is the modeled pan evaporation, $a$ is a constant, taken to be 2.4, which accounts for the additional energy exchanges due to the walls of the pan. $R_{\text{NPAN}}$ is the net radiation at the pan, the calculation of which is described below and other variables are as defined in Eq. (2). We reduce the predicted $E_{\text{PAN}}$ by scaling the model outputs for each location by a constant factor to account for the presence of bird guards on the pans. Through field trials, it has been found that bird guards reduce the evaporation from a pan by approximately 7% (van Dijk 1985), and hence the estimated monthly evaporation has been reduced by 7% for all locations and time steps.

For the PenPan model, the wind function is modified based on the measurements of a pan by Thom et al. (1981), with wind speed ($u$) in units of meters per second, as shown in Eq. (5), and the constant of 86 400 given to the evaporation in (4) in millimeters per day:

$$f_{\text{PAN}}(u) = 1.39 \times 10^{-8}(1 + 1.35u) \times 86400. \quad (5)$$

In summary, the PenPan equation differs from the Penman equation in the calculation of net radiation, including differences in the water surface albedo, the adopted wind function, and the inclusion of the constant $a$, to account for additional local energy supplied to the pan.

The PenPan model is used to calculate pan evaporation at station locations around Australia to attribute the pan evaporation trends to changes in other climatic
variables. We have also calculated pan evaporation using the PenPan model using reanalysis and GCM model outputs to analyze the strengths and weakness of these datasets in reproducing the observed pan evaporation trends for the twentieth century. For the future, we are interested in open water body evaporation estimates and thus the Penman equation is used.

To assist in the analysis of the results presented in sections 4 and 5, we will consider the contribution of the different drivers of evaporation to the observed trends and future projected changes. It is common to separate evaporation into the component driven by solar radiation and a second aerodynamic component, driven by wind speed and vapor pressure deficit, which defines the drying power of the air (Brutsaert 2005). We define these components as follows in Eqs. (6) and (7) for the Penman equation and the PenPan model, respectively, where \( E_{WR} \) and \( E_{WA} \) refer to the open water evaporation radiation and aerodynamic contributions, respectively, and \( E_{PANR} \) and \( E_{PANA} \) are used to denote the pan evaporation radiation and aerodynamic contributions, respectively:

\[
E_{WR} = \frac{\Delta R_n}{\Delta + \gamma p L_v},
\]

\[
E_{WA} = \frac{\gamma}{\Delta + \gamma} f(u)(e_s - e_a), \quad \text{and (6)}
\]

\[
E_{PANR} = \frac{\Delta}{\Delta + a \gamma} R_{NPAN},
\]

\[
E_{PANA} = \frac{a \gamma}{\Delta + a \gamma} f_{PAN}(u)(e_s - e_a). \quad \text{(7)}
\]

2) RADIATION CALCULATIONS

We require net (all wave) radiation to estimate both the open water body evaporation and pan evaporation. This is calculated for open water bodies as shown in (8), where \( R_S \) is the solar radiation, \( \alpha \) is the albedo of the water surface, taken to be 0.06 (Brutsaert 1982), and \( R_{nl} \) is the net longwave radiation:

\[
R_N = R_S(1 - \alpha) + R_{nl}. \quad \text{(8)}
\]

For the model of the class A evaporation pan, we need to estimate \( R_{NPAN} \) as shown in Eq. (9), where \( R_{SP} \) is the solar radiation received by the pan and \( \alpha_p \) is the albedo of the pan, assumed to be 0.14 (Rotstayn et al. 2006):

\[
R_{NPAN} = R_{SP}(1 - \alpha_p) + R_{nl}. \quad \text{(9)}
\]

For the station data, only some locations have measurements of \( R_S \). We need to calculate \( R_S \) for the remaining stations and \( R_{nl} \) and \( R_{SP} \) for all the stations. For the GCMs and reanalysis, we have \( R_S \) and downward longwave radiation outputs, so we only need to calculate upward longwave radiation and \( R_{SP} \). We now outline the process followed for the calculations of these quantities.

Solar radiation measurements were only available for 15 of the 27 stations and generally for relatively limited durations. To increase the length of the time series analyzed, an empirical relationship between solar radiation and sunshine duration developed by Prescott (1940), shown in (10), was used to estimate solar radiation for missing periods at stations with \( R_S \) measurements and for stations with no \( R_S \) measurements:

\[
R_S = R_A \left( a + b \frac{n}{N} \right), \quad \text{(10)}
\]

where \( R_A \) is the top of the atmosphere radiation, \( n \) and \( N \) are the actual and maximum sunshine hours for the location and time of year, and \( a \) and \( b \) are constants dependent on location and season, which take values of 0.25 and 0.5, respectively, in the absence of local calibration data. The implications of this empirical approach on the results are discussed in section 4. The pan solar radiation \( (R_{SP}) \) for the stations and GCMs was calculated using the procedures outlined in Rotstayn et al. (2006).

For both the station data and GCM calculations, downward clear sky longwave radiation \( (R_{ldc}) \) was calculated assuming a blackbody radiating at the air surface temperature (assumed to be the air temperature at 2 m). Downward clear sky longwave radiation \( (R_{ldc}) \) was calculated for station locations using Eq. (11) from Brutsaert (1982), where the atmospheric emissivity \( e_ac \) is a function of the actual vapor pressure, \( \sigma \) is the Stefan Boltzmann constant, and \( T_a \) is the taken to be the air temperature in degrees Celsius, in the absence of data on the water surface temperature:

\[
R_{ldc} = e_ac s(T_a + 237.2)^4. \quad \text{(11)}
\]

Net longwave radiation was found according to Eq. (12) (Brutsaert 1982), where \( a \) is taken to be 0.2 and \( n \) and \( N \) are as defined for Eq. (10):

\[
R_{nl} = (R_{ldc} - R_{lu}) \left[ a + (1 - a) \frac{n}{N} \right]. \quad \text{(12)}
\]

b. DATA SOURCES

1) STATION DATA

Observed pan evaporation data were sourced from the BOM high-quality database of monthly class A pan evaporation data (Jovanovic et al. 2007). These data have been corrected for known inhomogeneities in the records, such as the introduction of bird guards, station relocations, and changes in station exposure or observation
methodology. Data required for the PenPan estimates of evaporation include mean temperature, vapor pressure deficit, wind speed, and net radiation. Daily mean temperature data were sourced from the BOM high-quality database of daily mean temperature data. Forty-one stations had both high-quality pan evaporation and temperature datasets. In the absence of published high-quality datasets for the remaining variables (relative humidity, wind speed, and net radiation), data were sourced from the BOM (product IDCJHCO2.200706) and the MetAccess National Weather database, which is a database of daily historical meteorological data developed by CSIRO (Horizon Agriculture Pty Ltd 2006). Daily data from each of the data sources were collated and checked for inconsistencies and gaps. Gaps in the records were filled with monthly average values calculated for each station for each variable. Stations with fewer than 10 consecutive years of all variables required for the Penman estimates were eliminated from the analysis. The remaining 27 stations were used for the analysis.

2) GCM AND REANALYSIS DATA

GCM outputs for the trend analysis and estimates of open water body evaporation in future climates were obtained from the World Climate Research Programme’s (WCRP’s) Coupled Model Intercomparison Project phase 3 (CMIP3) multimodel dataset. The available models were ranked by averaging the skill scores of their performance over Australia from Perkins et al. (2007) and CSIRO and BOM (2007). The top five ranked models, as indicated in Table 2, were adopted for the analyses. We have also analyzed the trends in the National Centers for Environmental Prediction–National Center for Atmospheric Research (NCEP–NCAR) reanalysis data (Kalnay et al. 1996) to provide a comparison to the GCMs. It is acknowledged that there are deficiencies in the NCEP reanalysis data product, especially for surface variables. These are related to the assimilation of observations with the model-derived data (Reichler and Kim 2008), particularly for areas with sparse observations. However, it provides an observationally derived comparison to the GCM outputs at a similar resolution to the GCMs, whereas station-to-grid comparisons are difficult. Monthly climate variables used from each of the GCMs and the NCEP reanalysis to calculate pan and open water body evaporation are mean temperature, zonal and meridional wind speed, specific humidity, downward solar and longwave radiation, and surface pressure.

Two climate scenarios were used to estimate open water body evaporation in the future. The scenarios adopted for analysis were A2 (high emissions) and B1 (stabilization at 550 ppm; Nakicenovic et al. 2000). Table 3 summarizes the salient features of each of the models used in the analyses (CSIRO and BOM 2007). For each model and scenario, open water body evaporation was estimated for three decades in the future—2030s, 2050s and 2070s—whereas pan evaporation trends were calculated using the twentieth-century simulations from each model.

Three important steps in the analysis of GCM outputs are interpolation, grid cell averaging, and bias correction. For the data processing, the observed dataset has been taken from the NCEP–NCAR reanalysis data (Kalnay et al. 1996). The interpolation, averaging, and bias correction have been undertaken for each of the input variables to the evaporation calculations.

### Table 2. GCM skill scores for Australia. N/A indicates “not available.”

<table>
<thead>
<tr>
<th>Model</th>
<th>Skill score 1*</th>
<th>Skill score 2*</th>
<th>Average skill score</th>
<th>Rank</th>
</tr>
</thead>
<tbody>
<tr>
<td>BCCR</td>
<td>0.59</td>
<td>0.79</td>
<td>0.69</td>
<td>3**</td>
</tr>
<tr>
<td>CCCMA T47</td>
<td>0.52</td>
<td>0.71</td>
<td>0.61</td>
<td>10</td>
</tr>
<tr>
<td>CNRM</td>
<td>0.54</td>
<td>n/a</td>
<td>0.54</td>
<td>11</td>
</tr>
<tr>
<td>CSIRO Mk3.5</td>
<td>0.61</td>
<td>0.8</td>
<td>0.70</td>
<td>2**</td>
</tr>
<tr>
<td>GISS-AOM</td>
<td>0.56</td>
<td>0.75</td>
<td>0.66</td>
<td>7</td>
</tr>
<tr>
<td>IAP</td>
<td>0.64</td>
<td>0.73</td>
<td>0.68</td>
<td>4**</td>
</tr>
<tr>
<td>INMCM</td>
<td>0.63</td>
<td>N/A</td>
<td>0.63</td>
<td>9</td>
</tr>
<tr>
<td>IPSL</td>
<td>0.51</td>
<td>0.78</td>
<td>0.64</td>
<td>8</td>
</tr>
<tr>
<td>MIROC-m</td>
<td>0.61</td>
<td>0.83</td>
<td>0.72</td>
<td>1**</td>
</tr>
<tr>
<td>MRI</td>
<td>0.60</td>
<td>0.76</td>
<td>0.68</td>
<td>5**</td>
</tr>
<tr>
<td>NCAR CCSM</td>
<td>0.68</td>
<td>0.67</td>
<td>0.67</td>
<td>6</td>
</tr>
</tbody>
</table>

* Skill score 1 from CSIRO and Bureau of Meteorology (2007).
* Skill score 2 from Perkins et al. (2007).
** Models used for analyses.

### Table 3. GCM properties.

<table>
<thead>
<tr>
<th>Model ID</th>
<th>Full model name</th>
<th>Organization</th>
<th>SRES scenarios</th>
<th>Number of available model realizations</th>
<th>Horizontal resolution (km)</th>
</tr>
</thead>
<tbody>
<tr>
<td>BCCR</td>
<td>bccr_bccm2_0</td>
<td>BCCR, Norway</td>
<td>A2, B1</td>
<td>1</td>
<td>175</td>
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<tr>
<td>CSIRO</td>
<td>csiro_mk3_5</td>
<td>CSIRO, Australia</td>
<td>A2, B1</td>
<td>1</td>
<td>175</td>
</tr>
<tr>
<td>IAP</td>
<td>iap_fgoals1_o_g</td>
<td>LASG/Institute of Atmospheric Physics, China</td>
<td>B1</td>
<td>3</td>
<td>300</td>
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<tr>
<td>MIROC</td>
<td>miroc3_2_medres</td>
<td>Model for Interdisciplinary Research on climate, Centre for Climate Research, Japan</td>
<td>A2, B1</td>
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<td>250</td>
</tr>
<tr>
<td>MRI</td>
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<td>Meteorological Research Institute, Japan</td>
<td>A2, B1</td>
<td>5</td>
<td>250</td>
</tr>
</tbody>
</table>
For the pixel-based bias correction discussed later, we require the GCM output and the NCEP reanalysis data to be on the same grid. Because the reanalysis data have been compared to all five selected GCMs, its grid size of 2.5° × 2.5° has been adopted as the constant, and all GCM outputs have been interpolated to this grid, using bilinear interpolation. The gridcell averaging has been carried out by calculating the value at each grid cell as the mean of the nine closest grid cells by Euclidean distance. This was undertaken because Wilby and Wigley (2000) found that the highest correlations of a variable with its predictor variables did not necessarily occur within the same grid cells. By averaging over a number of grid cells, we can allow for this result. Bias correction recognizes that the GCM outputs for the current climate may have biases when compared to observed data, either ground-based data or reanalysis data. The correction process adjusts the GCM outputs to match the mean and variance of the recorded historical data. The bias correction is then applied to future projections, assuming that the bias will not change over time. For each variable and grid cell, the bias correction was undertaken by subtracting the monthly modeled mean and dividing by the modeled standard deviation. The variables are then rescaled by the observed (in this case NCEP reanalysis) monthly means and standard deviations for 1961–90 for each variable.

4. Observed and modeled pan evaporation
   a. Observed pan evaporation trends

Figure 1 shows the modeled monthly evaporation compared to observations at each of the 27 stations, along with the line of best fit to the data. The correlation between the observations and modeled values is very high, although there is some bias in the relationship for large evaporation totals. The root-mean-square error of the predictions is 29 mm month⁻¹. We calculated modeled (E_PAN) and observed (E_OBS) pan evaporation trends for each of the stations for the period 1975–99. This period was chosen so that the trends can be compared to those calculated from the GCM twentieth-century outputs. Trends in evaporation were calculated for each month using linear regression and then summed to give an annual trend (Roderick et al. 2007). This was undertaken so that in the case of missing values in the historic data, the other data available for the year could still be used in the trend calculations. The analysis period of the trends varies between stations as a result of data availability, with the years analyzed for each station listed in Table 4.

The modeled and observed pan evaporation trends at the 27 stations across Australia are presented in Table 4. It can be seen that the trends at 22 of the stations are negative across Australia, particularly for coastal stations. The PenPan trends are generally in the same direction as the observed trends, although on average they are smaller in magnitude. The average observed trend, with standard error, across Australia is −0.5 ± 3.1 mm yr⁻², and the modeled trend is −0.4 ± 2.7 mm yr⁻². The correlation between the modeled and observed trends at the 27 stations is large (r = 0.78). To evaluate the uncertainty of the trend estimates, we have constructed confidence limits based on the assumption of no observed trend at each station. The 95th percentile confidence limit is estimated as the 95th percentile trend from a set of randomized samples that are recreated from the original historic data by randomly bootstrapping the observations (Sharma 2000). These results are presented in Table 4. It can be seen that the trends at 22 of the stations lie outside the 95% confidence limits from the historic resampling and are therefore considered significant.

We can see from Table 4 and from Fig. 3c that the trends in the radiative (E_PANR) and aerodynamic (E_PANA) components of the estimates at each station are also listed. Figure 2 presents a comparison of the direction of the observed (E_OBS) and modeled (E_PAN) pan evaporation trends across Australia, whereas Fig. 3 shows scatterplots of the trends and their components at all stations. The majority of observed pan evaporation trends are negative across Australia, particularly for coastal stations. The PenPan trends are generally in the same direction as the observed trends, although on average they are smaller in magnitude. The average observed trend, with standard error, across Australia is −0.5 ± 3.1 mm yr⁻², and the modeled trend is −0.4 ± 2.7 mm yr⁻². The correlation between the modeled and observed trends at the 27 stations is large (r = 0.78). To evaluate the uncertainty of the trend estimates, we have constructed confidence limits based on the assumption of no observed trend at each station. The 95th percentile confidence limit is estimated as the 95th percentile trend from a set of randomized samples that are recreated from the original historic data by randomly bootstrapping the observations (Sharma 2000). These results are presented in Table 4. It can be seen that the trends at 22 of the stations lie outside the 95% confidence limits from the historic resampling and are therefore considered significant.
If we look at the meteorological variables involved, then the highest correlation between the modeled observed trends is with wind speed trend (r = 0.63). The net radiation shows a very weak correlation with the observed trends (r = 0.22). Further investigation is required of the causes of the trends in the different climatic variables contributing to the changes to evaporation. However, this is outside the scope of the current study. McVicar et al. (2008) suggest that the primary driver of wind speed decreases in Australia is the poleward expansion of the Hadley cell (Lu et al. 2007; Seidel et al. 2008). Shuttleworth et al. (2009) also show that large-scale changes in wind speed are the primary reason for decreasing pan evaporation in Australia. The implications of localized land use changes on evaporation trends are also discussed in McVicar et al. (2008) and Rayner et al. (2008) suggest that the primary driver of wind speed decreases in Australia is the poleward expansion of the Hadley cell (Lu et al. 2007; Seidel et al. 2008). Shuttleworth et al. (2009) also show that large-scale changes in wind speed are the primary reason for decreasing pan evaporation in Australia. The implications of localized land use changes on evaporation trends are also discussed in McVicar et al. (2008) and Rayner et al. (2008).
It is acknowledged that the radiation component of the calculation is based on solar radiation estimated from sunshine duration, rather than actual measurements. If changes to aerosols (either anthropogenic or natural) have led to changes in radiative energy at the earth’s surface, then these changes may not be reflected in the sunshine duration measurements. However, an investigation into the sunshine duration–radiation relationship [Eq. (10)] indicated an overall good match to Prescott’s (1940) coefficients when estimated over the entire historical record, with deviations when the estimation was based over shorter periods or smaller regions (results available on request). There may be some sites though where the relationship has changed over time, and for these locations we will not accurately represent the $E_{\text{PANR}}$ trends. However, we think that by estimating the $E_{\text{PANR}}$ directly for each station, we provide a comparison to the Roderick et al. (2007) methodology that calculated the $E_{\text{PANR}}$ trends as the residual of the observed $E_{\text{PAN}}$ trend and $E_{\text{PANR}}$ trend for 34 of the 41 sites analyzed. With both methods, it is found that the $E_{\text{PANA}}$ trends contribute the most to the total $E_{\text{PAN}}$ trends.

The trend analysis supports the findings of two other recent attribution studies on pan evaporation trends in Australia. Rayner (2007) found that solar radiation made the smallest contribution to pan evaporation trends. Roderick et al. (2007) found that changes in the aerodynamic component, and specifically the wind speed changes, were responsible for most of the trends in the pan evaporation data. Kirono et al. (2009) found a correlation of 0.51 between the modeled and observed monthly pan trends, with an average 60% of sites agreeing with the direction of the trends for a particular month. On the basis of the PenPan modeling, we find a correlation of 0.71 between the observed and modeled monthly trends, and an average of greater than 80% of sites agreeing in the directions of the monthly trends. The improvement in the results using the PenPan model compared to Morton’s point potential evaporation as in Kirono et al. (2009) may be because it explicitly includes wind speed, which is shown to be an important component of the Australian pan evaporation trends. Morton’s point potential evaporation does not use wind speed, instead it includes a vapor transfer coefficient.

It is important to note that the trends recorded and modeled for the pans will be larger than those for a hypothetical open water body in the same location. Szilagyi (2007) and Kahler and Brutsaert (2006) show that in a water-limited environment, the change in pan evaporation will be larger than the corresponding change in actual evaporation because 1) there is additional energy available to the pan through the base and sides of the pan and 2) the pan is subject to local advection. For the stations analyzed for this paper, trends calculated using the Penman equation were on average 65% of those calculated for the class A pans, as expected from Szilagyi (2007) and Kahler and Brutsaert (2006). Considering the monthly evaporation totals, rather than trends, we...
found that the PenPan monthly evaporation estimates were on average 16% higher than the Penman estimates. This is equivalent to an average pan coefficient of 0.86, although values for individual locations range from 0.78 to 0.93.

b. GCM and reanalysis representation of observed pan evaporation trends

Moving now to the reanalysis and GCM trend calculations, average trends across Australia for 1975 to 1999 from all the GCMs analyzed are presented in the first column of Table 5. The results in the other columns of Table 5 are discussed in the following paragraphs. The estimated NCEP pan evaporation trends are negative over much of Australia. Overall, the NCEP data reflects the average trend from the observed pan data well. On the other hand, the average pan evaporation trend is negative for only 5 out of 13 GCMs. Figure 4 shows the trends across Australia from the NCEP data and Bjerknes Centre for Climate Research–Bergen Climate Model version 2 (BCCR-BCM2.0) and CSIRO Mark version 3.5 (Mk3.5) model outputs. We can see that there is significant spatial variations in the trends across Australia as well as differences in the predictions from the two GCMs. Cells where trends are significant at the 5% level are marked. Spatially, the trends at the majority of cells from the GCM predictions are not significant, mainly as a result of the large interannual variability in the predictions.

Splitting the pan evaporation trends into $E_{\text{PAN}}$ and $E_{\text{PANA}}$, we find that as for the station-level analysis, trends are primarily generated by the aerodynamic component. Columns 2 and 3 of Table 5 list the contribution from the two components, respectively. Figure 5 shows two scatterplots with the correlations between trends in the aerodynamic and radiative components of evaporation compared to the trend in total evaporation.

We can see the strong correlations between aerodynamic trends and total evaporation trends. This agrees well with the findings for the station-based pan evaporation estimates. The magnitude of the reanalysis $E_{\text{PANA}}$ trend is similar to that found for the pan data. For the GCMs the results are varied with only a few of the models showing the expected negative trend in $E_{\text{PANA}}$.

Although the contribution of the radiative component to the overall evaporation trend is small, we have examined the trends in the radiation outputs from the reanalysis and GCMs. Trends for 1975–99 are not significant at the 90% level at the majority of locations for any of the GCMs, for either shortwave or longwave radiation. Averaged over all the GCMs analyzed, the shortwave radiation trend is $-0.02\%$ and the longwave radiation trend is $-0.07\%$. For the reanalysis data, the radiation trends are significant over much of southern Australia. The average shortwave trend is $-0.08\%$, with longwave radiation decreasing by approximately $0.2\%$ yr$^{-1}$.

To understand the drivers in the large changes in the aerodynamic components of evaporation, particularly in the reanalysis data, we use the methodology of Roderick et al. (2007) to estimate the contribution of the changes from wind speed, vapor pressure deficit, and temperature according to Eq. (13), where $U^*$, $D^*$, and $T^*$ represent the changes in $E_{\text{PANA}}$ due to wind speed, vapor pressure deficit and temperature, respectively. The values of $U^*$, $D^*$, and $T^*$ are presented in Table 5 for each model,

$$
\frac{dE_{\text{PANA}}}{dt} \approx \frac{\partial E_{\text{PANA}}}{\partial u} \frac{du}{dt} + \frac{\partial E_{\text{PANA}}}{\partial D} \frac{dD}{dt} + \frac{\partial E_{\text{PANA}}}{\partial T} \frac{dT}{dt} = U^* + D^* + T^*. \tag{13}
$$
We first look at the NCEP reanalysis results, which showed decreasing $E_{\text{PANA}}$ as expected. The average of $U^*$ across Australia is $0.8 \text{ mm yr}^{-2}$ and looking at individual grid cells, 68% of the land cells have increasing wind speed trends. By way of comparison, Roderick et al. (2007) found that the average $E_{\text{PANA}}$ trend across Australia was $-2.6 \text{ mm yr}^{-2}$, with $U^*$ equal to $-2.7 \text{ mm yr}^{-2}$ and $D^*$ and $T^*$ making negligible contributions to the total $E_{\text{PANA}}$ trend based on the analysis of data from 41 meteorological stations. Recent analysis by McVicar et al. (2008) highlighted that the NCEP reanalysis fails to capture recorded wind run trends across Australia. The vapor pressure deficit effects ($D^*$) on the other hand are generally negative with an average of $-3.1 \text{ mm yr}^{-2}$, and it is this component that contributes to the negative $E_{\text{PANA}}$ trend across Australia. Thus, the apparently good agreement between the observed pan trends and reanalysis occurs for different reasons.

For the GCMs, the CSIRO Mk3.5 model does the best in capturing the observed split between $U^*$, $D^*$, and $T^*$ with the vapor pressure deficit and temperature components close to zero, and the wind speed trend leading to the overall $E_{\text{PANA}}$ trend. Figure 6 shows the spatial pattern of the NCEP and CSIRO $E_{\text{PANA}}$ component trends. The $E_{\text{PANA}}$ trend for the remaining models is primarily due to the trends in vapor pressure deficit unlike the station data. Future work will investigate why the CSIRO model performs better in this respect than the other GCMs considered. Temperature changes, from all of the GCMs and the reanalysis, do not contribute strongly to the estimated evaporation trends, in agreement with Roderick et al.'s (2007) findings for the station data.

5. Future evaporation projections

We have used the GCMs to assess trends in pan evaporation across Australia for the latter part of the twentieth century. But of more interest is what the projected changes in evaporation for the future will be. As explained in the methodology, for this analysis we have considered open water body evaporation projections for the future, calculated using the Penman equation. In the previous section, we showed that there are considerable uncertainties in the way that the GCMs represent the observed trends in evaporation. This may raise questions as to the appropriateness of examining future changes in evaporation using these same models. However, we argue that given the importance of evaporation in the hydrologic cycle, it is important to look at the future changes and to understand where the sensitivities in the projections occur. This way, when current trends as modeled by the GCMs are understood better, we can use the future sensitivities to assess their impact on the future projections.

Tables 6 and 7 summarize the average percentage changes across Australia for each GCM, with the ensemble means presented for the GCMs that have
multiple ensemble runs available. The percentage change has been calculated compared to the average for 1990–2000 from each of the models. The mean percentage change in open water body evaporation across Australia was found to be 2.2% for 2030, 3.9% for 2050, and 6.8% for 2070 in SRES A2 and 1.7%, 3.9%, and 4.8% for 2030, 2050, and 2070, respectively, for the SRES B1 scenario. The CSIRO GCM projects the largest increases for all three periods, with the MIROC models projecting the smallest increases.

Tables 6 and 7 also show the contributions to the total changes from the aerodynamic and radiative components. The radiative and aerodynamic contributions to the increases vary between models. In some cases, for example, CSIRO, the aerodynamic component contributes approximately 60% of the increase for all three time windows considered. Other models indicate that radiation increases will contribute more to increasing open water body evaporation. For the SRES B1 scenario (Table 7), the models are more consistent in attributing increases in open water body evaporation to aerodynamic component increases.

Figure 7 shows the spatial variation of the projected changes in total open water body evaporation over time. We show the mean, minimum, and maximum percentage changes projected at each grid cell from all the GCMs for 2030, 2050, and 2070 for the SRES A2 emissions scenario. Spatially, the patterns of change are generally consistent for the minimums, mean, and maximums for all three periods. The spatial patterns are similar for SRES B1 (not shown here), with generally smaller increases projected than for the SRES A2 scenario, as also evident from Table 7. Evaporation is projected to increase in the southwest of Australia in all cases, with even the minimum projections from the multiple GCMs being positive. For the rest of Australia, we see in Fig. 7a that the minimum change in 2030 is actually a decrease in evaporation compared to 1990 values. Decreasing evaporation in 2030 is projected for at least some grid cells by all three of the MIROC ensemble runs and four of the five MRI ensemble runs.

The results presented here differ from the evaporation projections in CSIRO and BOM (2007), in which all models project either no change or increases in potential evapotranspiration. The differences between the two results are likely resulting from the analysis method used. As previously noted, the CSIRO and BOM (2007) report used the CRAE model (Morton 1983) to calculate the changes in potential evapotranspiration. The CRAE model does not use wind speed in calculating evaporation.

To further examine the variability in the outputs from the different GCMs evident in Tables 6 and 7, we examine the convergence of the model projections using the methodology of Johnson and Sharma (2009). In Fig. 8 we present plots showing the spatial variation of the coefficient of variation (CV) of the model projections of $E_W$, $E_{WR}$, and $E_{WA}$. The rationale behind assessing model agreement using CV values is that the ensemble mean can be expected to give the best projection of the likely state of the climate in the future (Johnson and Sharma 2009). We therefore examine the spread of the models at each grid cell around the ensemble mean for that location; in places where the GCMs all lead to
similar projections, the CV values are small, with larger values resulting when there is less agreement between the models. The left column in Fig. 8 shows the convergence in $E_W$ over time, with slightly higher CV values occurring in the eastern part of Australia and no strong variations with time in the spatial patterns. The middle column of Fig. 8 shows that divergence between the models is primarily driven by the estimates of the aerodynamic component of the evaporation, with relatively large CV values occurring over much of eastern half of the continent. In contrast, the radiative component shows good model convergence and no strong spatial trends in convergence. Interestingly, the model convergence does not change significantly over time for either of the components or the total evaporation estimates. Similar analysis for the variables making up the aerodynamic components (results available on request) indicate that vapor pressure deficits contribute to the variability of $E_{WA}$ in inland areas and eastern Australia, whereas wind speed projections show the greatest divergence between the models in the southern parts of the continent.

Table 6. Future climate projections of evaporation for SRES A2 scenario: mean percentage change with 95% confidence limits and percentage contribution from radiative and aerodynamic components, where $dA/dE + dR/dE = 100\%$. The asterisk denotes the average of ensemble runs.

<table>
<thead>
<tr>
<th>Model</th>
<th>2030</th>
<th></th>
<th></th>
<th>2050</th>
<th></th>
<th></th>
<th>2070</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>BCCR</td>
<td>2.6 ± 0.3</td>
<td>37.3</td>
<td>62.7</td>
<td>2.9 ± 0.5</td>
<td>59.9</td>
<td>40.1</td>
<td>4.9 ± 0.5</td>
<td>38</td>
<td>62</td>
</tr>
<tr>
<td>CSIRO</td>
<td>5.2 ± 0.2</td>
<td>66.7</td>
<td>33.3</td>
<td>5.7 ± 0.3</td>
<td>64.8</td>
<td>35.2</td>
<td>8.6 ± 0.4</td>
<td>61.9</td>
<td>38.1</td>
</tr>
<tr>
<td>MIROC*</td>
<td>0.9 ± 0.3</td>
<td>51.3</td>
<td>48.7</td>
<td>2.5 ± 0.3</td>
<td>7.6</td>
<td>92.4</td>
<td>5.9 ± 0.4</td>
<td>21.7</td>
<td>78.3</td>
</tr>
<tr>
<td>MRI*</td>
<td>2.3 ± 0.1</td>
<td>64</td>
<td>36</td>
<td>4.6 ± 0.2</td>
<td>64.5</td>
<td>35.5</td>
<td>7.4 ± 0.2</td>
<td>63.3</td>
<td>36.7</td>
</tr>
</tbody>
</table>
6. Conclusions

We investigated pan evaporation trends for the period 1975–99 using the PenPan model and found that wind speed changes are the primary driver of decreasing pan evaporation trends across Australia, in general agreement with the findings of Rayner (2007) and Roderick et al. (2007). The PenPan model was then applied to the model outputs from the NCEP reanalysis and five GCMs for the same period. We found that the $E_{\text{PAN}}$...
trends from the reanalysis reflected the general pattern and magnitude of the observed station trends across Australia. Some of the GCMs modeled the trends well but most showed an average positive pan evaporation trend for Australia. Splitting the total trend into aerodynamic and radiative components confirmed that, as for the station data, trends are primarily driven by the aerodynamic component. However, further analysis demonstrated that the reanalysis trends occur mainly because of vapor deficit changes, rather than wind speed trends, as was found to be the case for the station data. Half the GCMs considered show increasing wind speed trends and most show larger changes in $E_{PAN}$ due to vapor pressure deficit than we would expect given the station level $D^*$ components. It is important to note that these conclusions relate specifically to class A pans, rather than open water or landscape evaporation.

The average increase in open water body evaporation in 2070 is approximately 7% for the SRES A2 scenario and 5% for the SRES B1 scenario using the outputs of all five GCMs considered. In the 2030s and 2050s, the predictions are more variable, and in some cases the predicted decreases in the aerodynamic component of evaporation completely offset increases in the radiative component. We therefore conclude that, as for the current climate, evaporation changes for the future are not straightforward and no speculation should be made. Commonly held beliefs of increasing potential evaporation increases because

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**FIG. 8.** GCM agreement in future projections of (a),(d),(g) total open water body evaporation, (b),(e),(h) aerodynamic, and (c),(f),(i) radiative components of evaporation. Model agreement is assessed using the CV of the set of model projections at each grid cell for (a)–(c) 2030, (d)–(f) 2050 and (g)–(i) 2070. The CV values are presented as percentages to improve the clarity of the figures. Darker shading indicates areas where the CV is larger—that is, there is a larger spread in the model projections for the future.
of rising temperatures may need to be reassessed when wind speed or vapor pressure deficit changes are also considered.

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