Generating Australian potential evaporation data suitable for assessing the dynamics in evaporative demand within a changing climate

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Photographer: Randall Donohue
Description: The Tasman Flax Lily (Dianella tasmanica), a native to south-eastern Australia.
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SUMMARY

Evaporative demand can be modelled using one of numerous formulations of potential evaporation. Physically, evaporative demand is driven by four key variables—net radiation, vapour pressure, wind speed, and air temperature—each of which have been changing across the globe over the past few decades. Analyses of long-term changes in potential evaporation require a fully dynamic formulation where the effects of changes in each of the driving variables are accounted for. Often, however, adequate input data describing all four variables are unavailable.

In this research we sought to produce a potential evaporation data set suitable for the analysis of long-term dynamics in evaporative demand. Prior to the calculation of potential evaporation, we tested the temporal accuracy of the surface-based input data, by comparing trends derived from the input surfaces with equivalent trends from the underlying observation data. Another test of the input data compared trends in modelled US Class A pan evaporation, generated using the input surfaces, with observed trends in pan evaporation. Results indicated that the input data were suitable for looking at long-term temporal dynamics in evaporative demand.

We generated five different daily potential evaporation datasets for Australia, spanning 1981-2006, using the: (i) Penman; (ii) Priestley-Taylor; (iii) Morton point; (iv) Morton areal; and (v) Thornthwaite formulations. A novel aspect of this process was the use of a dynamic net radiation model that utilised spatially and temporally varying remotely sensed measures of surface albedo.

We assessed how well each potential evaporation formulation captured dynamics in evaporative demand by analysing the spatial, annual, and seasonal trends in each against changes in actual evaporation, assuming that they should vary in an approximately inverse manner. Results show that only potential evaporation modelled with a fully physical formulation (i.e., Penman), or with Morton’s point formulation, displayed such characteristics. An attribution analysis was performed to quantify the contribution each input variable made to the overall trends in a fully physical formulation (in this case, Penman). Even though changes in air temperature played an important role in the overall magnitude of trends in potential evaporation, it was the contribution of vapour pressure, net radiation (primarily due to albedo) and wind speed that produced the complementary behaviour, which is in agreement with previous findings.

For the conditions tested, we found that only the Penman formulation displayed realistic values of potential evaporation rates and trends, and we conclude that this is the model of choice for examining evaporative demand dynamics when all input data are available. This highlights the need for all inputs to be treated as variables and, consequently, the need for dynamic input data. Few formulations dynamically include wind speed and conclusions about changes in evaporative demand from such formulations are likely to be misleading. Of the formulations that omit wind speed dynamics, the Priestley-Taylor and Morton areal formulations produced reasonable estimates of potential evaporation rates. Whilst neither should be relied upon to reproduce temporal dynamics, the simplicity of the Priestley-Taylor model makes it the better model for estimating potential evaporation rates when wind speed data are absent.
1. INTRODUCTION

Analyses of catchment hydrological dynamics require estimates of the supply of water and of the evaporative demand for water. Estimates of potential evaporation are generally used to represent evaporative demand. Conceptually, potential evaporation represents the maximum possible evaporation rate (e.g., Granger 1989; Lhomme 1999) and is the rate that would occur under given meteorological conditions from a continuously saturated surface (Thornthwaite 1948). Notionally, the concept of potential evaporation is simple. However, the practical implementation of the concept is problematic and ambiguous due to the many ways potential evaporation can be, and has been, formulated. Here our focus is on how input variables are treated within several common formulations.

Even though potential evaporation is primarily driven by four meteorological variables (net radiation, vapor pressure, wind speed and temperature) it is a conceptual entity that can not be measured directly (Thornthwaite 1948). Many different methods of estimating potential evaporation from one or more of these four variables have been developed according to local climatic conditions and the availability of suitable data (see Shuttleworth 1993; Singh and Xu 1997; Xu and Singh 2000, 2001). Some formulations, such as Thornthwaite's (1948), use a single variable (i.e., air temperature) that is related to potential evaporation rates via empirical relationships. These typically need to be recalibrated to maintain accuracy when applied outside the original spatial and temporal contexts (Xu and Singh 2001). Other formulations, by assuming the surface is extensive and continually saturated, omit the effects of the 'advective' variables (i.e., wind speed and vapor pressure), and account only for the vertical heat and mass fluxes. Such formulations are often referred to as 'areal' or 'wet area' potentials and are best suited to energy-limited environments. Alternatively, fully physical models, such as the Penman and the Penman-Monteith equations (Penman 1948; Monteith 1981), are physically derived (except for any resistance terms) and explicitly incorporate all the driving variables. Although these formulations are data intensive they are universally applicable.

The relationship between potential evaporation and actual evaporation differs depending on what process is the dominant limit to evaporation. In water-limited landscapes, where the available energy exceeds the available water, the actual evaporation rate is less than the potential rate and is largely determined by the supply of water. Alternatively, in energy-limited environments where the supply of water exceeds that of energy, actual evaporation rates closely follow those of potential (McIlroy and Angus 1964; Budyko 1974; Thornthwaite 1948; Linacre 2004).

This research was prompted by the need for spatially explicit potential evaporation data that are suitable for the analysis of long-term dynamics in evaporative demand. Widespread changes in climatic conditions have been reported, with long-term trends observed in global average air temperature (e.g., IPCC 2007), in vapour pressure (e.g., Durre et al. 2009), precipitation (e.g., New et al. 2001), net radiation (e.g., Wild 2009), and wind speed (e.g., McVicar et al. 2008). This is no less true for Australia, where temperature and precipitation have been increasing on average over the past 3 or so decades (Bureau of Meteorology, 2007) as has vapour pressure (this study), whilst wind (Roderick et al. 2007; Rayner 2007; McVicar et al. 2008) and net radiation (this study) have been decreasing. All these changes will have inevitably led to changes in evaporative demand. Given the extremely variable nature of the drivers of potential

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evaporation, any methods used to examine long-term analyses of evaporative demand need to be capable of accounting for the observed, and expected, changes in all relevant input variables (McKenney and Rosenberg 1993) and should ideally be applicable in both water- and energy-limited environments.

Our aim is to produce, and characterise, an Australian potential evaporation data set suitable for the analysis of long-term dynamics in evaporative demand. Towards this end, we created a dynamic representation of net radiation that utilised remotely sensed data. For Australia, from 1981 to 2006, datasets of daily potential evaporation were generated using a variety of formulations, namely the: (i) Penman (1948); (ii) Priestley-Taylor (1972); (iii) Morton (1983) point; (iv) Morton (1983) areal; and (v) Thornthwaite (1948) potential evaporation formulations. We analysed the annual, seasonal and spatial trends of each formulation as well as attributing, for two of the formulations, how each input variable contributed to the overall trends. This allowed us to make an assessment of the suitability of each potential evaporation formulation for representing long-term dynamics in evaporative demand.

Potential evaporation can not be measured directly and so no means exists by which modelled potential evaporation data can be directly validated either spatially or temporally. However, the quality of the input data used to generate potential evaporation estimates can be tested. Spatial surfaces of meteorological variables are increasingly being used in hydro-meteorological analyses. Little attention has been given to assessing the temporal accuracy of such surfaces. Here, prior to conducting analyses of potential evaporation dynamics, we undertake two rigorous tests of the temporal accuracy of the input surface data. Firstly, we compare surface-derived trends in the input variables with trends present in the underlying point data from which the surfaces were generated. Secondly, we use the input data and the Penpan model (Rotstayn et al. 2006) to estimate US Class A pan evaporation rates and trends, and compare these with rates and trends of observed pan evaporation.

This paper is organised as follows. In the next Section 'Data and Methods' we describe: (i) the data used in these analyses and the validations performed to test their temporal accuracy; (ii) the generation of Australia-wide daily net radiation surfaces; (iii) the five different potential evaporation formulations used; (iv) the determination of pan coefficients; (v) the calculation of trends in potential evaporation; and (iv) an attribution analysis to quantify the contribution of each input variable to potential evaporation trends. Results are presented using this same structure, followed by a discussion of results. We then provide conclusions and recommendations.
2. MATERIALS AND METHODS

2.1 Input data description and validation

Data in the form of daily grids were used for these analyses, spanning January 1981 through to December 2006 (see Table 1). This time span was chosen to match that of the remotely sensed vegetation cover data of Donohue et al. (2008) from which estimates of albedo and surface emissivity were derived. Elevation was derived from the DEM-9S dataset of Geoscience Australia (2007). Meteorological data describing precipitation, air temperature and vapour pressure were sourced from the Jones et al. (2006) and wind speed data McVicar et al. (2008). For comparison, an alternative spatial dataset of daily wind speed was generated using the same input data as used by McVicar et al. (2008), but here the data were spatially interpolated using Triangular Irregular Networks (TINs). All input spatial data were converted to the same spatial resolution (0.05°), the same extent (112.0–154.0°E and 10.0–44.0°S ) and to SI units prior to analyses.

Before generating the surfaces of potential evaporation, we undertook two tests of the temporal accuracy of the input surfaces. Firstly, the temporal accuracy of the input data was compared to the trends present in the underlying point data. This is essentially a test of the accuracy of the interpolation technique. Monthly trends in total precipitation ($P$, mm.mth$^{-1}$), and in daily maximum and minimum air temperature ($T_n$ and $T_x$, respectively, in K), daily actual vapour pressure ($e_a$, Pa) and daily average wind speed ($u_2$, m.s$^{-1}$) were calculated using the input daily surfaces described above (see section 2.5 for details on the calculation of trends). Point-based data were extracted from the Monthly Australian Data Archive for Meteorology database (Bureau of Meteorology 2006). For $T_n$, $T_x$, dew point temperature (used to calculate $e_a$), and $u_2$, data were extracted using a simple completeness-of-record criteria for the period 1981–2006: (i) each month needed at least 25 days of data to be considered complete; (ii) each year needed at least 9 complete months of data; and (iii) each station had to have at least 20 complete years of data. This procedure determined how many stations were used for the validation of each input variable. For $P$ data, the number of observation stations was restricted, purely for reasons of efficiency, to the stations that had an adjacent ‘complete’ pan evaporation record (see below). The point-based monthly values and annual trends were compared to the equivalent values extracted from the monthly grids at the corresponding locations.
The second test of the input data was to use the input surfaces and the Penpan model (Rotstayn et al. 2006) to estimate US Class A pan evaporation rates and trends and to compare these with observed pan evaporation rates and trends. This provides a rigorous test of the data and gives a good indication of the accuracy of subsequently modelled potential evaporation data for two reasons: (i) Roderick et al. (2007) have shown that the Penpan model can accurately reproduce both rates and trends in US Class A pan evaporation with high quality point-based input data; and (ii) pan evaporimeters integrate the effects of radiation, humidity, wind and temperature on wet-surface evaporation rates (Stanhill 2002), and so provide measurements of evaporation that are conceptually similar to potential evaporation rates (e.g., McVicar et al. 2007). We modelled Penpan evaporation using the spatial input grids (using the TIN-based wind speed). Point-based pan evaporation observations were extracted.
from the original database (Bureau of Meteorology 2006) using the completeness
procedure outlined above, resulting in 102 sites (Figure 1). Penpan evaporation ($E_{pp}$,
mm.d$^{-1}$) is a Penman-based model of US Class A pan evaporation rates and was
calculated according to:

$$E_{pp} = \frac{\Delta R_p + ayD(1.39 \times 10^{-8}(1+1.35u_2))86400}{\Delta + a\gamma}.$$  \hspace{1cm} (1)

Here $R_p$ (in water-equivalent units, mm.d$^{-1}$) is the net radiation of the pan (see Rotstayn
et al. 2006). Deriving $R_p$ requires estimates of the diffuse fraction of incoming radiation
which were derived following Roderick (1999). $\Delta$ is the slope of the saturation vapour
pressure curve (Pa.K$^{-1}$ at air temperature), $a$ is a dimensionless constant (2.4), $\gamma$ is the
psychrometric constant (Pa.K$^{-1}$), $D$ is the vapour pressure deficit (Pa), and $u_2$ is daily
average wind speed at 2m height (m.s$^{-1}$). $\Delta$ is calculated as a function of saturated
vapour pressure ($e_s$, Pa) and mean air temperature ($T_a$, K):

$$\Delta = \frac{4098 e_s}{(T_a - 35.86)^2}. \hspace{1cm} (2)$$

$T_a$ was calculated as the daily average of $T_x$ and $T_n$. $e_s$ was calculated as the daily
average of the saturated vapour pressure determined for that day’s $T_x$ and $T_n$, according to:

$$e_s = 610.8 e^{\left(\frac{17.27(T-T_x)}{T-35.86}\right)}. \hspace{1cm} (3)$$

Note that in this and all equations temperature has been converted to K. The
psychrometric constant ($\gamma$, Pa.K$^{-1}$) varies with atmospheric pressure ($P_a$, Pa),

$$\gamma = 6.65 \times 10^{-4} P_a, \hspace{1cm} (4)$$

where $\lambda$ is the latent heat of vaporisation of water (2.45 x 10$^6$ J.kg$^{-1}$). $P_a$ is estimated
here as a function of elevation (z, m):

$$P_a = 101300 \left(\frac{293 - 0.0065 z}{293}\right)^{5.26}. \hspace{1cm} (5)$$
2.2 Modelling net radiation

Net radiation \((R_n, \text{W.m}^{-2})\) is defined as the sum of the component longwave and shortwave fluxes:

\[
R_n = R_{si} - R_{so} + R_{li} - R_{lo}
\]  

(6)

where \(R_{si}\) is the incoming shortwave radiation, \(R_{so}\) is outgoing shortwave radiation, \(R_{li}\) incoming longwave radiation, and \(R_{lo}\) outgoing longwave radiation (all in units of \(\text{W.m}^{-2}\)). Incoming shortwave radiation was calculated as the top-of-atmosphere incoming radiation \((R_o, \text{W.m}^{-2})\) modified by an estimate of atmospheric transmissivity \((\tau_a)\).

\[
R_{si} = R_o \tau_a
\]  

(7)

\(R_o\) was calculated using the method of Iqbal (1983) and Roderick (1999). A locally calibrated (McVicar and Jupp 1999) version of the Bristow-Campbell (1984) relationship was used to derive \(\tau_a\):

\[
\tau_a = (0.807 + 0.00001 \times z) \times (1 - e^{-0.175 \times T_r \times 0.0001})
\]  

(8)

with \(T_r\) representing the daily temperature range (calculated as \(T_x - T_n, \text{K}\)). Following Bristow and Campbell (1984), \(T_n\) was determined as the average of the current day’s and the following day’s minimum values.

Outgoing shortwave radiation was calculated as:

\[
R_{so} = \alpha R_{si}
\]  

(9)

where \(\alpha\) is the surface albedo, which was estimated using calibrated Advanced Very High Resolution Radiometer red \((\rho_R, \%)\) and near-infrared \((\rho_N, \%)\) monthly reflectances (Donohue et al. 2008), following Saunders (1990):

\[
\alpha = \frac{\rho_R + \rho_N}{2}
\]  

(10)

There were occasional gaps in the monthly \(\alpha\) data due to cloud cover or high satellite viewing angles (Donohue et al. 2008). Wherever a pixel contained a gap in its time series, linear regressions were performed on that pixel’s time series for each month-of-year (i.e., all Januaries, all Februaries, etc.). Gaps were then filled with the values derived from the appropriate month’s regression model. Each month’s albedo value was used to represent daily values for that month.

Outgoing longwave radiation was calculated as:

\[
R_{lo} = e \sigma T_x^4
\]  

(11)
where $\varepsilon_s$ is the surface emissivity, $\sigma$ the Stefan-Boltzmann constant ($5.67 \times 10^{-8}$ W.m$^{-2}$K$^{-4}$), and $T_s$ the surface temperature (K). Here $T_a$ was used to approximate $T_s$. Daily $T_a^4$ was calculated as the average of the fourth power of both that day’s $T_x$ and $T_n$. Surface emissivity was estimated as a function of monthly vegetation fractional cover ($f_v$), scaled between 0.97 and 0.92 for fully vegetated and bare surfaces, respectively (Monteith and Unsworth 1990):

$$\varepsilon_s = 0.97 \times f_v + 0.92 \times (1 - f_v).$$

(12)

Fractional cover ($F_v$) was derived from AVHRR fraction of Photosynthetically Active Radiation absorbed by vegetation ($F$) data (Donohue et al. 2008):

$$f_v = \frac{F}{0.95}.$$  

(13)

The fractional cover data were gap-filled using the same method as used for albedo.

An adapted version of the FAO56 method (Allen et al. 1998) was used for calculating incoming longwave radiation. The adaptation included the incorporation of surface emissivity and the use of Australian coefficients (McVicar and Jupp 1999) in estimating clear-sky radiation (see Appendix 1).

$$R_{li} = \varepsilon_s \sigma T_o^4 \left( 1 - \left( 0.34 - 0.14 \sqrt{\varepsilon_s/1000} \right) \left( \frac{1.35 R_{si}}{0.807 + 1 \times 10^{-5} z} - 0.35 \right) \right)$$  

(14)

The monthly time series of modelled $R_{si}$ and $R_{li}$ were validated using ground-based measurements. Monthly observations of $R_{si}$ and $R_{li}$ (W.m$^{-2}$) originate from the daily radiation observations collected and published by the BOM (which were subsequently summarised by Roderick and Farquhar (2006)). The $R_{si}$ data came from 25 stations across Australia and the $R_{li}$ from 10 stations (Figure 1).
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2.3 Potential evaporation formulations

2.3.1 Penman potential evaporation

Potential evaporation ($E_p$, mm.d$^{-1}$) was calculated using Penman's (1948) formulation as given in Shuttleworth (1993):

$$E_p = \frac{\Delta}{\Delta + \gamma} R_n + \frac{\gamma}{\Delta + \gamma} \frac{6430(1 + 0.536u_2)}{\lambda} D$$

(15)

where $E_{pR}$ and $E_{pA}$ represent the radiative and aerodynamic components of the Penman equation, respectively. $R_n$ is daily net radiation (mm.d$^{-1}$) as calculated previously.

2.3.2 Priestley-Taylor potential evaporation

Priestley-Taylor potential evaporation ($E_{pt}$, mm.d$^{-1}$) is a radiation-based model and was formulated as a function of radiation and, via $\Delta$, of air temperature (Priestley and Taylor 1972):

Figure 1. Distribution of stations with long-term radiation and pan evaporation observations. Also shown areas that are water/energy-limited on an annual average basis. Of the 102 pan evaporation stations, 96 lie within water-limited landscapes.
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\[ E_{pt} = 1.26 \frac{\Delta}{\Delta + \gamma R_n} \cdot \tag{16} \]

### 2.3.3 Morton’s point and areal potential evaporations

Morton (1983) formulated a point potential evaporation \( (E_{mp}, \text{mm.d}^{-1}) \) and an areal or ‘wet environment’ potential evaporation \( (E_{ma}, \text{mm.d}^{-1}) \) where the ‘equilibrium’ temperature is iteratively determined by simultaneously solving the vapour transfer and energy balance equations. Potential evaporation is then calculated for the equilibrium temperature. The Morton formulations include three of the four driving variables: \( R_n \), \( e_a \), and \( T_a \). The first step was to calculate three coefficients. The stability factor \( (\xi) \) is:

\[
\frac{1}{\xi} = 0.28 \left( 1 + \frac{e_a}{e_s} + \frac{\Delta R_n}{\gamma (P_s / P_a)^{0.5} f_z (e_s - e_a)} \right). \tag{17}
\]

Here \( R_n \) is in \( \text{W.m}^{-2} \), \( P_s \) is mean sea level pressure \( \left( 101300 \text{ Pa} \right) \) and \( f_z \) is \( 0.280 \text{ W.m}^{-2}.\text{Pa}^{-1} \) for \( T_a \) at or above \( 273.16 \text{ K} \) and \( 0.322 \) for \( T_a \) below \( 273.16 \text{ K} \). The vapour transfer coefficient \( (C, \text{W.m}^{-2}.\text{Pa}^{-1}) \) is

\[
C = \left( \frac{P_s}{P} \right)^{0.5} \frac{f_z}{\xi}, \tag{18}
\]

and the heat transfer coefficient \( (H, \text{Pa.K}^{-1}) \) is

\[
H = \gamma + \frac{2.087 \times 10^{-7} (T_a)^3}{C}. \tag{19}
\]

The second step is to iteratively calculate the equilibrium temperature, \( T_p (\text{K}) \). This is done by initially setting \( T_p \) to \( T_a \), setting the equilibrium vapour pressure, \( e_p \), to \( e_a \), and setting the equilibrium saturation vapour pressure slope, \( \Delta_p \), to \( \Delta \). A temperature increment \( (\delta T) \) is calculated according to:

\[
\delta T = \frac{R_s / C + H (T_a - T_p) + e_a - e_p}{\Delta_p + H}. \tag{20}
\]

Estimates of equilibrium temperature \( (T_{p'} \) \), vapour pressure \( (e_{p'}) \) and saturation vapour pressure slope \( (\Delta_{p'}) \) are derived in each iteration:

\[
T_{p'} = \delta T + T_p. \tag{21}
\]
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\[ e_p' = 610.8 e^{\frac{17.27(T_p' - 273.16)}{T_p' - 35.86}}, \]  
(22)

and

\[ \Delta_p' = \frac{4098e_p'}{\left(T_p' - 35.86\right)^2}. \]  
(23)

However, if \( T_p' \) is below 273.16 K, then

\[ e_p' = 610.8 e^{\frac{21.88(T_p' - 273.16)}{T_p' - 7.66}}, \]  
(24)

and

\[ \Delta_p' = \frac{5809e_p'}{\left(T_p' - 7.66\right)^2}. \]  
(25)

\( T_p \) is then set to \( T_p' \), \( e_p \) to \( e_p' \) and \( \Delta_p \) to \( \Delta_p' \) and the iteration [Eqs. (20)-(25)] is repeated until the absolute value of \( \delta T \) is less than 0.01 K. Morton’s point potential evaporation (\( E_{mp}, \text{mm.d}^{-1} \)) is calculated prior to calculating \( R_{np} \) (W.m\(^{-2}\)), the net radiation that would occur at the equilibrium temperature. Finally \( E_{ma} \) is calculated:

\[ E_{np} = 0.0353 \left( R_n - HC \left( T_p - T_a \right) \right), \]  
(26)

\[ R_{np} = 28.33E_{np} + \gamma C(T_p - T_a), \]  
(27)

\[ E_{ma} = 0.0353 \left( 14 + \frac{1.2\Delta_p R_{np}}{\Delta_p + \gamma} \right). \]  
(28)

2.3.4 Thornthwaite potential evaporation

Thornthwaite (1948) potential evaporation (\( E_{th}, \text{mm.mth}^{-1} \)) uses air temperature as the sole input and is calculated at a monthly time-step. Following Xu and Singh (2001), the annual heat index, \( i \), is calculated as the sum of the 12 monthly heat indices, \( i \), each of which is a function of the mean monthly air temperature, \( T_m \) (K):

\[ i = \left( \frac{T_m - 273.16}{5} \right)^{1.51}. \]  
(29)
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For each month, potential evaporation is then estimated as

\[ E_{ch} = \frac{16d}{360} \left( \frac{10(T_m - 273.16)}{I} \right)^a \]  

(30)

where \( a \) is equal to \( 0.49 + 0.019 I - 0.0000771 I^2 + 0.000000675 I^3 \), and \( d \) is the monthly average day-length (hours).

2.4 Pan coefficients

Surfaces of daily pan coefficients (\( K_{pan} \)) were derived for each of the five potential evaporation formulations. \( K_{pan} \) values were determined as:

\[ K_{pan} = \frac{E_s}{E_{np}} \]  

(31)

where \( E_s \) represents one of the five potential evaporation formulations.

2.5 Analysis of trends

Long-term dynamics in potential evaporation were examined in terms of linear trends calculated using ordinary least squares regressions on a month-of-year basis (i.e., calculate the trend for all Januaries, then for all Februaries, etc.). Annual trends were calculated as the sum of the twelve monthly trends. For the spatial data, regressions were performed for every pixel across Australia and Australia-wide trends were calculated as the spatial averages of all the pixel trends. Trends in point-based data were calculated in the same month-of-year manner. In this way, long-term changes in the radiation balance and in the five formulations of potential evaporation—including trends in the inputs variables used in each of the models—were calculated. Here we present trends in flux variables in units of \( x.yr^{-2} \) (i.e., the change over time \([yr^{-1}]\) in the rate \([x.yr^{-1}]\)), and in units of \( x.mth^{-1}.yr^{-1} \) (i.e., the change over time \([yr^{-1}]\) in the rate \([x.mth^{-1}]\)).

One way of testing the ability of each formulation of potential evaporation to realistically capture changes in evaporative demand in water limited environments is to compare the trends in potential evaporation with trends in precipitation. The pattern generally expected is an inverse relationship due to the feedbacks between evaporative demand and precipitation (e.g., Yang et al. 2006). That is, in water limited environments, an increase in precipitation should be associated with increased latent heat flux because of increases in surface moisture availability, and should be associated with decreased incoming shortwave radiation due to increased cloudiness and humidity. It has recently been shown that the role of changes in wind speed in these feedbacks does not produce a simple inverse relation (Shuttleworth et al. 2009). Given this caveat, this test of inverse proportionality—though approximate—constitutes a useful means of examining potential evaporation dynamics.
2.6 Attribution of trends

Another means of examining the modelled trends in potential evaporation is to attribute the changes in potential evaporation to changes in the component input variables. This allows the effects of the assumptions in formulations (that is, which variables are held constant) to be quantified on the overall dynamics in potential evaporation. The attribution of trends was undertaken by performing partial differentiations on the input variables of both the Penman (Eq. (15)) and the Priestley-Taylor (Eq. (16)) formulations. These two formulations were chosen as representatives of the Penman-based equations and the radiation-based equations, respectively. Attribution of the temperature-based Thornthwaite formulation is not needed, as any changes in $E_{th}$ are directly attributed to $dT_a/dt$.

As per Roderick et al. (2007), the change in $E_p$ can be attributed to changes in the radiative and aerodynamic components,

$$\frac{dE_p}{dt} = \frac{dE_{pR}}{dt} + \frac{dE_{pA}}{dt}. \quad (32)$$

Dynamics in the radiative component are due to changes in $\Delta$ (which itself is a function solely of $T_a$) and $R_n$:

$$\frac{dE_{pR}}{dt} = \frac{\partial E_{pR}}{\partial \Delta} \frac{d\Delta}{dT_a} \frac{dT_a}{dt} + \frac{\partial E_{pR}}{\partial R_n} \frac{dR_n}{dt}; \quad (33)$$

where

$$\frac{\partial E_{pR}}{\partial \Delta} \frac{d\Delta}{dT_a} \frac{dT_a}{dt} = \frac{R_n \gamma}{(\Delta + \gamma)^2} \frac{d\Delta}{dT_a} \frac{dT_a}{dt}; \quad (34)$$

$$\frac{\partial E_{pR}}{\partial R_n} \frac{dR_n}{dt} = \frac{\Delta}{\Delta + \gamma} \frac{dR_n}{dt}, \quad (35)$$

Given that $D$ is the difference between $e_s$ and $e_a$, changes in the aerodynamic component are

$$\frac{dE_{pA}}{dt} = \frac{\partial E_{pA}}{\partial \Delta} \frac{d\Delta}{dT_a} \frac{dT_a}{dt} + \frac{\partial E_{pA}}{\partial u_2} \frac{du_2}{dt} + \frac{\partial E_{pA}}{\partial e_s} \frac{de_s}{dT_a} \frac{dT_a}{dt} + \frac{\partial E_{pA}}{\partial e_a} \frac{de_a}{dt}, \quad (36)$$

with the contributions from $\Delta$, $u_2$, $e_s$, and $e_a$ estimated as:

$$\frac{\partial E_{pA}}{\partial \Delta} \frac{d\Delta}{dT_a} \frac{dT_a}{dt} = -6430 \gamma D \left(1 + 0.536u_2\right) \frac{d\Delta}{dT_a} \frac{dT_a}{dt} \frac{d\Delta}{dT_a} \frac{dT_a}{dt}; \quad (37)$$
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\[
\frac{\partial E_{pt} \, du_z}{\partial u_z \, dt} = \frac{3446.48 \, \gamma \, D \, du_z}{(\Delta + \gamma) \, \lambda \, dt}; \quad (38)
\]

\[
\frac{\partial E_{pt} \, de_s \, dT_a}{\partial e_s \, dT_a \, dt} = \frac{6430 \, \gamma \, (1 + 0.536 \, u_z) \, de_s \, dT_a}{(\Delta + \gamma) \, \lambda \, dT_a \, dt}; \quad \text{and} \quad (39)
\]

\[
\frac{\partial E_{pt} \, de_a \, dt}{\partial e_a \, dT_a \, dt} = \frac{-6430 \, \gamma \, (1 + 0.536 \, u_z) \, de_a}{(\Delta + \gamma) \, \lambda \, dt}. \quad (40)
\]

For Priestley-Taylor, the change in \( E_{pt} \) and its partial differentials can be similarly expressed:

\[
\frac{dE_{pt}}{dt} = \frac{\partial E_{pt}}{\partial \Delta} \, \frac{d\Delta}{dT_a \, dt} + \frac{\partial E_{pt}}{\partial R_n} \, \frac{dR_n}{dt}. \quad (41)
\]

Again, ignoring the affect of \( dT_a/dt \) on \( dR_n/dt \) and assuming \( \Delta \) is a function solely of \( T_a \), the attribution of \( T_a \) and \( R_n \) can be expressed, respectively, as:

\[
\frac{\partial E_{pt} \, d\Delta \, dT_a}{\partial \Delta \, dT_a \, dt} = \frac{1.26 \, R_n \, \gamma \, d\Delta \, dT_a}{(\Delta + \gamma)^2 \, dT_a \, dt}; \quad \text{and} \quad (42)
\]

\[
\frac{\partial E_{pt} \, dR_n}{\partial R_n \, dt} = \frac{1.26 \, \Delta \, dR_n}{\Delta + \gamma \, dt}. \quad (43)
\]

In quantifying these partial differentials, the Australian average trend is used to represent the derivative (i.e., \( dx/dt \)) and the Australian, long-term annual average value is used to represent the coefficients. For example, to attribute the changes in \( E_p \) to changes in \( T_a \), Equations (37), (39), (42) and (44) can be combined as

\[
\frac{\partial E_{pt}}{\partial T_a} \, dT_a = \frac{\partial E_{pt}}{\partial \Delta} \, d\Delta \, dT_a + \frac{\partial E_{pt}}{\partial R_n} \, dR_n \, dT_a + \frac{\partial E_{pt}}{\partial e_s} \, de_s \, dT_a + \frac{\partial E_{pt}}{\partial e_a} \, de_a \, dT_a \quad (44)
\]

or more fully as

\[
\frac{\partial E_{pt}}{\partial T_a} \, dT_a = \frac{R_n \, \gamma \, d\Delta \, dT_a}{(\Delta + \gamma)^2 \, dT_a \, dt} + \frac{-6430 \, \gamma \, D \, (1 + 0.536 \, u_z) \, d\Delta \, dT_a}{(\Delta + \gamma)^2 \, dT_a \, dt} + \frac{6430 \, \gamma \, (1 + 0.536 \, u_z) \, de_a \, dT_a}{(\Delta + \gamma) \, \lambda \, dT_a \, dt} \quad (45)
\]

Inserting the values within Table 2 into Equation (45) gives:
\[
\frac{\partial E_D}{\partial T_a} \frac{dT_a}{dt} = 0.4 - 0.7 + 1.8 = 1.5 \text{ mm yr}^{-2}
\]  

(46)

Table 2. Australia-wide annual average values and trends (first derivatives) for selected input variables.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Annual average</th>
<th>Differential</th>
<th>Trend</th>
</tr>
</thead>
<tbody>
<tr>
<td>( T_a )</td>
<td>295 K</td>
<td>( \frac{dT_a}{dt} )</td>
<td>0.016 K yr(^{-1} )</td>
</tr>
<tr>
<td>( e_s )</td>
<td>3071 Pa</td>
<td>( \frac{de_s}{dT_a} \frac{dT_a}{dt} )</td>
<td>3.08 Pa yr(^{-1} )</td>
</tr>
<tr>
<td>( D )</td>
<td>1730 Pa</td>
<td>( \frac{dD}{dT_a} \frac{dT_a}{dt} )</td>
<td>2.2 Pa yr(^{-1} )</td>
</tr>
<tr>
<td>( U_2 )</td>
<td>2.0 m s(^{-1} )</td>
<td>( \frac{du_2}{dt} )</td>
<td>-0.01 m s(^{-1} ) yr(^{-1} )</td>
</tr>
<tr>
<td>( \gamma )</td>
<td>65.3 Pa K(^{-1} )</td>
<td>( \frac{d\Delta}{dT_a} \frac{dT_a}{dt} )</td>
<td>0.17 Pa K(^{-1} ) yr(^{-1} )</td>
</tr>
<tr>
<td>( \Delta )</td>
<td>183.8 Pa K(^{-1} )</td>
<td>( \frac{d\Delta}{dT_a} \frac{dT_a}{dt} )</td>
<td>0.17 Pa K(^{-1} ) yr(^{-1} )</td>
</tr>
<tr>
<td>( R_n )</td>
<td>153 W m(^{-2} )</td>
<td>( \frac{dR_n}{dt} )</td>
<td>-0.06 W m(^{2} ) yr(^{-1} )</td>
</tr>
</tbody>
</table>
3. RESULTS

3.1 Input data validation

Monthly observations in \( P, T_x, T_n, e_a \) and \( u_2 \) are compared, in Figure 2, with their equivalent values obtained from the input grid data. Although \( P \) was not used in the calculation of potential evaporation, it is included here: (i) to illustrate the relationship between the accuracy of spline interpolation and the density of input data points; and (ii) as it is subsequently used as a surrogate for actual evaporation. The monthly values from spline-derived BAWAP data match the observations well for all variables (Figure 2a–d). The spline-derived \( u_2 \) data do not compare well with observed trends whereas those from the TIN-derived \( u_2 \) do accurately match the observations (Figure 2e–f).

From the comparison of annual spline-derived trends in these same variables (Figure 3a–e), it can be seen that spline-interpolated \( P \) data capture underlying trends well, \( T_x \) and \( T_n \) data less so, \( e_a \) less again, and with \( u_2 \) being generally unable to capture underlying trends. The average number of stations across Australia used to create the \( P \) grids was 5760, for the temperature grids there were 721 stations, for \( e_a \) 670 (Jones et al. 2007) and for \( u_2 \) 162 stations (McVicar et al. 2008). As intuitively expected, the greater the density of input data used in spline-based spatial interpolations, the greater the accuracy with which the splines capture the underlying temporal trends in the observed data. Even though TINs produce less realistic spatial patterns, they more accurately capture the temporal trends present in the input data (Figure 3f) when the density of data points is low. It was for this reason that the TIN-based \( u_2 \) dataset was produced.

The comparison of values and trends in modelled Penpan evaporation \( (E_{pp}) \) with values and trends in pan observations \( (E_{pan}) \) provides a robust test of the input data (Figure 4); these comparisons are quantified by linear regression. Modelled \( E_{pp} \) derived using the spline-based \( u_2 \) dataset (Figure 4a) is well related to \( E_{pan} \) values, with a slope of 0.90, an \( r^2 \) of 0.90 and a 29 mm.mth\(^{-1}\) RMSE (Root Mean Square Error). Figure 4c shows that, when using \( E_{pp} \) derived using the TIN-based \( u_2 \) dataset, these statistics improve to be 0.99, 0.92, and 27 mm.mth\(^{-1}\), respectively. A similar level of accuracy between modelled and observed values was attained by Roderick et al. (2007) using solely point-based data. The relation between trends in the spline-based \( E_{pp} \) and trends in \( E_{pan} \) has a slope of 0.26 and \( r^2 \) of 0.29 (Figure 4b); these values changed to 0.43 and 0.31, respectively, when using the TIN-derived \( E_{pp} \). Trends in \( E_{pp} \) only moderately match those of pan observations (Figure 4b), presumably due to the compounding effect of the input variables’ inability to perfectly capture temporal trends (see Figure 3). However, the average Australian trend in \( E_{pp} \) from the grid is 0.0 mm.yr\(^{-2}\) (with a standard error of 2.3 mm.yr\(^{-2}\)) and is comparable to the average of the observed trends at the 102 points of Figure 4d, which is -1.5 mm.yr\(^{-2}\) (with a standard error of 4.0 mm.yr\(^{-2}\)). Given that the modelled \( E_{pp} \) values reproduced \( E_{pan} \) values extremely well (Figure 4c) and reproduced temporal trends moderately well (Figure 4d), the input datasets can be used with reasonable confidence to calculate the five formulations of potential evaporation which are subsequently assessed for their dynamics. In the remainder of this work, only the TIN-based \( u_2 \) dataset is used.
Figure 2. Comparison of observed and interpolated monthly meteorological data.
Plot: (a) precipitation; (b) maximum air temperature; (c) minimum air temperature; (d) dew-point temperature; (e) wind speed derived from spline-interpolated data; and (f) wind speed derived from TIN-interpolated data. The dotted line is the 1:1 line, the dashed line is the equation of best fit (given on each plot), n is the number of observations, the offset and RMSE statistics are in ordinate units.
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Figure 3. Comparison of observed and interpolated annual trends in meteorological data. Plot: (a) precipitation; (b) maximum air temperature; (c) minimum air temperature; (d) dew-point temperature; (e) wind speed derived from spline-interpolated data; and (f) wind speed derived from TIN-interpolated data. The dotted line is the 1:1 line, the dashed line is the equation of best fit (given on each plot), n is the number of observations, the offset and RMSE statistics are in ordinate units.
3.2 Net radiation validation

The use of McVicar and Jupp’s (1999) locally calibrated coefficients within the Bristow-Campbell (1984) relation improved the accuracy of modelled $R_{si}$ when compared to using the standard Bristow-Campbell formulation from $r^2$ and RMSE values of 0.72 and 43 W.m$^{-2}$ to 0.93 and 18 W.m$^{-2}$, respectively (Figure 5a and b). Likewise, the addition of the local calibrations and the remotely sensed estimates of $\varepsilon_s$ improved $R_{s}$ estimates from $r^2$ and RMSE values of 0.91 and 11 W.m$^{-2}$ to 0.92 and 9 W.m$^{-2}$, respectively (Figure 5c and d).
3.3 Potential evaporation formulations

Estimates of potential evaporation rates using the five formulations vary substantially in their magnitudes and ranges (Figure 6). Australian-average annual potential evaporation varies between 1765 and 3670 mm.yr⁻¹, whilst the smallest seasonal variation is approximately 80 mm and the greatest is 300 mm.mth⁻¹. $E_{mp}$ has the highest rate, and range, followed by $E_p$ and $E_{ma}$. Pan evaporimeters, due to their 3-dimensional, above-ground geometry, are capable of absorbing more energy than can a flat surface (Linacre 1994; McVicar et al. 2007; Rotstayn et al. 2006). Hence, $E_{pan}$ should be higher than any rates of potential evaporation. Given this, and that the average $E_{mp}$ value for Australia is 2894 mm.yr⁻¹, the values of $E_{mp}$ seem unrealistically high, over-estimating potential rates by as much as 25%.
The values of $E_p$ are estimates of open-water evaporation and the Penman formulation effectively has a surface resistance ($r_s$) of zero. $E_{pt}$ and $E_{ma}$ have similar average values and temporal patterns, each being less than $E_p$. The temperature-based $E_{th}$ bears the least resemblance to any other formulation, both in terms of the seasonal range and the temporal pattern in values.

Figure 6. Australian-average monthly potential evaporation estimated using five formulations of potential evaporation. Ordinate units are mm.mth$^{-1}$. Annual averages are in mm.yr$^{-1}$. 
3.4 Pan coefficients

Long-term Australian average $K_{\text{pan}}$ values, calculated using the Australian grids of $E_{\text{pp}}$ and each of the five potential formulations, are shown in Table 3. As rates of potential evaporation should be lower than rates of $E_{\text{pan}}$, so $K_{\text{pan}}$ should be $<1$. Hence, the annual average $K_{\text{pan}}$ for $E_{\text{mp}}$ is unrealistically high. $K_{\text{pan}}$ for $E_p$ is approximately the same as the widely used annual average value for converting $E_{\text{pan}}$ to evaporation rates from open water bodies (0.7, Linacre 1994; Stanhill 2002). The remaining potential evaporation formulations have $K_{\text{pan}}$ values of around 0.5–0.6, except for $E_{\text{th}}$ which shows almost no relationship with $E_{\text{pp}}$. Figure 7 gives two examples of grids of daily $K_{\text{pan}}$ values which demonstrate that $K_{\text{pan}}$ varies both spatially and temporally. Long-term, spatially averaged $K_{\text{pan}}$ values have traditionally been used to convert pan rates to potential rates; now spatially and temporally explicit estimates of $K_{\text{pan}}$ are available.

Table 3. Pan coefficient values for each of the five potential evaporation formulations.

<table>
<thead>
<tr>
<th>Formulation</th>
<th>Pan coefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td>Penman potential ($E_p$)</td>
<td>0.71</td>
</tr>
<tr>
<td>Priestley-Taylor potential ($E_{pt}$)</td>
<td>0.49</td>
</tr>
<tr>
<td>Morton point potential ($E_{mp}$)</td>
<td>1.12</td>
</tr>
<tr>
<td>Morton areal potential ($E_{ma}$)</td>
<td>0.55</td>
</tr>
<tr>
<td>Thornthwaite potential ($E_{th}$)</td>
<td>0.20</td>
</tr>
</tbody>
</table>

Figure 7. An example of Australia-wide, daily pan coefficient values.
Here the pan coefficient is for Penman potential evaporation for (a) the first of January 1981 and (b) the first of July 1981.

3.5 Analysis of trends

The Australia-wide trends in the inputs to the radiation modelling, as well as the modelled radiation components themselves, are shown in Table 4. Each component of the radiation balance has increased over the study period, with similar magnitude trends being experienced for both the two incoming components and for both the two outgoing components (see Table 4). As the combined trend in outgoing radiation is greater than that of incoming radiation (almost 1.5 times greater), net radiation has
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decreased overall (down approximately 1% over the 26-year period). Differentiation of Equations (6) and (9) indicate that 90% of the increase in $R_{so}$ is due to the increase in $\alpha$. If $\alpha$ was held constant in the modelling, the change in $R_{so}$ would have been 0.01 W.m$^{-2}$.yr$^{-1}$ and $R_n$ would have increased by an average of 0.028 W.m$^{-2}$.yr$^{-1}$. This result demonstrates the importance of understanding the role that even subtle changes in albedo can play in dynamics in the surface energy balance.

Figure 8 shows the spatial distributions of trends in the inputs used in the radiation modelling, and Figure 9 shows those of $R_{si}$, $R_{li}$, and $R_n$. The spatial patterns in the trends of $R_{si}$ and $R_{li}$ reflect the patterns in $T_r$ and $T_a$ trends, respectively. Across most of eastern Australia, and across the far north, $R_n$ has decreased over the study period. Conversely, throughout the western interior $R_n$ has increased. In general, $R_n$ has increased where $\alpha$ has decreased, which—in many areas—has occurred where $P$ has increased, and vice versa (see Figure 9). The incorporation of remotely sensed $\alpha$ has a marked effect on $R_n$, as it has produced a fine scale patterning within the $R_n$ trends governed by observed changes in land-surface properties.


<table>
<thead>
<tr>
<th>Attribute</th>
<th>Trend</th>
<th>Standard error</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Albedo ($\alpha$)</td>
<td>0.00037 yr$^{-1}$</td>
<td>0.0002</td>
<td>0.34</td>
</tr>
<tr>
<td>Minimum temperature ($T_n$)</td>
<td>0.007 K.yr$^{-1}$</td>
<td>0.01 K</td>
<td>0.98</td>
</tr>
<tr>
<td>Maximum temperature ($T_x$)</td>
<td>0.024 K.yr$^{-1}$</td>
<td>0.01 K</td>
<td>0.30</td>
</tr>
<tr>
<td>Air temperature ($T_a$)</td>
<td>0.016 K.yr$^{-1}$</td>
<td>0.01 K</td>
<td>0.47</td>
</tr>
<tr>
<td>Diurnal temperature range ($T_r$)</td>
<td>0.017 K.yr$^{-1}$</td>
<td>0.01 K</td>
<td>0.58</td>
</tr>
<tr>
<td>Actual vapour pressure ($e_a$)</td>
<td>0.88 Pa.yr$^{-1}$</td>
<td>1.4 Pa</td>
<td>0.30</td>
</tr>
<tr>
<td>Saturated vapour pressure ($e_s$)</td>
<td>3.08 Pa.yr$^{-1}$</td>
<td>1.7 Pa</td>
<td>0.55</td>
</tr>
<tr>
<td>Incoming shortwave ($R_{si}$)</td>
<td>0.068 W.m$^{-2}$.yr$^{-1}$</td>
<td>0.07 W.m$^{-2}$</td>
<td>0.91</td>
</tr>
<tr>
<td>Incoming longwave ($R_{li}$)</td>
<td>0.073 W.m$^{-2}$.yr$^{-1}$</td>
<td>0.06 W.m$^{-2}$</td>
<td>0.44</td>
</tr>
<tr>
<td>Outgoing shortwave ($R_{so}$)</td>
<td>0.100 W.m$^{-2}$.yr$^{-1}$</td>
<td>0.05 W.m$^{-2}$</td>
<td>0.49</td>
</tr>
<tr>
<td>Outgoing longwave ($R_{lo}$)</td>
<td>0.103 W.m$^{-2}$.yr$^{-1}$</td>
<td>0.04 W.m$^{-2}$</td>
<td>0.23</td>
</tr>
<tr>
<td>Net radiation ($R_n$)</td>
<td>-0.062 W.m$^{-2}$.yr$^{-1}$</td>
<td>0.05 W.m$^{-2}$</td>
<td>0.32</td>
</tr>
</tbody>
</table>
RESULTS

Figure 8. Annual trends (1981–2006) in the variables used to calculate net radiation.
(a) minimum air temperature; (b) maximum air temperature; (c) mean air temperature; (d) diurnal air temperature range; (e) actual vapour pressure; (f) saturated vapour pressure; (g) vapour pressure deficit; and (h) albedo.
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Annual Australia-average trends in potential evaporation (Table 5) show that $E_{th}$ and $E_{mp}$ have increased over the study period, $E_{ma}$ has changed little and the trends for the remaining formulations have decreased over time. Despite the large error bounds of these trend estimates, the seemingly small changes in rates of potential evaporation can have important implications on the water balance in energy-limited catchments and in the more humid water-limited catchments (which are where the majority Australia’s water supplies originate) over several decades. For comparison, the annual Australia-average (1981–2006) trends in $P$ and $E_{pp}$ are 1.3 and 0.0 mm.yr$^{-2}$, respectively (Table 5).

Trends in the variables used to calculate potential evaporation are presented in Figure 10. The effects of $T_a$ on potential evaporation are expressed through $R_n$, $e_s$ and $\Delta$. Overall, $T_a$ has increased across the majority of Australia, especially in the central-east (Figure 10a), the annual Australia-average trend is 0.016 K.yr$^{-1}$ (Table 4). As previously indicated, $R_n$ has decreased by 0.062 W.m$^{-2}$.yr$^{-1}$ (down 1%). Actual vapour pressure has increased by about 1.7% overall, at a rate of 0.88 Pa.yr$^{-1}$ (Table 4). The largest increases in $e_s$ have occurred in the central-west of the country (Figure 10c), a region which has also experienced some of the largest increases in $P$ (Figure 9d). The average trend in $u_2$ is -0.01 m.s$^{-1}$.yr$^{-1}$ (down 13% over 26 years). A disadvantage of using TIN-based $u_2$ interpolations is the triangular spatial structure in the data as can be seen in Figure 10d.

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The equivalent trends in precipitation and Penpan evaporation are shown for reference. P-values are determined using a two-sided Kendall tau test (Kendall and Gibbons 1990) performed on Australian-average annual values.

<table>
<thead>
<tr>
<th>Formulation</th>
<th>Trend (mm.yr⁻²)</th>
<th>Standard error of trend (mm.yr⁻¹)</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Thornthwaite potential (E_t)</td>
<td>0.6</td>
<td>1.3</td>
<td>0.39</td>
</tr>
<tr>
<td>Morton point potential (E_m)</td>
<td>0.2</td>
<td>1.3</td>
<td>0.49</td>
</tr>
<tr>
<td>Morton areal potential (E_a)</td>
<td>0.0</td>
<td>0.5</td>
<td>0.37</td>
</tr>
<tr>
<td>Priestley-Taylor potential (E_p)</td>
<td>-0.3</td>
<td>0.6</td>
<td>0.24</td>
</tr>
<tr>
<td>Penman potential (E_p)</td>
<td>-0.8</td>
<td>1.2</td>
<td>0.15</td>
</tr>
<tr>
<td>Precipitation (P)</td>
<td>1.3</td>
<td>2.1</td>
<td>0.41</td>
</tr>
<tr>
<td>Penpan potential (E_{pp})</td>
<td>0.0</td>
<td>2.3</td>
<td>0.44</td>
</tr>
</tbody>
</table>

Long-term trends in potential evaporation calculated using the five formulations can be seen in Figure 11a-e, with trends in \(P\) also being provided for context (Figure 11f). The spatial patterns in the trends of the Penman-based potential (Figure 11a) are dominated by changes in \(u_2\), with decreases occurring across much of the north of Australia and increases in regions in the centre and the east (partially corresponding to where \(P\) has decreased). Morton point potential (Figure 11c) has a less distinct pattern and largely follows changes in \(R_n\) (and therefore in \(\alpha\)). As with the Penman-based potentials, \(E_{mp}\) is also decreasing across the north, however this time it is primarily due to decreases in \(e_s\). Patterns in \(E_{Pt}\) and \(E_{ma}\) trends (Figure 11b and d) are very similar, generally following \(R_n\) trends, and the pattern in \(E_{th}\) trends (Figure 11e) are entirely a product of those in \(T_a\).
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Figure 10. Annual trends in the variables used to calculate potential evaporation (1981–2006).
(a) air temperature; (b) net radiation; (c) vapour pressure; and (d) wind speed.
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Figure 11. Annual trends in potential evaporation (1981–2006). (a) Penman; (b) Priestley-Taylor; (c) Morton point; (d) Morton areal; and (e) Thornthwaite formulations. Annual precipitation trends are also shown for reference (Donohue et al. 2009)—note the reversed legend for precipitation.

Given that Australia is predominantly water-limited (Figure 1), and taking changes in $P$ as a useful surrogate for changes in actual evaporation, we assess trends in potential evaporation as to whether they display an approximate complementary relation to trends in $P$. Figure 12 shows the per-month trends in potential evaporation and in $P$. In Figure 12a, two formulations ($E_p$ and $E_{mp}$) have a distinct seasonal pattern with trends showing a sharp decrease in summer (DJF) and a slight increase in winter (JJA), and, for $E_{mp}$, large increases in spring (SON) values. Changes in $E_{pt}$ and $E_{ma}$ are similar and reasonably uniform across all months (Figure 12a). Correlations between the per-
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Month potential evaporation trends (Figure 12a) and the per-month P trends (Figure 12b) show a complementary relationship for the Penman formulation and, to a lesser extent, for $E_{mp}$ (Table 4). Note that the seasonal pattern in P trends is present in the trends of Australian vegetation cover over the study period (Donohue et al. 2009) and is mirrored by trends in $\alpha$ (Figure 12b). This seasonal assessment of complementarity provides a stronger test of the potential evaporation trends than does an assessment done purely on Australia-average annual trends.

![Figure 12](image-url)

Figure 12. Monthly trends in Australia-wide potential evaporation (1981–2006). Plot (a) shows the monthly trends in potential evaporation and (b) the monthly trends in Australia-wide precipitation (black) and albedo (grey).

P-values are determined using a two-sided Kendall tau test (Kendall and Gibbons 1990) performed on Australian-average annual values; $n = 12$ in all cases.

<table>
<thead>
<tr>
<th>Formulation</th>
<th>$r$</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Penman potential ($E_p$)</td>
<td>-0.69</td>
<td>0.04</td>
</tr>
<tr>
<td>Priestley-Taylor potential ($E_{pt}$)</td>
<td>-0.22</td>
<td>0.27</td>
</tr>
<tr>
<td>Morton point potential ($E_{mp}$)</td>
<td>-0.60</td>
<td>0.13</td>
</tr>
<tr>
<td>Morton areal potential ($E_{ma}$)</td>
<td>-0.37</td>
<td>0.22</td>
</tr>
<tr>
<td>Thornthwaite potential ($E_{th}$)</td>
<td>-0.17</td>
<td>0.49</td>
</tr>
</tbody>
</table>

Figure 13 examines which formulations of potential have trends that are complementary with P trends at the 102 long-term pan evaporimeter locations across Australia. Only $E_p$ and $E_{mp}$ (Figure 13a and b) show a substantial negative relationship with changes in P (although each has a reasonable degree of scatter). $E_{pt}$ and $E_{ma}$ display little complementarity with P trends (Figure 13b and d) and $E_{th}$ essentially displays none at all (Figure 13e).
RESULTS

Figure 13. Comparison of annual trends of precipitation and potential evaporation (1981–2006) at the 102 locations.

(a) Penman; (b) Priestley-Taylor; (c) Morton point; (d) Morton areal; and (e) Thornthwaite formulations of potential evaporation, respectively. The dashed line is the equation of best fit (given on each plot), n is the number of observations, the offset and RMSE statistics are in ordinate units.
3.6 Attribution of trends

The Australia-wide trend in Penman potential evaporation over 1981-2006 is -0.8 mm.yr\(^{-2}\) (see Table 5). Table 7 shows that the results of attributing the changes in \(E_p\) were, in order of magnitude, due to: (i) \(dT/a\)dt (1.5 mm.yr\(^{-2}\)); (ii) \(du_2/\)dt (-1.3 mm.yr\(^{-2}\)); (iii) \(dR_n/\)dt (-0.6 mm.yr\(^{-2}\)); and (iv) \(dea/\)dt (-0.4 mm.yr\(^{-2}\)). The spatial distributions of the effects of each governing meteorological variable on \(dE_p/\)dt are shown in Figure 14. If \(u_2\) was held constant (i.e., in the absence of available wind speed data), \(dE_p/\)dt would have been approximately 0.5 mm.yr\(^{-2}\). Further, if both \(u_2\) and \(a\) were held constant, \(dE_p/\)dt would have been around 1.0 mm.yr\(^{-2}\). Albedo and wind speed both substantially influence potential evaporation trends and these results demonstrate the importance of treating these variables dynamically. Attribution of \(dE_p/\)dt on a per-month basis (Figure 15) indicates that the distinct seasonality in \(dE_p/\)dt is due to the combined effects of \(du_2/\)dt, \(dea/\)dt, and \(dR_n/\)dt, as the monthly changes in \(dT/a\)dt have little impact on the monthly variability of \(dE_p/\)dt.

<table>
<thead>
<tr>
<th>Change in Penman potential evaporation (dE_p/)dt</th>
</tr>
</thead>
<tbody>
<tr>
<td>Radiative component (dE_p/)dt</td>
</tr>
<tr>
<td>Saturation vapour pressure slope (\partial E_p/\partial \Delta dT_a/\partial t)</td>
</tr>
<tr>
<td>Saturation vapour pressure slope (\partial E_p/\partial \Delta dT_a/\partial t)</td>
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<td>Saturation vapour pressure slope (\partial E_p/\partial \Delta dT_a/\partial t)</td>
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<td>Saturation vapour pressure slope (\partial E_p/\partial \Delta dT_a/\partial t)</td>
</tr>
<tr>
<td>Saturation vapour pressure slope (\partial E_p/\partial \Delta dT_a/\partial t)</td>
</tr>
<tr>
<td>0.4</td>
</tr>
<tr>
<td>-0.2</td>
</tr>
</tbody>
</table>
RESULTS

The Australia-wide Priestley-Taylor potential evaporation trend over 1981-2006 is -0.3 mm.yr⁻² (see Table 6). Table 8 shows that changes in $R_n$ account for -0.8 mm.yr⁻² of the overall change, whilst $dT_a/dt$ accounts for 0.5 mm.yr⁻². The spatial distributions of $\delta E_{pt}/\delta T_a$ $dT_a/dt$ and $\delta E_{pt}/\delta R_n$ $dR_n/dt$ are shown in Figure 16. The seasonal patterns in $dE_{pt}/dt$ are indistinct (Figure 17) compared to those in $dE_{pt}/dt$ (Figure 15), but are most influenced by $dR_n/dt$. Given that 90% of the trend in $R_{so}$ is due to changes in $\alpha$, if the
formulation of $R_n$ assumed $\alpha$ was constant, then $dE_{pt}/dt$ would be have been positive (~0.4 mm yr$^{-2}$) and the spatial and monthly patterns would resemble those of the temperature-based potential evaporation formulations.

Table 8. Attribution of the changes in Australia-wide Priestley-Taylor potential evaporation (1981–2006) due to changes in $\Delta$ and net radiation. All units are mm yr$^{-2}$.

| Change in Priestley-Taylor potential evaporation $\frac{dE_{pt}}{dt}$ | 
| --- | --- |
| Temperature $\frac{\partial E_{pt}}{\partial \Delta} \frac{\partial \Delta}{\partial T_a} \frac{dT_a}{dt}$ | Net radiation $\frac{\partial E_{pt}}{\partial R_n} \frac{dR_n}{dt}$ |
| 0.5 | -0.3 |

Figure 16. Attribution of the annual trends in Priestley-Taylor potential evaporation (1981–2006). (a) air temperature; and (b) net radiation.

Figure 17. Attribution of the Australia-wide, monthly trends in Priestley-Taylor potential evaporation from 1981–2006.
4. DISCUSSION

4.1 The availability and quality of appropriate input data

Recently Roderick et al. (2007) and McVicar et al. (2008) demonstrated that wind speed across Australia has been declining over the past three decades, and that this decline has been the main cause of the observed declines in pan evaporation (Roderick et al. 2007; Rayner 2007). Donohue et al. (2009) have found that, on-average, Australian vegetation cover has been increasing since the early 1980s. This change has been incorporated into the potential evaporation modelling through the dynamics in albedo. In the work presented here, the dynamics of these two variables ($u_2$ and $\alpha$) have been explicitly included in the calculation of potential evaporation (as appropriate according to each formulation). Xu et al. (2006) examined the temporal dynamics in FAO56 reference evaporation (Allen et al. 1998)—however this formulation prescribes a constant $\alpha$. As far as we are aware, the work presented here is the first time the effect of observed spatial and temporal dynamics in these two variables on a variety of potential evaporation formulations has been reported.

Until recently, Australia-wide, daily wind speed data did not exist and McVicar et al.’s (2008) research is an important step in the ability to undertake such analyses as those presented here. Exploration of the characteristics of the McVicar et al.’s (2008) wind data revealed a need to implement an alternative interpolation technique to the 3D smoothing splines because of the paucity of wind observation data. The TIN-interpolated wind speed data more accurately represented the underlying observations both spatially and temporally. The use of TIN-based $u_2$ data improved the accuracy of the modelled pan evaporation data, when compared to the spline-based results (Figure 4). There is a limit to how accurately coarse resolution grids can replicate point-based data; nonetheless, the relationship between trends in modelled and observed pan evaporation could be further improved. Given the tightness of fit between the TIN-based and point-based $u_2$ data (Figure 3f), and the loose fit between the grid-based and point-based $T_x$, $T_n$ and $e_a$ data (Figure 3b-d), a first step in improving the accuracy of trends in modelled pan evaporation would be to improve these latter input data sets.

The calculated trends in $e_a$ and $e_s$ need to be interpreted carefully as both have been calculated from measurements made at different times during the day. Trends in $e_a$ are trends in 9am (local time) vapour pressure, not in daily integrals of vapour pressure. $e_s$ has been calculated using daily $T_x$ and $T_n$, the times of which are unknown and will differ from day-to-day (McVicar and Jupp 1999). This means that $e_a$ and $e_s$ are not concurrent measurements and consequently the effects of changes in the diurnal cycle of $T_a$ and/or $e_a$ may not necessarily be reflected in the calculated trends in $D$ or $e_s$.

4.2 Difficulties in parameterising surface conditions in potential evaporation formulations

Conceptually, potential evaporation is the evaporation rate that occurs from a location where energy is the dominant limit to evaporation. This is widely interpreted as being the evaporation that would occur from a large, saturated surface. Technically, this should mean the surface is parameterised as actually being saturated (e.g.,
Shuttleworth 1993), meaning $\alpha \leq 0.1$ (Oke 1987). Here we choose to parameterise the surface with actual $\alpha$ values instead (McVicar et al. 2007), as enforcing a hypothetical saturated-surface $\alpha$: (i) divorces the surface from the meteorological measurements made above the surface; and (ii) removes both temporal and spatial dynamics in surface conditions which is counter-intuitive when examining surface energy dynamics. Thus, our concept of potential evaporation does not enforce an actual saturated surface; it estimates evaporation from a surface as if all (most) available energy at that surface was to be converted into the latent heat flux under the extant surface and aerodynamic conditions.

The addition of measured $\alpha$ in the calculation of $R_n$ is an important component of the net radiation model presented here. Australian-average $\alpha$ increased by approximately 6% over the past 26 years. On a per-pixel basis both increases and decreases in $\alpha$ have been observed. Previously Donohue et al. (2009) found that vegetation cover across Australia changed considerably over the same period, generally increasing but with positive and negative trends across large areas of Australia. While the link between trends in $\alpha$ and vegetation cover are not straightforward (it is complicated by soil colour variations), it is reasonable that $\alpha$ has been, and is, changing. Although the magnitude of changes in $R_n$ formulated with, and without, a dynamic $\alpha$ varies moderately (-0.062 versus 0.028 W.m$^{-2}$.yr$^{-1}$), the spatial and seasonal patterns introduced by measured $\alpha$ are important characteristics in a dynamic $R_n$ model.

4.3 Findings and recommendations

The hypothesis in undertaking this research was that the fully physical formulations of potential evaporation, calculated using spatially and temporally dynamic input data, would yield the most realistic estimates of changes in potential evaporation. The results generally support this premise, as the greater the number of the four key variables used within a formulation, the more realistic the trends from that formulation became. $E_p$, which includes dynamic estimates of $T_a$, $R_n$, $e_a$, and $u_2$, has the most realistic temporal dynamics as it showed the greatest degree of complementarity with actual evaporation trends (as represented by $dP/dt$) when considering: (i) Australia-wide annual average trends (Table 5); (ii) spatial trends (Figure 11); (iii) seasonal trends (Figure 12); and (iv) trends at selected long-term meteorological stations (Figure 13). The $E_p$ attribution analysis showed that, even though $T_a$ and $u_2$ were the biggest contributors to the overall $E_p$ trends (having similar but opposite magnitudes), it was $R_n$ (due to $da/dt$), $e_a$, and $u_2$ that produced the seasonal complementarity in trends.

Morton point potential is a radiation-vapour pressure-temperature-based formulation—it does not explicitly include $u_2$ as a variable. Its rates of potential are extremely high (see Figure 6 and Table 3), over-estimating potential by up to one quarter of what seems reasonable (assuming potential evaporation rates should be no higher than $E_{pan}$). Despite this, $E_{mp}$ still displays similar patterns in trends in potential as does the Penman model. The Morton formulations are complex. Why the Morton point formulation captures trends but not actual values is unclear and, because of this, should be avoided as a means of estimating potential evaporation generally.

The radiation-temperature-based Priestley-Taylor formulation displays very weak complementarity with trends in actual evaporation (i.e., $dP/dt$) both spatially (Figure 11) and seasonally (Figure 12 and Table 6). The monthly pattern in $E_{pt}$ trends (Figure 17) is mainly caused by $dR_n/dt$, which itself is primarily a product of $da/dt$. If $E_{pt}$ was
formulated with a static $\alpha$, it would effectively mimic a temperature-based formulation under the climatic conditions of this study. However, considering the approximate similarity in modelled values between $E_{pt}$ and $E_p$, for the application considered here $E_{pt}$ is probably the optimal formulation in the absence of either $e_a$ or $u_2$ data. $E_{pt}$ should not be used for examining trends in water-limited environments, however. The temperature-based Thornthwaite estimates of potential did not produce realistic values in either rates or trends of potential evaporation, and should not be used (Hobbins et al. 2008).

Overall our results indicate that the more variables that are held constant when estimating potential evaporation, the less realistic the results become. This concurs with previous findings globally (e.g., McKenney and Rosenberg 1993; Chen et al. 2005; Shenbin et al. 2006; Garcia et al. 2004). We argue that Penman-based potential formulations should be the preferred means of examining long-term dynamics in potential evaporation.

This assessment of potential evaporation dynamics has been done only with respect to the inherent characteristics of the potential evaporation data itself. No analysis has been performed of the effects of the potential evaporation on the long-term dynamics of actual evaporation. The choice of which formulation to use and how it is parameterised can be crucial, for example: (i) in energy-limited catchments where actual evaporation is mainly determined by potential evaporation; (ii) in catchments that seasonally switch between energy- and water-limited states where actual evaporation follows potential for parts of the year (such catchments are crucial in Australia as these yield the majority of Australia’s water supplies); or (iii) when actual evaporation is calculated as a fraction of potential regardless of the climate type (e.g., McVicar and Jupp 2002; Guerschman et al. 2009).

The work presented here emphasises the fact that increases in mean air temperature over the past few decades does not necessarily mean that potential evaporation rates have also increased. Consideration of all the factors driving potential evaporation is critical, and will continue to be so as climate change continues. An important implication of this is that, to predict future potential evaporation rates, Generalised Circulation Models need the capacity to predict the dynamics in all the relevant variables with reasonable accuracy (Johnson and Sharma 2009), including those in wind speed and albedo.
5. SUMMARY AND CONCLUSIONS

Evaporative demand is driven by four variables—net radiation, vapour pressure, wind speed, and air temperature. Analyses of long-term dynamics in potential evaporation, therefore, should ideally use a fully dynamic formulation where the effects of the variability in each of the driving variables are accounted for. In Australia, changes in wind speed, albedo (and net radiation), air temperature and vapour pressure have been observed since the early 1980s. To date, no Australia-wide, long-term potential evaporation datasets have been available that dynamically incorporate all these variables.

Two key inputs used in the generation of potential evaporation data reported here are spatially and temporally dynamic representations of albedo (allowing for a fully dynamic representation of net radiation) and wind speed. The availability of these two datasets allowed the contribution of each of these variables on trends in potential evaporation to be quantified. We show that both these variables play an important role in evaporative demand dynamics.

Inputs to these analyses were daily surfaces interpolated from networks of observational data. A significant component of this work was the testing of the temporal accuracy of these input datasets. This was first done by comparing surface-derived trends in the input variables with the equivalent trends derived from the underlying observational point data. We found for wind speed data that the Triangular Irregular Network (TIN) interpolation method more accurately captured the underlying site data characteristics than the spline-based interpolation method. Another test undertaken compared trends in modelled US Class A pan evaporation—calculated using the input surface datasets—with observed trends in pan evaporation. Results from these tests provided reasonable confidence in the temporal accuracy of the input data and therefore in the modelled potential evaporation data. This accuracy is currently limited by the temporal accuracy of the air temperature and vapour pressure datasets.

In order to assess which formulations of potential evaporation are the most suitable for use in analyses of long-term dynamics, we generated daily potential evaporation datasets using five different formulations: (i) Penman; (ii) Priestley-Taylor; (ii) Morton point; (iv) Morton areal; and (v) Thornthwaite potential evaporation formulations. Spatial, annual, and seasonal trends in each were assessed in terms of whether they displayed approximate complementary characteristics with trends in actual evaporation (using precipitation as a proxy for actual evaporation). We also examined the contribution that trends in each input variable made to the overall trends in a fully physical formulation (Penman) and in a radiation-based formulation (Priestley-Taylor) of potential evaporation. Attribution of the Penman formulation showed that the complementary nature of trends in Penman potential were due to the dynamics in radiation (and particularly albedo), vapour pressure and wind speed.

From first principles, fully physical formulations, such as Penman, are expected to best capture trends in potential evaporation, and our results confirmed this. Only the Penman formulation displayed realistic values of both potential evaporation rates and trends for the conditions tested, and these should be the models of choice when all input data are available. The trends in Morton point potential, a formulation which uses all variables except wind speed, were similar to those in the Penman model. However,
its estimated rates of potential were unrealistically high—consequently, its use is not recommended. Both Priestly-Taylor and Morton areal formulations produced similar rates of potential, which were approximately similar to those from the Penman model. This, along with the simplicity of the Priestley-Taylor formulation, presents a strong argument for Priestley-Taylor being the best means of estimating potential evaporation rates when wind speed data are absent. Neither Priestley-Taylor nor Morton areal should be relied upon to reproduce temporal dynamics. Finally, Thornthwaite potential evaporation was shown to be unsuitable for use.
6. ACKNOWLEDGEMENTS

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REFERENCES


REFERENCES


McIlroy IC, Angus DE (1964) Grass, water and soil evaporation at Aspendale. *Agricultural Meteorology*, 1, 201-224.


REFERENCES


APPENDIX A – Derivation of incoming longwave radiation

Allen et al. (1998) present a formulation of net longwave radiation ($R_{ln}$) which Roderick et al. (1999) re-arranged to obtain incoming longwave radiation. Here the same re-arrangement is presented except that we have included surface emissivity in the formula of outgoing longwave, have converted $e_a$ to Pa, and have used Australian coefficients in estimating clear sky shortwave radiation. The rearrangement follows. Let

$$R_{ln} = R_o - R_{lo},$$  \hspace{1cm} (A1)

(in which it is implied that $R_{ln}$ is a negative flux due to $R_{lo}$ being larger than $R_o$) and

$$R_o = \varepsilon_a \sigma T_a^4.$$  \hspace{1cm} (A2)

Here $T_a$ is used to approximate $T_s$. In Allen et al.’s (1998) definition of net longwave radiation, $R_{ln}$ is a positive flux:

$$R_{ln} = \sigma T_a^4 \left(0.34 - 0.14 \sqrt{e_a}/1000\right) \left(\frac{1.35}{\sigma} \frac{R_{si}}{R_{cs}} - 0.35\right)$$  \hspace{1cm} (A3)

where $R_{cs}$ is clear sky incoming shortwave radiation. To render (A1) and (A3) equivalent, $R_{ln}$ in (A3) needs to become a negative flux. Further, we have adapted this to include surface emissivity, to be in SI units, and to incorporate the Australian coefficients for the Bristow-Campbell relation. Hence

$$R_{ln} = -\varepsilon_s \sigma T_s^4 \left(0.34 - 0.14 \sqrt{e_a}/1000\right) \left(\frac{1.35}{\sigma} \frac{R_{si}}{R_{cs}} - 0.35\right)$$  \hspace{1cm} (A4)

Combining Equations (A1), (A2) and (A4) and rearranging for $R_{li}$ gives

$$R_{li} = \varepsilon_s \sigma T_s^4 - \varepsilon_s \sigma T_s^4 \left(0.34 - 0.14 \sqrt{e_a}/1000\right) \left(1 - \frac{1.35}{\sigma} \frac{R_{si}}{R_{cs}} \frac{1}{R_o} - 0.35\right)$$  \hspace{1cm} (A5)

or

$$R_o = \varepsilon_s \sigma T_s^4 \left(1 - \left(0.34 - 0.14 \sqrt{e_a}/1000\right) \left(1 - \frac{1.35}{\sigma} \frac{R_{si}}{R_{cs}} \frac{1}{R_o} - 0.35\right)\right)$$  \hspace{1cm} (A6)

which is formulation for $R_{li}$ as presented in the manuscript in Eq 14.