Ecological research and large scale land-atmosphere feedbacks: lesson from the Bouchet’s complementary relationship

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Abstract

Acceleration of the global water cycle over recent decades, which is hypothesized by several studies, remains uncertain because of the high inter-annual variability of its components. Observations of pan evaporation ($E_{\text{pan}}$), a proxy of potential evapotranspiration ($ET_p$), may help to identify trends in the water cycle over long time periods. The complementary relation (CR; Bouchet, 1963) states $ET_p$ and actual evapotranspiration ($ET_a$) depend on each other in a complementary manner, through land-atmosphere feedbacks in water limited environments. Using a long time series of $E_{\text{pan}}$ observations in Australia, we estimated monthly $ET_a$ values using the CR and compared our estimates with $ET_a$ measured at eddy covariance stations in Fluxnet. Our results confirm that CR can be reliably applied to estimate $ET_a$ and produces better results than a global vegetation model run without specific calibration. In addition, our analysis indicated that, on average, $ET_a$ did not show any significant trend between 1975 and 2009 in Australia, but short-term analysis including anomaly periods may give the idea of a rapid climate change that is not perceived in a long-term perspective.

1 Introduction

Understanding spatial and temporal variability of the hydrological cycle to global change is a very difficult task (Allan and Liepert, 2010), since its components (e.g. precipitation, evaporation, run-off) may have inter-annual variability more than an order of magnitude higher with respect to any trends larger than decades (Dolman and de Jeu, 2010). Land surface evaporation is likely the most uncertain parameter, though it has been suggested to have intensified in recent decades. Brutsaert (2006) reported an increase in terrestrial evaporation of 0.44 mm yr$^{-1}$ during the second half of the 20th century. This study showed that in many regions worldwide, despite global dimming, pan evaporation ($E_{\text{pan}}$) decreased and actual evapotranspiration...
(ET<sub>a</sub>) complementarily increased. Tueling et al. (2009) reported an increase of ET<sub>a</sub> during the global dimming period (1958–1982) in North America and related this trend to an increase in precipitation. In the brightening period that followed (1983–2006), they observed a general decrease in both precipitation and ET<sub>a</sub>, that was not consistent with other studies suggesting the water cycle has been accelerating over the last 50 yr (Ramirez and Hobbins, 2005; Lawrimore and Peterson, 2000). Attempts to quantify trends in ET<sub>a</sub> have been made using modeling and data assimilation techniques, but these are based on relatively short-term global datasets or require a large amount of information and complex algorithms to be applied (Jung et al., 2010). Plot experiments causing ET<sub>a</sub> variation, are certainly useful to improve the physical basis. However, manipulation could only change the local conditions, not guaranteeing the same land-atmosphere interaction generated at large scale, when an environmental factor changes (e.g., precipitation, wind, CO<sub>2</sub> concentration etc.) (Miglietta et al., 2011).

In this context, observations of E<sub>pan</sub> as a proxy for potential evapotranspiration (ET<sub>p</sub>; e.g., evapotranspiration driven by the atmospheric demand) may be particularly useful, because E<sub>pan</sub> has been measured in many parts of the world over the past century and it has been widely established that empirical correlations (e.g., pan factors) can be used to convert measured E<sub>pan</sub> rates into ET<sub>p</sub> rates (Hobbins et al., 2008), and because a number of studies have demonstrated the significant negative correlation between E<sub>pan</sub> and ET<sub>a</sub> (Ozdogan et al., 2006; Pettijohn and Salvucci, 2006; Hobbins et al., 2004), especially in water limited environments (Roderick et al., 2009). The link between ET<sub>p</sub> (E<sub>pan</sub>) and ET<sub>a</sub> has been elaborated in Bouchet’s complementary relationship (CR; Bouchet, 1963), which states that ET<sub>a</sub> and ET<sub>p</sub>, in water limited environments at constant energy input complement each other, i.e., ET<sub>p</sub> + ET<sub>a</sub> = kET<sub>w</sub>, where ET<sub>w</sub> represents the regional wet-environment evaporation and k is a constant (originally set to 2) that makes the relationship perfectly symmetric (Fig. 1). According to the CR, ET<sub>a</sub> and ET<sub>p</sub> co-vary along a soil moisture gradient from desert situations, where ET<sub>p</sub> is high and ET<sub>a</sub> is low, to more moist environments where ET<sub>p</sub> and ET<sub>a</sub> converge at ET<sub>w</sub>. If this relation is proved to be valid and consistent, E<sub>pan</sub> observations...
can be used to derive ET<sub>a</sub> also at territorial level if a pan evaporimeter network is present. Estimation of ET<sub>a</sub> from pan evaporimeters provides a good coverage in space and time, yet the algorithm is simple to implement.

In this paper we: (i) verify the validity of the CR formulation on a monthly basis in Australia by deriving ET<sub>a</sub> values from \( E_{\text{pan}} \) observations by means of the CR and comparison with ET<sub>a</sub> measured by eddy covariance at different sites; and (ii) use long term observations of \( E_{\text{pan}} \) to investigate the inter-annual variability and long-term trend of ET<sub>a</sub> on the Australian continent.

2 Material and methods

2.1 Developing monthly ET<sub>a</sub> using the CR

In this study we used monthly \( E_{\text{pan}} \) data to estimate the corresponding ET<sub>a</sub> values using the CR and compared the results of our calculations with monthly ET<sub>a</sub> values derived from eddy-covariance measurements. Our study was undertaken in Australia because: (1) the Australian Bureau of Meteorology (BoM) provides a freely available high-quality dataset of meteorological observations including \( E_{\text{pan}} \) (Jovanovic et al., 2008); (2) eddy-flux towers of the Fluxnet community (Hutyra et al., 2005) are present at several sites in the country and provide direct measurements of ET<sub>a</sub>; (3) the country is on average a water-limited environment where the CR can be verified (Donohue et al., 2010). We collected monthly summaries of measured ET<sub>a</sub> from the following Fluxnet stations: Wallaby Creek (AU-Wac, 37.43° S, 145.19° E); Tumbarumba (AU-Tum, 35.65° S, 148.15° E); Howard Springs (AU-How, 12.49° S, 131.15° E). From each of these locations, we selected the closest BoM station where monthly time series of measured \( E_{\text{pan}} \) were available and covered the last 30–40 yr. In all cases we were able to find an BoM station within a maximum distance of 150 km and in a similar climate zone to the Fluxnet tower. These were Lake Eildon for AU-Wac (60 km to the Fluxnet tower), Darwin for AU-How (45 km) and the average values of Canberra and Rutherglen for AU-Tum (100 and 150 km, respectively). When
a time series of precipitation was not available at the selected BoM station, we used values from the closest alternative BoM stations. Precipitation data derived from the BoM were compared with the data coming from the Fluxnet sites for the years available; the total precipitations at BoM were 28% lower than Fluxnet, while the coefficient of correlation ($r$) was 0.88. Since our approach is insensitive to a bias in precipitation as shown in Fig. 1, such high correlation guarantees the correctness of using BoM precipitation dataset as a proxy of moisture index. We investigated the CR on a monthly basis, first by estimating $ET_p$ as $ET_p = E_{pan}k_p$, where $k_p$ was set to 0.8, in agreement with van Dijk (1985), Ramirez and Hobbins (2005), Hobbins et al. (2008). We defined a potential humidity index as equal to total precipitation ($P$), assuming that in the years with the greatest humidity index (i.e., most precipitation), $ET_p$ and $ET_a$ converged to a value that represents ET under purely energy-limited conditions ($ET_w$) (Fig. 1). With such an assumption we were able to adopt a purely data driven approach, thus avoiding the use of additional models and meteorological variables to estimate $ET_w$, such as the Priesley Taylor formula (Szilagyi, 2001). The original CR formulation is based on the heuristic hypothesis that there is a one to one correspondence between $ET_a$ decrease and $ET_p$ increase (and vice versa) and hence it is not a physical model taking into account driving variables such as radiation, temperature, humidity and wind speed. Although exogenous variation of these variables may likely result in a CR failure, it is also true that CR has successfully predicted measured $ET_a$ values worldwide (Yu et al., 2009; Ozdogan et al., 2006; Ramirez and Hobbins, 2005; Kahler and Brutsaert, 2006). The complex land-atmosphere feedbacks and interactions between global and local conditions, intrinsically contained in the CR, have lead to different implementations of it (Lhomme and Guilioni, 2006). For example, there is general evidence that measured data from pan evaporimeters, which received more energy per unit of horizontal area than the surrounding area and are subject to local advection (Kahler and Brutsaert, 2006), clearly result in an asymmetric CR function formulation, as in our case: $1.25 ET_a + E_{pan} = 2.5 ET_w$ (that is the rearrangement of the equation $ET_a + ET_p = 2 ET_w$ where $ET_p = 0.8 E_{pan}$).
Figure 2 shows ET_p and the calculated ET_a using the data from Canberra and Rutherglen, as an example. The complementary between ET_a and ET_p was strong in summer (December–March), when water supply was limiting. Approaching winter (June–September), the environment became energy limited and the complementary relationship was less evident, according to the CR original formulation. Estimated ET_a values were well in agreement with those measured by eddy covariance station at AU-Tum and AU-Wac sites (Fig. 3); in these temperate-climate Fluxnet sites most evapotranspiration takes place between October and April, under water limiting conditions. At the AU-How site, the procedure used for ET_a calculation was slightly modified because of the tropical climate of this area with a very wet rainy season in the Austral summer months followed by a very dry winter. Average monthly total precipitation from December to March at this site ranged between 250 and 426 mm per month, making the summer an energy limited environment. In contrast, the period of May to September is very dry (average precipitation 1.3 to 28 mm month^{-1}), and ET_a is partially sustained by the access of deep-rooted vegetation to deep soil water (Beringer et al., 2003). For this reason ET_a was considered equal to ET_p in the energy limited months; ET_a was calculated using the CR only for those months when the ET_p values decreased as function of P, reaching invariant values beyond a P threshold (ET_p = ET_w according to CR). The driest months (June to September) were excluded, due to the influence of the soil water storage in maintaining unexpected relatively high ET_a values (Beringer et al., 2003). Considering this data driven approach, the overall agreement between estimated and measured ET_a (Fig. 3) was very good, with linear regression resulting in a slope of 1.08 and an r^2 of 0.75 for all sites considered.

### 2.2 Modelling application

To further verify our approach, we also ran the Lund-Postdam-Jena Dynamic Global Vegetation Model (LPJ-DGVM) (Sitch et al., 2003) at the AU-Tum site without any specific calibration. For this site LPJ simulated ET_a was less correlated with measured values than ET_a derived with the CR approach proposed in the present paper (Fig. 4).
The complexity of global vegetation models in representing land-atmosphere carbon and water exchanges and vegetation dynamics means that without calibration to the actual vegetation observed at the eddy covariance site, we might not expect the DGVM to perform very well, particularly in a temperate region with strong seasonality and vegetation that has uniquely adapted water use strategies (e.g., Eucalyptus spp.).

3 Results and discussion

Two researches, based on completely different approaches, have recently confirmed that the global water cycle trend was strongly affected by the El Niño event occurred in 1997. Syed et al. (2010), estimating the freshwater discharge as the difference between ocean precipitation and evaporation (taking into account also the global-ocean mass change), indicated a freshwater discharge increase of 2256 km$^3$ yr$^{-1}$, during the period 1994–1999. This water cycle acceleration was also confirmed by Jung et al. (2010) who reported a land ET increase during the period 1982–1997, using data assimilation techniques based on global datasets of measured surface fluxes. After the El Niño event, the ocean evaporation trend (1999–2006) decreased more with respect to the previous period (396 vs. 2256 km$^3$ yr$^{-1}$) as did the freshwater discharge ($-756$ km$^3$ yr$^{-1}$). The lower land precipitation supplied by the ocean evaporation has consequently caused a decreasing trend in land ET ($-27.9$ mm per year per decade) during the period 1998 to 2008 (Jung et al., 2010).

To verify these trends across Australia, we used the high-quality dataset of spatially interpolated $P$ and $E_{\text{pan}}$ variables (Jovanovic et al., 2008), for the period 1975–2009. The linear regression across the entire period indicated a slight, but not significant ($P > 0.05$), decrease in $E_{\text{pan}}$ over the last 35 yr ($-1.6$ mm yr$^{-1}$). If a long-term trend has not emerged statistically, contrasting trends were evident for fractions of the time period. According to the breakpoint in the water cycle trend, found by Syed et al. (2010), we presented $P$ and $E_{\text{pan}}$ trends over Australia in the 1982–1998 and 1999–2009 sub-periods (Fig. 5). The measured precipitation values were consistent
with the abovementioned results; when precipitation increased (decreased), ET_p decreased (increased), strictly in agreement with the CR. In particular the coefficient of correlations (r) between ET_p and P were −0.77 and −0.93 in the period 1982–1998 and 1999–2009, respectively. Furthermore, the negative linear regression between E_pan and year in the period 1999–2009 was also significant (P = 0.05). Given that we verified the CR between ET_p and ET_a for three very different Australian ecosystems using eddy covariance fluxes, we have evidence that ET_a had an increasing trend in the period 1982–1998 and opposite behavior since 1999. Another indirect evidence of this trend was provided by Gobron et al. (2010), who reported positive fraction of absorbed photosynthetic active radiation (fAPAR) anomalies for the years 1999–2001 and generally negative values across Australia thereafter. In fact, across water-limited ecosystems, an increase or a decrease in precipitation generally results in an increase or decrease of net primary production (NPP) and transpiration (Ferguson and Veizer, 2007).

Despite the aim of this paper is not to demonstrate the physical mechanisms responsible for this trend but rather to verify the suitability of a simple data-driven approach, recent researches have focused on the main land-atmospheric feedbacks in relation to the climate forcing. Roderick et al. (2007) using a Penman’s combination equation adapted for pan evaporation, conducted a study over 41 Australian sites for the period 1975–2004. They found that the major contribution to the observed E_pan decrease was due to wind speed decrease. Even though CR is intrinsically based on a land-atmosphere feedback it is difficult to understand how much the wind change is part of this feedback or acts as an exogenous factor. In fact, Ozdogan et al. (2006) testing the Bouchet-Morton CR by a mesoscale climate scenario and observations, estimated a 50 % E_pan decrease in 20 yr and even more in wind speed under a progressive irrigation scenario in Southeastern Turkey. They concluded that the importance of reduced wind velocity in maintaining complementary was unexpected and the possible mechanisms associated with irrigation were the increased surface roughness, decreased thermal convection that influences momentum transfer, and the development of anomalous
high pressure that counteracts the background wind field. These studies suggest that probably wind speed and pan evaporation are positively correlated through direct forcing, changing aerodynamic resistance to vapor transfer. Therefore, the high negative correlation between precipitation and $E_{\text{pan}}$ we found in our study ($r = -0.82$), may be a results of complex feedback generated by the change in water availability, involving the variation of atmospheric aerodynamic component, the available energy partition into latent and sensible heat fluxes, and the planetary boundary layer dynamic (Seneviratne et al., 2010). A mechanicistic explanation of land-atmospheric feedbacks was recently explored by Van Heerwaarden et al. (2010), using a couple-land atmospheric 1-D model. The sensitivity analysis varying some forcing factors (precipitation, radiation, wind and air temperature) showed a strong sensitivity of the vapor pressure deficit (VPD) to change in relative soil moisture and a clear complementary between $E_{\text{pan}}$ and $\text{ET}_a$ simulated. In particular increasing precipitation resulted in decreasing $E_{\text{pan}}$ and VPD and increasing $\text{ET}_a$.

4 Conclusions

Quantification and changes of $\text{ET}_a$ over time are critical to water resource management because of the large share of the water budget typically composed of $\text{ET}_a$. This variable results from complex processes in which land and atmosphere are coupled, and the spatial dimension has a direct effect on the feedbacks generated. For this reason the indications from plot experiment manipulations should be evaluated with care, considering the possible large scale feedbacks that may be ignored.

The use of remote sensing algorithms to derive $\text{ET}_a$ is promising, but time series are limited. The same applies for direct observations such as Fluxnet data, that lack both spatial and temporal coverage in many areas of the world. This leads to the risk off confounding short-term climate variability with the long-term trend. However, direct measurements of $\text{ET}_a$ (e.g. by eddy correlation methods) provide valuable data to improve the quality of hydrological and land-atmosphere modeling through providing

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constraints and reducing the uncertainty of the modeled ET_a component. Our approach based on Bouchet’s complementary theory can be applied to long-term observations of ET_p, either derived from E_pan or from meteorological data, and allows the study of ET_a trends and their variability over decades. The proposed approach is simple yet provides very robust results. We did not obtain more accurate results when running a state of the art global vegetation model (LPJ, without site specific calibration).

Trends in the Australian long-term time series of precipitation, ET_p, and the derived ET_a did not seem to indicate an abrupt water cycle change in the last 35 yr, even though subsets of anomaly periods can provide contradictory indications to the long-term time series analysis.

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References


van Dijk, M. H.: Reduction in evaporation due to the bird screen used in the Australian class –
Fig. 1. Black lines are a schematic representation of the Bouchet's complementary relation (CR) where: $\text{ET}_{p}$ refers to potential evapotranspiration dependent only by the atmospheric demand, usually represented by Penam-Monteith models; $\text{ET}_{w}$ is wet environment evapotranspiration commonly calculated with the Priestly-Taylor model and $\text{ET}_{a}$ is the actual evapotranspiration. Red dotted lines are a schematic representation of CR insensitivity to a bias in precipitation ($P$), used as moisture index.
Fig. 2. Monthly $ET_p$ values and corresponding $ET_a$ calculated by the CR using the average $E_{pan}$ from Camberra and Rutherglen sites. $ET_p$ was calculated as $E_{pan} \times K_p$. 

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Fig. 3. Comparison between the monthly $ET_a$ values measured at the Fluxnet sites and the estimated $ET_a$ values in the corresponding BoM stations. Estimated $ET_a$ values for AU-How site were calculated with a slightly different approach due to the tropical climate conditions, as reported in the text.
**Fig. 4.** Comparison between monthly $\text{ET}_a$ values measured at the AU-Tum fluxnet station and: (a) simulated $\text{ET}_a$ with LPJ global vegetation model; (b) $\text{ET}_a$ values calculated by CR relationship.
Fig. 5. Precipitation (a) and $E_{\text{pan}}$ (b) trend for the period 1975–2009. Dotted line is the long-term trend (1975–2009), while two sub-trend are represented for the period across the ENSO event of 1997.