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A framework to quantify the inter-annual variation in near-surface air temperature due to change in precipitation in snow-free regions

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Abstract

A negative correlation between near-surface air temperature \((T_a)\) and precipitation \((P)\) has long been recognized over many land regions, but a predictive quantitative relationship has not yet been established. In this study, we examine inter-annual variations in \(T_a\) with \(P\) and investigate how the \(T_a-P\) relationship varies with aridity in regions without snow coverage. The wetness index is used as a measure of aridity (defined as the ratio of mean annual \(P\) to \(E_o\), with \(E_o\) the net radiation expressed as an equivalent depth of water), with wetness index more (less) than 1.0 used to define the wet (dry) regions. Results show that variations in \(T_a\) are independent of \(P\) in wet environments, while in dry environments the variations in \(T_a\) with \(P\) increase with aridity. We use that relationship to establish a quantitative framework to \textit{a priori} predict the \(T_a-P\) relation based on aridity. The results highlight the importance of inter-annual variations in \(P\) in changing \(T_a\) in dry environments, since it has similar magnitude with the decadal global warming signals over land.

1. Introduction

The near-surface air temperature \((T_a)\) is usually higher during a low precipitation \((P)\) year (Namias 1960, Madden and Williams 1978). This negative \(T_a-P\) relation has been very widely observed and documented at daily, intra-/inter-annual and even longer time scales over land (Trenberth and Shea 2005, Adler et al 2008, Berg et al 2015, Sharma and Mujumdar 2019). The correlation of \(T_a\) and \(P\) has important implications for the concurrence of dry and hot extremes (Mueller and Seneviratne 2012, Hao et al 2013), which are expected to change in a warmer climate (Wu et al 2020). While the \(T_a-P\) relation has been extensively documented in both observations and model simulations, there is, as yet, no formal quantitative theory to \textit{a priori} predict the variations in \(T_a\) due to those in \(P\).

One approach to explore the impact of variations in \(P\) on \(T_a\) is to investigate the relation between soil moisture and evapotranspiration (Seneviratne et al 2006, Koster et al 2009, Lorenz et al 2016), which originates from the classical soil moisture \((SM)\) and evaporative fraction \((EF)\) relation (Budyko 1974, Eagleson 1978). Here the underlying mechanism is for low \(SM\) to lead to a lower evaporative flux and hence an enhanced sensible heat flux (i.e. lower \(EF\)) that in turn increases \(T_a\) (Seneviratne et al 2010). That form of the \(SM-EF\) relation has been widely used with fully coupled climate model simulations by separately considering both the \(EF-T_a\) and \(SM-T_a\) coupling (e.g. Schwingshackl et al 2017). The \(SM-T_a\) interactions have been helpful to explain the \(T_a-P\) relation (Vogel et al 2018), with the change of \(T_a\) greatly reduced in the absence of soil moisture change in climate model simulations or vice versa (Berg et al 2015, 2016). One potential challenge to this approach is that the \(SM-EF\) relation may not be unique and could therefore vary with surface and meteorological conditions (Haghighi et al 2018).

The \(SM-EF\) approach has been widely recognised as a suitable conceptual framework for understanding the negative \(T_a-P\) correlation. However, it is difficult to apply in many practical applications because
of a lack of suitable observed SM data. In that context we seek a practical approach explicitly recognises the SM–$T_a$ coupling and SM–EF framework but can also be used with the available observations. Previous studies have shown that the correlation between $T_a$ and $P$ is strongly negative in arid regions (e.g. figure 1 in Berg et al 2015). In addition to that correlation, Yin et al (2014) also noted that the magnitude of the variations in $T_a$ with $P$ seems to generally increase with the background aridity. The above results led us to hypothesize that the background aridity may play a crucial role in setting the increase in $T_a$ during low $P$ years. Furthermore, we hypothesize that it might be possible to quantitatively estimate the magnitude of $T_a$–$P$ relation based on the background aridity.

The aim of this paper is to quantitatively investigate the $T_a$–$P$ relation. We use annual data but note that the approach is, in principle, suitable for use at shorter time steps, such as monthly or seasonal time steps. We begin by briefly (re-)investigating the $T_a$–$P$ correlation using readily available gridded climate observations. We then go beyond previous qualitative correlations by establishing a quantitative framework to predict variations in $T_a$ due to those in $P$ (i.e. the slope of $T_a$–$P$ regression) using the regional background aridity as the predictive variable. The proposed framework is tested using independent data from Texas (USA), the Murray-Darling Basin (MDB, Australia) and a hyper-arid region in western Australia.

2. Data and methods

2.1. Climate data

Radiation and meteorological data are used to explore the empirical relation between the slope of the $T_a$–$P$ relation and aridity (wetness index is used here as the measure of aridity, see section 2.3). Global $T_a$ and $P$ observations were sourced from the widely used Climatic Research Unit (CRU) TS4.01database (monthly, $0.5^\circ \times 0.5^\circ$, 1901–2016) (Harris et al 2014). To quantify the aridity, we use the above-noted CRU precipitation data supplemented by radiation data from the NASA/GEWEX Surface Radiation Budget (SRB) Release-3.0 (monthly, $1^\circ \times 1^\circ$, 1984–2007) database (Stackhouse et al 2011). The SRB database documents the four surface radiative flux components (incoming and outgoing shortwave and longwave radiative fluxes), and we use those to calculate the net radiation and further calculate the aridity. We use the calendar year period 1984–2007 to define the study period and integrate the CRU $T_a$ and $P$ databases to the spatial resolution of $1^\circ$ used in the SRB database.

To investigate the application of the empirical $T_a$–$P$ relation, we conduct regional case studies in three regions, i.e. Texas in USA, the Murray-Darling basin (MDB) in southeast Australia and a hyper-arid region in western Australia (West AU). Long-term observations of $T_a$ and $P$ in the three regions, i.e. Texas (1895–2018), MDB (1910–2018) and West AU (1914–2013) were independently sourced from the U.S. Climate Divisional Dataset (referred to as NOAA-NCEI) (Vose et al 2014, http://www.ncdc.noaa.gov/cag), the Australian Bureau of Meteorology (http://www.bom.gov.au/) and the Australian Water Availability Project (AWAP) (Raupach et al 2009, 2012) respectively. The long-term data were used to estimate the relations between $T_a$ and $P$ anomalies in the three case study regions, and the slopes of the regression were compared with the slopes predicted independently using the aridity-based $T_a$ and $P$ relation (see section 3.3).

2.2. Spatial masks to define study extent

In order to minimise potential problems caused by inaccurate precipitation data, we restricted the analysis extent to those grid-cells that had at least one precipitation measurement station (e.g. Sun et al 2012). The aim was to restrict the analysis extent to those areas of the globe with more comprehensive $P$ observations. In more detail, we use grid-cells having at least one precipitation measurement station for 90% of months over the 1984–2007 period to define regions with the highest possible $P$ data quality (figure 1(a)).

To avoid any complication in this initial analysis we exclude irrigation areas because the increase in evapotranspiration due to irrigation is well known to decrease $T_a$ independently of $P$ (Lobell et al 2009, Puma and Cook 2010). To identify those grid-cells, we used a digital map from the Food and Agriculture Organization of the United Nations (Siebert et al 2013) to identify grid-cells having at least 10% of their area specified as being subject to irrigation (figure 1(b)) and those regions were excluded from the study extent. Finally, we also excluded regions having snow/ice cover to avoid complications arising from prominent seasonal changes in albedo. Grid-cells that were snow/ice free (figure 1(c)) were identified using monthly data during the 2001–2007 period from the MODIS/Terra Snow Cover dataset (Hall and Riggs 2015). The final resulting mask was constructed from the above three components and identified 550 grid-cells (figure 1(d)). The resulting mask (figure 1(d)) was held fixed over the entire study period. The study area is dominated by grid-cells in Australia, southeast Asia and southern parts of the US with a scattering of grid-cells from other continents. As shown in figure 1 the study area is mainly located at low and middle latitudes, therefore, we have cropped the maps after figure 1 to a latitude range between 50° S and 50° N.

2.3. Measure of aridity

As our measure of aridity, we use the wetness index defined in the Budyko approach as the ratio of mean annual $P$ to $E_o$ (\(P/E_o\), with $E_o$ defined
as the net radiation $R_n$ expressed as an equivalent depth of water $E_o = R_n/L$, with $L$ the latent heat of vaporisation (Budyko 1974). This ratio has recently been found to best represent aridity in the coupled mass-energy balance at the surface in climate model output (Roderick et al 2014, Milly and Dunne 2016, 2017) and is consistent with the original Budyko framework (Budyko 1974). The dimensionless index was calculated at each grid-cell using the 1984–2007 mean annual $P$ (from CRU) and $E_o$ (from SRB). The spatial distribution of $P/E_o$ across the study region is shown in figure S1 (available online at https://stacks.iop.org/ERL/15/114028/mmedia). Grid-cells with $P/E_o > 1.0$ are described here as wet (energy-limited) and regions where $P/E_o < 1.0$ are described here as dry (water-limited) (Donohue et al 2007). The spatial pattern of aridity is generally consistent with previous studies (Mcvicar et al 2012, Greve and Seneviratne 2015).

3. Results

3.1. Variation in $T_a$ with $P$

We investigate the relationship between $T_a$ and $P$ across the study region using the CRU observations for 1984–2007. For that, we first linearly detrended the $T_a$ and $P$ time series (i.e. subtract the linear trend from original time series to derive the detrended anomalies) and fitted a regression to the anomalies ($\Delta T_a$ and $\Delta P$) (figure 2). (The results of $\Delta T_a-\Delta P$ regression without detrending (maps not shown) are more or less identical to (figure 2). As has been noted on many occasions previously (see papers in the Introduction), we also find that $\Delta T_a$ is negatively correlated with $\Delta P$ over much of the study region (figure 2(a)). The slope of the $\Delta T_a-\Delta P$ regression is more negative in arid regions (e.g. central Australia, Southern and Northern Africa and Southwest US) and approaches zero in wet regions (e.g. Southeast Australia, central Africa, most of South America, Southeast US and Southeast Asia) (figure 2(b), figure S1). We also note that the $\Delta T_a-\Delta P$ regression has, in general, a higher level of statistical significance (defined by $p$-value $\leq 0.05$) in arid regions than in wetter regions (figure 2(c), figure S1).

3.2. Relating the $\Delta T_a-\Delta P$ regression to aridity

To investigate how the $T_a-P$ relation varies with aridity, the slope of the $\Delta T_a-\Delta P$ regression (see figure 2(b), and denoted as $dT_a/dP$ here) is plotted against the wetness index $P/E_o$ (see figure S1) at each grid-cell (figure 3). The result shows a characteristic structure with markedly negative $\Delta T_a-\Delta P$ slopes ($dT_a/dP$) under arid conditions (i.e. $P/E_o \leq 1$). In contrast, under wet conditions (i.e. $P/E_o > 1$) the resulting slope is near zero and $\Delta T_a$ is more or less independent of $\Delta P$. We determined separate linear regressions on either side of this threshold (figure 3).

The result indicates some scatter in the relation between slope of $T_a-P$ regression and aridity, particularly in dry conditions. That scatter is found to be separated by the statistical significance of the $\Delta T_a-\Delta P$ regressions (see $p$-value in figure 2(c)), with the statistically significant regressions consistently showing more negative $\Delta T_a-\Delta P$ slopes (figure 3).

Here we have used detrended climate data (figure 3) to calculate the anomalies, and the results show the same characteristic structure if the data are not detrended (Fig. S2) with negative $\Delta T_a-\Delta P$ slopes under arid conditions but close to zero slopes in
Results of linear regression between the detrended annual air temperature ($\Delta T_a$) and precipitation ($\Delta P$) anomalies for 1984–2007 using the CRU database. Results are shown for the (a) correlation coefficient, (b) slope and (c) $p$-value of the linear regression.

3.3. Application

Based on the empirically determined $T_a$-$P$-aridity relation (figure 3), we can predict the change of $T_a$ due to $P$ in regions that have limited influence of snow/ice cover and irrigation. To investigate application of this method, we conducted tests using independent data over three separate regions (figure 4(a)).

Using detrended anomalies, the independent observations showed negative $\Delta T_a$-$\Delta P$ relations with slopes of $-0.0016$ K mm$^{-1}$ for Texas (figure 4(b)), $-0.0019$ K mm$^{-1}$ for the MDB (figure 4(c)) and $-0.0022$ K mm$^{-1}$ for West AU (figure 4(d)). (We obtained more or less identical results using anomalies that were not detrended (figure S4).) To account for the aridity ($P/E_o$) in three case study regions, the $P$ and $E_o$ are calculated for the 1984–2007 period in each region. The value of $P/E_o$ for each region was then used to predict the $\Delta T_a$-$\Delta P$ relation (per figure 3) that was subsequently compared with the observations (figure 4(e)). The results show that the observation-based $\Delta T_a$-$\Delta P$ relation in each of the three case study regions are predicted by the empirical regression for dry environments ($\Delta T_a/dP \sim -0.0023P/E_o - 0.0023$).

4. Discussion

A negative relation between precipitation ($P$) and air temperature ($T_a$) has long been noted over land regions. That is, years with lower than average precipitation also tend to be warmer, and vice versa. In previous work we found that the slope of the $\Delta T_a$-$\Delta P$ regression appeared to become more negative as the
Figure 3. Relation between slope of the $\Delta T_a - \Delta P$ regression (as per figure 2(b), and denoted as $dT_a/dP$ here) and the wetness index ($P/E_o$, figure S1) ($n = 550$ grid-cells). Colours (and legend) are for the $p$-value of the $\Delta T_a - \Delta P$ regression (as per figure 2(c)). Two separate linear regressions (dry environment: $P/E_o \leq 1$, wet environment: $P/E_o > 1$) have been estimated, and full details of the regressions are shown in table S1.

Figure 4. Locations and application of the empirical $\Delta T_a - \Delta P$ relation for three case study regions. (a) Locations for Texas, the Murray-Darling Basin (MDB) and West Australia (West AU). Observed long-term $\Delta T_a - \Delta P$ relation (b) for Texas from NOAA-NCEI observations (1895–2018), (c) for MDB from Bureau of Meteorology (BoM) observations (1910–2018), (d) for West AU from Australian Water Availability Project (AWAP) model outputs (1914–2013). (e) Observed $\Delta T_a - \Delta P$ relations compared with the empirical prediction in equation (1) (solid lines) in the three case study regions.
overall aridity increased (Yin et al 2014) but that earlier finding was only based on four regions. Here we have extended that result by examining the $\Delta T_a$-P regression over 550 ($10^5 \times 10^5$) grid-cells using CRU-SRB grid-based observations (figure 2) that specifically exclude the influence of irrigation and snow/ice (figure 1). We further proposed an empirical relation between the $\Delta T_a$-P slopes and aridity (figure 3), which confirms and quantitatively extends the earlier finding. The empirical results show that the variations in $T_a$ are independent of P in wet environments, while in dry environments the variations in $T_a$ with P increase as the hydrologic environment becomes more arid.

Taken together those empirical results follow the long standing hydrologic notion that the responses of surface energy components to variations in P in wet and dry environments are different. In wet environments the surface energy balance (and hence $T_a$) is not particularly sensitive to variations in P but responds primarily to variations in energy supply, hence, the year-to-year variations in P would mostly result in year-to-year variations in runoff (Budyko 1974). In contrast, in dry environments the surface energy balance responds strongly to variations in P via variations in the four surface radiation components (incoming and outgoing short- and long-wave) and variations in the latent and sensible heat fluxes (e.g. Yin et al 2014) which alters $T_a$.

The empirical results reported in the study provide a quantitative empirical framework to a priori predict the $T_a$-P relation using a standard and widely used measure of aridity. With this method, one can estimate the magnitude of inter-annual variations in $T_a$ due to those in P (denoted as $dT_a/dP$) by using piecewise linear functions separating regions for dry and wet environments (figure 3). This new framework was evaluated by independent tests in three arid regions and found to be both practical to apply, as well as being effective in predicting the $T_a$-P relation in climatically different regions (figure 4). The variations in the empirical relation (particularly in dry conditions) are shown to be separated by the statistical significance of the $\Delta T_a$-$\Delta P$ regressions, with the statistically significant regressions consistently showing more negative $\Delta T_a$-$\Delta P$ slopes (figure 3). That pattern indicates that in addition to the primarily thermodynamic processes considered here (i.e. wetness index in this study), the atmospheric dynamics also play an important role in changing $T_a$ (Suarez-Gutierrez et al 2020). It should be noted that this study was conducted at $\sim$100 km spatial scale, we expect the general findings would hold but show slight difference with a change in spatial resolution because of different dynamical and thermodynamical processes being resolved. Future studies are needed to better separate and attribute the contribution of various dynamical and thermodynamical drivers of $T_a$ change.

We note that under extremely arid conditions ($P/E_o \to 0$) the empirical relation reported here (figure 3) predicts that the mean annual $T_a$ would increase by around 0.002 K for a decrease in annual P of 1 mm. Hence for a decrease in annual P of say 100 mm, which would be typical of the inter-annual variations that actually occur in many arid environments, we anticipate inter-annual variations in $T_a$ of up to 0.2 K in a single year due to inter-annual variation in P. The magnitude of that variation is important given that the current global warming signals over land have a typical magnitude of 0.2 K per decade (IPCC 2013). This highlights the potential importance of hydro-climatic extremes (e.g. droughts) or long-term trends of P in modifying $T_a$ independently of long term climate trends.

It should be noted that the above empirical relation is only applicable in regions that have limited influence of snow/ice cover and irrigation. Further, we focus on the annual time scale and implicitly assume that precipitation (P) is the only source of water. At shorter time scales, e.g. seasonal, we expect that variations in soil moisture and ground water will also play an important role in the $T_a$-P relation, particularly in dry regions (e.g. Berg et al 2015, Schwingshackl et al 2017). We suspect that ignoring changes in storage might also explain some of the scatter in the inter-annual $T_a$-P relation (see figure 3). Therefore, future work that includes the effect of changes in water storage at monthly-seasonal time scales is needed.

5. Conclusions

In this study, we quantitatively estimate the dependence of near-surface air temperature $T_a$ on variations in precipitation P (denoted as $dT_a/dP$) using aridity as a predictor. Observations generally show $T_a$ to be negatively correlated with P in dry environments but independent of P in wet environments. We then develop a quantitative (empirical) regression to predict $T_a$-P relation based on aridity ($P/E_o$, with $E_o$ defined as the net radiation but expressed as an equivalent depth of water). With this proposed framework, the inter-annual variations in $T_a$ due to those in P are estimated using separate piecewise linear functions for dry ($P/E_o \leq 1$, $dT_a/dP \sim 0.0023 \times P/E_o - 0.0023$) and wet ($P/E_o > 1$, $dT_a/dP \sim 0$) environments. This framework is further tested in three independent regions and found to be both practical to apply, and also effective in predicting the regional $T_a$-P relations. This new framework will be useful, especially in dry environments, to quantify variations in air temperature during wet/dry extremes. Future work that includes the effect of changes in water storage at monthly-seasonal time scales is needed.
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Data availability statement

The data that support the findings of this study are openly available at the following DOI: https://doi.org/10.1038/s41597-020-0453-3.

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