

Assessing temperature-based *PET* equations under a changing climate in temperate, deciduous forests

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Abstract:

Despite the availability of numerous approaches to estimate potential evapotranspiration (*PET*), temperature-based *PET* equations such as the Hamon equation and Thornthwaite equation are still used to predict changes in hydrology in a changing climate as temperature is one of the primary reported outputs from general circulation models. To isolate the actual dependence of *PET* on temperature, we analysed meteorological and energy balance measurements from five AmeriFlux deciduous forest sites in the eastern United States during periods with minimal soil moisture control on transpiration. For all five sites, when *PET* measurements with similar net radiation are grouped, temperature does not correlate to *PET* within each group. Conversely when *PET* measurements with similar temperature are grouped, net radiation strongly correlates to *PET* within each group. In terms of assessing standard *PET* models, when dormant and growing season *PET* are separated, we found that the Priestley–Taylor equation (a model primarily dependent on net radiation) consistently explained more of the variation in *PET* than temperature-based methods such as the Hamon equation (median R^2 of 0.88 vs 0.66). We illustrate that the moderate ability of temperature-based equations to predict *PET* arises from the correlation between temperature and net radiation when the meteorological observations are averaged over at least several days. However, we suggest that because temperature is not the fundamental driver of *PET* and because the relationship between temperature and net radiation underlying temperature-based equations will shift with climate change, temperature-based equations in their current state will likely exaggerate *PET* in a changing climate. Copyright © 2010 John Wiley & Sons, Ltd.

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INTRODUCTION

Accurate estimates of regional terrestrial water balances are needed to make sustainable water allocation decisions under a changing climate. At its simplest, the water balance consists of incoming precipitation (P) and outgoing evapotranspiration (ET), with their difference being available terrestrial water (Q). In many cases, ET is modelled as the potential evapotranspiration (PET) scaled by a soil moisture availability function. Despite the centrality of PET to the water balance, there exist numerous methods to estimate PET and limited consensus on which are the most preferable, as reflected by the wide range of methods that continue to be used in water balance studies. For example, Najjar *et al.* (2009) summarized five water balance studies from the last decade in the Mid-Atlantic Region of the United States. Of the five, three different PET methods were used; one method was the Penman–Monteith equation (used by Hayhoe *et al.*, 2007), but the others were the temperature-based Hamon equation (used by Wolock and McCabe, 1999) and the Thornthwaite equation (used by Najjar *et al.*, 1999; Neff *et al.*, 2000; Frei *et al.*, 2002). Depending on which method was used, varying predictions were made

for future streamflow; temperature-based methods consistently predicted greater declines in streamflow in the Mid-Atlantic Region than other methods (Najjar *et al.*, 2009).

The Penman–Monteith equation is often considered the most physically correct PET model given that it has a solid theoretical basis and a dependency on all relevant meteorological factors: wind speed, air temperature (T), net radiation (R_N), and vapour pressure. In contrast, temperature-based equations were developed as empirical estimations of the correlation between temperature and PET . Despite the limited physical justification for using simple temperature-based PET equations (Shuttleworth, 1993), their use has persisted because temperature readings are often the most readily available meteorological data that relates to PET . This is especially true in climate change studies in which the primary reported output from the general circulation model (GCM) runs used as input to hydrologic models continues to be precipitation and temperature, (refer Gardner, 2009 and Yu and Wang, 2009 for recent examples).

The continued use of temperature-based equations is even more surprising given their greater sensitivity to temperature changes than other more physically sound PET models, a fact that has long been recognized (McKenney and Rosenberg, 1993). As a matter of illustration, in Figure 1 we show the percentage change in PET estimates from the Hamon,

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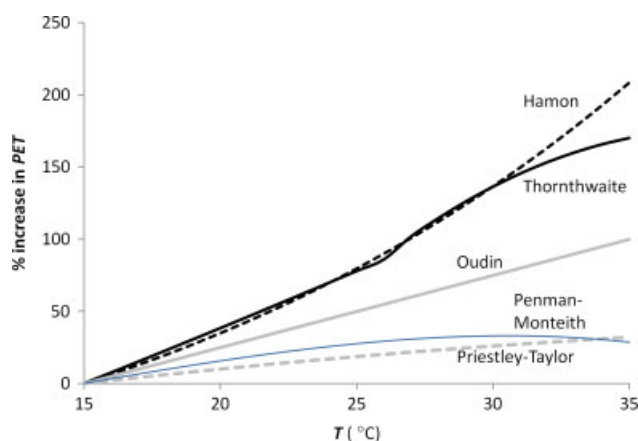


Figure 1. Sensitivity of different *PET* equations to temperature. The percentage change is relative to *PET* at a temperature of 15°C. For equations dependent on additional factors than on temperature, we assumed a wind speed of 1 m s⁻¹, a relative humidity varying linearly from 70 to 50% from 15 to 35°C, and R_N of 8.5 MJ m⁻² d⁻¹. For Penman–Monteith, the surface resistance was assumed to be constant at 15 s m⁻¹ and the canopy resistance was assumed to vary only with *VPD* using the relationship from Whitley *et al.* (2009)

Thornthwaite, Priestley–Taylor, Oudin *et al.* (2005), and Penman–Monteith equations as a function of temperature. The Priestley–Taylor and Oudin equations have a dependency on radiation as well as temperature while the Penman–Monteith equation is dependent on R_N , vapour pressure deficit, wind speed, and humidity. Notably, the Oudin *et al.* (2005) equation depends on expected solar radiation as calculated from Julian day and latitude and not on the measured radiation; its only true independent variable is temperature. Thus the Oudin *et al.* (2005) equation as well as equations such as those by Hargreaves and Samani (1985) are often referred to as temperature-based equations but actually have a strong dependency on radiation. In this paper, we consider the Thornthwaite and Hamon equations as the prime examples of purely temperature-based *PET* equations. As the Hamon and Thornthwaite equations are only dependent on temperature (disregarding adjustments for day length), the curves in the graph closely represent the range of the functions. The other equations notably can produce a much wider variation in *PET* estimates than shown when other variables (such as radiation) are changed. But the figure gives a sense of how the equations predict *PET* given changes in temperature alone.

Despite such obvious differences in sensitivity to temperature, there has not been a definitive argument to dismiss temperature-based equations outright. For instance, Vorosmarty *et al.* (1998) applied 11 different *PET* estimation methods to 679 gaged watersheds in the United States modelled at the 0.5° grid cell scale and assessed the average bias compared to annual water balances. They found that the Penman–Monteith day–night formulation produced the least average bias across all 679 watersheds but that simple methods such as the Hamon equation also had limited bias. Kingston *et al.* (2009) found a 100% difference between six common *PET* methods (including

Penman–Monteith and Hamon) applied to GCM scenarios with a 2°C global temperature rise. Instead of presuming that Penman–Monteith was the more accurate, Kingston *et al.* (2009) posed the question of whether ‘more reliable estimation of changes in *PET* can be obtained from physically based methods with uncertain data quality, or more empirical methods with more reliable input data’. Also of note in the possible defense of temperature-based models, Oudin *et al.* (2005) tested 27 different *PET* methods to assess which gave the best results in simulating observed daily discharges from 308 watersheds in Australia, France, and the United States. On the basis of the average Nash–Sutcliffe criteria from all 308 sites, Oudin *et al.* found that there was relatively little sensitivity to the *PET* formulation, but a model only dependent on temperature worked best (even compared to Penman–Monteith). However, as mentioned earlier, Oudin *et al.*’s (2005) preferred model also included a dependency on mean daily solar radiation, a fact that is sometimes downplayed as it is calculated indirectly instead of requiring the input of an actual measured value.

In this paper, our aim is to provide a further assessment of common *PET* models. In particular, we propose using eddy covariance data (from AmeriFlux) as an alternative to the catchment water balances more frequently used to assess simple *PET* models. Owing to the need to assume change in storage is near zero, catchment water balances are most accurately applied annually, requiring that temperatures be described by mean annual values and that temperature variations be assessed across multiple sites with potentially confounding differences in factors such as vegetation, soils, and latitude. There have been few instances (Davi *et al.*, 2006; Sun *et al.*, 2008) of directly comparing *PET* methods used in water balances to eddy covariance data. Thus, eddy covariance data offers a still relatively untapped data source that is able to provide new insights into the proper formulation for predicting *PET* in a changing climate.

Our objectives in this paper are to (1) assess the sensitivity of *PET* as determined by eddy covariance measurements at five AmeriFlux sites to the meteorological parameters of temperature, vapour pressure deficit, and R_N ; (2) assess the suitability of common *PET* equations (Hamon, Thornthwaite, Oudin, Priestley–Taylor, and Penman–Monteith equations) against eddy covariance measurements; and (3) assess the sensitivity of future *PET* projections to the choice of *PET* equation. We limit ourselves to assessing *PET* at five primarily deciduous forest sites in the eastern United States, the typical land use for major water supplies in the region. This paper is not intended to provide new theory but to provide a direct argument as to why predictions of *PET* determined from temperature-based equations used in climate change projections should be considered with caution. Thus, the primary audience is not intended to be scientists who are specialists in land–atmosphere interactions, but, instead, scientists who are seeking a *PET* estimate as one of many inputs into an analysis of ecological, geomorphological,

Table I. Site information

Station	Latitude	Longitude	Elevation (m)	Wet year used	Wet year P/mean P (cm)	Growing season mean T (°C)
Harvard Forest, MA	42.54	-72.17	340	1996	156/122	15.4
Great Mountain Forest, CT	41.97	-73.23	493	2000	124/119	16.6
Morgan Monroe State Forest, IN	39.32	-86.41	275	2006	158/116	20.1
Duke Forest Hardwoods, NC	35.98	-79.10	168	2003	145/120	22.4
Walker Branch, TN	35.96	-84.29	343	1996 and 1997	169 and 143/139	20.7

biogeochemical, or other non-climate problem far from the concerns of how exactly to model water vapour flux.

METHODS

Data

We used FLUXNET AmeriFlux eddy covariance data (Baldocchi *et al.*, 2001) from five predominantly hardwood forest sites at differing latitudes in the eastern United States: Harvard Forest, MA (Goulden *et al.*, 1996); Great Mountain, CT (Lee and Hu, 2002); Morgan Monroe State Forest, IN (Schmid *et al.*, 2000); Duke Forest, NC (Pataki and Oren, 2003; Oishi *et al.*, 2008); and Walker Branch, TN (Wilson and Baldocchi, 2000). On the basis of International Geosphere-Biosphere Programme (IGBP) vegetation class, Harvard Forest, Morgan Monroe, and Duke Forest are classified as deciduous broadleaf and the two remaining sites are classified as mixed forest. Forest canopy heights are ~25 m for all the sites. Additional site information is provided in Table I or in literature specific to each site as cited above. For each site we accessed 30- or 60-min averages of T , vapour pressure deficit (VPD), sensible heat flux (H), R_N , and water vapour flux available from the Carbon Dioxide Information Center web portal (http://cdiac.esd.ornl.gov/programs/ameriflux/data_system/aamer.html as of 20 November 2009).

Eddy covariance water vapour flux is only a measure of PET if soil water is not limited and $ET = PET$. Prior work at Duke Forest (Stoy *et al.*, 2006) and Walker Branch (Wilson and Baldocchi, 2000) suggest that in temperate hardwood forests, water vapour flux may not be subject to water limitations during any summers that are at least moderately wet (i.e. based on several observation years, fluxes do not greatly increase between moderately wet and very wet summers). To insure that the relationships between water vapour flux and the meteorological factors are not influenced by water limitations, we only use years with above average rainfall over both the course of the year and during the growing season (effectively avoiding dry periods when there may be some soil moisture control). Table I indicates the annual rainfall in each year used and the long-term average annual rainfall for each site (growing season rainfall has not been shown). As a check on the robustness of the results when only using wet years, we also repeated certain analysis for all available years in the site records. Throughout the rest of the paper, we will

refer to eddy covariance water vapour flux as PET . While PET has been defined in multiple ways in the academic literature, here we use it in reference to the AmeriFlux site water vapour flux measurements to suggest that they are not water limited.

There were occasional gaps in the data that occurred at irregular time intervals. As different meteorological parameters could be missing at different times and for different time intervals, manually selecting periods with sufficient data was difficult. Therefore, we programmed a random sampling scheme to identify consecutive 24- or 120-h periods with <5% of missing values of T , VPD , R_N , or PET combined (i.e. for a 120-h period, <20 of $4 \times 120 = 480$ possible value). If >5% of the values were missing, we did not use the time period. An average value was substituted for missing values in the case when 5% or less was missing. As an exception, at Duke Forest we used gap-filled data; data gaps at Duke Forest were generally shorter (on the order of hours) but more frequent, making it difficult to obtain 120-h intervals without gap filling. However, these short gaps were conducive to filling by interpolation. As we randomly drew data values, each sampling trial was slightly different. We report the mean of 100 trials.

Energy balance closure was evaluated by averaging over the 100 trials from each site during a wet year. We do not make an attempt to close the energy balances as we are primarily interested in relative relationships. However, we present the energy balances as a quality check on the data and our method of aggregating the data. The primary components of the energy balance consist of R_N , latent heat flux (LE ; equivalent to PET with a conversion factor), H , and energy exchange with the ground (G). In cases where G was not directly reported within the flux tower network data, G was calculated using the change in soil temperature over the 5-day averaging window multiplied by the soil depth and the effective soil heat capacity (assumed to be $2.1 \text{ MJ m}^{-3} \text{ }^\circ\text{C}^{-1}$, Shuttleworth, 1993, Eqn. 4.2.17). Closure was assessed by regressing $LE + H$ against $R_N - G$ and determining the slope and intercept. A regression line slope near 1 and an intercept near 0 indicate closure of the energy balance. The literature indicates that turbulent fluxes ($LE + H$) are generally less than the measured available energy ($R_N - G$) (Foken, 2008). Observed ranges in the literature for single-day, day-time energy balances include slopes from 0.55 to 0.99, intercepts from -32.9 W m^{-2} to 36.9 W m^{-2} , and

Table II. Energy balance closure at sites

Site	$R_N - G$ (W m^{-2}) versus $LE + H$ (W m^{-2})		
	R^2	Slope	Offset
Harvard Forest	0.91	1.07	-23.95
Great Mountain	0.53	0.94	11.9
Morgan Monroe	0.93	0.67	-9.46
Duke Forest	0.72	0.73	-7.14
Walker Branch	0.85	0.62	17.4

coefficients of determination ranging from 0.64 to 0.96 (Mahrt *et al.*, 1998; Twine *et al.*, 2000; Wilson *et al.*, 2002; Shi *et al.*, 2008). Table II summarizes the mean closure for the sampled periods at the five sites used in our study; the degree of closure for the sampled periods used in this analysis is consistent with the closure typically reported in the literature.

Analysis

We undertake several different analyses with the site data. Some analyses are comparative across sites and some only use data from single sites for illustrative purposes. In many cases, we focus on relationships during the growing season. The growing season was assumed to extend from 1 June to 1 October at Harvard Forest, Great Mountain, and Morgan Monroe and from 1 May to 1 November at Duke Forest and Walker Branch.

First, we regress T , VPD , and R_N for each site against PET . This serves to indicate the univariate relationship between the respective meteorological variables and PET . We also relate predicted PET from the Hamon, Thornthwaite, Priestley–Taylor, Oudin *et al.* (2005), and Penman–Monteith equations against observed PET . A Jarvis–Stuart model (Whitley *et al.*, 2009) is used with the Penman–Monteith equation to determine canopy resistance. In assessing the PET equations, we best-fit a scalar value to account for the general underestimation of PET due to lack of an energy balance closure; in most cases the PET equation outputs are scaled by ~ 0.7 . The models' equations are presented in the Appendix. Except for the Penman–Monteith equation, for these comparisons, we use 5-day means. For Penman–Monteith, we calculate 0.5- or 1-h PET (depending on the site) using meteorological values at the same respective time interval and then average over 5 days. We use 5-day means because GCM output is typically generated at a monthly time step and only sometimes downscaled to weekly or daily values. Thus, we wished to assess relationships appropriate to the multi-day time scale at which many model studies are completed. As we only use 1–2 years of AmeriFlux data for each site (i.e. wet year data), a longer averaging window (>5 days) would offer a small number of unique combinations of water vapour flux and meteorological parameters.

Second, using daily values for all sites, we assess the relationship between PET and T when R_N remains nearly

constant. Near constant R_N values are considered to fall within a range of 20 W m^{-2} . Conversely, we also assess the relationship between PET and R_N when T remains nearly constant. Near constant T -values are assumed to fall within a range of 2°C . This analysis serves as a means to explicitly separate the effects of T and R_N on PET . Additionally, but for only a subset of the sites (Harvard Forest and Morgan Monroe), we also assess the relationship between PET and T when VPD is near constant and the converse (PET vs VPD when T is near constant).

As a third analysis, we illustrate the relationship between T and R_N over four different temporal averaging windows: 1-, 5-, 15-, and 60-day values. In this case, we only use data from Harvard Forest from 2003 to 2009 because Harvard Forest has the longest available record with minimal gaps and is best suited to looking at a range of time scales. Also using the Harvard Forest data, we look at the relationship between T and VPD and T and R_N at the 1-day time averaging window.

RESULTS

Univariate analysis

Figures 2a and 3a plot measured mean 5-day PET against mean 5-day T while concurrently plotting PET estimated by the Hamon equation against T (the Hamon and Thornthwaite equations behave quite similarly so only the Hamon equation is shown). In Table III, the suitability of fit (as indicated by a Nash–Sutcliffe efficiency R^2) between PET and T , the Hamon equation, and the Thornthwaite equation is summarized for the five sites. For all five sites, T alone has a weak to moderate ability to explain variation in PET . Notably, there is scatter in the PET versus T relationship, and many PET values can result from the same T -value. Not unexpectedly, the Hamon model—being a univariate model dependent on T —results in a similar amount of scatter in PET estimates.

Figures 2b and 3b plot measured mean 5-day PET against mean 5-day R_N , while concurrently plotting PET estimated by the Priestley–Taylor equation against R_N . Note that measured PET values have been segregated by whether they occur in the dormant or growing season. In contrast to T , as long as measured PET is separated by growing/dormant season, the relationship between PET and R_N has relatively little scatter. In Morgan Monroe (Figure 3b), the outliers below the primary curve are associated with mean $T < 17^\circ\text{C}$. The Priestley–Taylor equation closely matches the primary curve but seems to overestimate PET during the cooler days. The Priestley–Taylor equation does also have some dependency on temperature but the Morgan Monroe data suggests that it may exaggerate PET in some cases. In Table III, the suitability of fit between PET and R_N and the Priestley–Taylor equation is summarized for the five sites. For the growing season, R_N is consistently a better

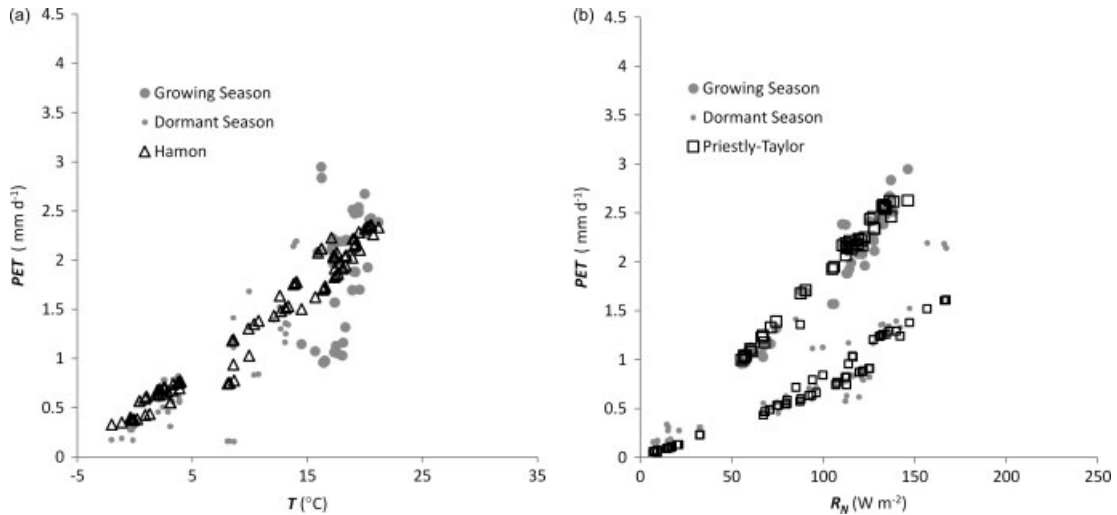


Figure 2. Relation of (a) measured *PET* and Hamon equation estimates of *PET* to *T* and (b) measured *PET* and Priestley–Taylor equation estimates of *PET* to *R_N* at Harvard Forest, MA, for a 5-day averaging window during a wet year (1996). Large circles indicate *PET* measurement during the growing season while smaller circles are measurements during the dormant season. In (b), the Priestley–Taylor equation is scaled by different values during the dormant and growing seasons

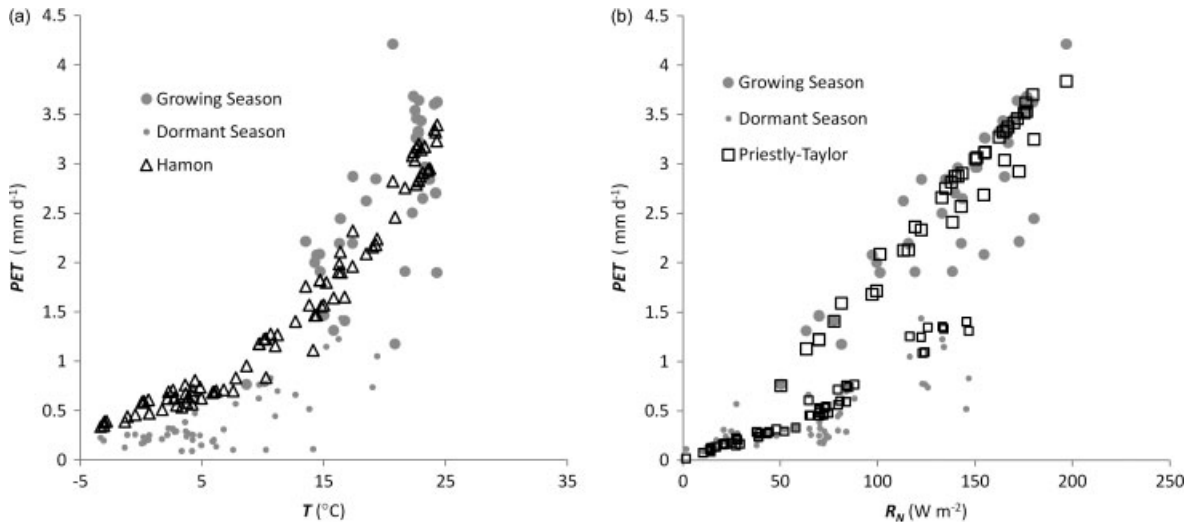


Figure 3. Relation of (a) measured *PET* and Hamon equation estimates of *PET* to *T* and (b) measured *PET* and Priestley–Taylor equation estimates of *PET* to *R_N* at Morgan Monroe, IN, for a 5-day averaging window during a wet year (2006). Large circles indicate *PET* measurements during the growing season while smaller circles are measurements during the dormant season. In Figure 2b, the Priestley–Taylor equation is scaled by different values during the dormant and growing seasons

Table III. Suitability of fit (as indicated by Nash–Sutcliffe efficiency *R*² value) of observed 5-day mean vapour flux during wet years to different *PET* models

	<i>T</i>	<i>VPD</i>	<i>R_N</i>	Hamon	Thornthwaite	P–T	P–M
Harvard Forest (1996)	0.30	0.81	0.89	0.46	0.45	0.87	0.93
Great Mountain (2000)	0.10	0.71	0.84	0.02	–0.05	0.74	0.71
Morgan Monroe (2006)	0.53	0.71	0.79	0.66	0.66	0.89	0.82
Duke Forest (2003)	0.71	0.28	0.81	0.74	0.70	0.88	0.52
Walker Branch (1996 and 1997)	0.78	0.82	0.91	0.84	0.73	0.92	0.89

For *T*, *VPD*, and *R_N*, a linear regression was used. For the Hamon, Thornthwaite, Priestley–Taylor (P–T), and Penman–Monteith (P–M) equations, a best-fit scaling value was applied before the *R*² was calculated. This scaling value was typically around 0.7 and is intended to account for a lack of closure in the energy balance.

predictor of *PET* than *T* when applied to the growing season and dormant seasons separately.

In Table III, we have also included results when *VPD* is used as a lone predictor variable and when the

Penman–Monteith equation is used as an alternate model. We do not consider *VPD* in the same depth as *T* or *R_N* as there is no commonly used model that is primarily dependent on *VPD* the same way Hamon and Thornthwaite

are dependent on T and Priestley–Taylor is dependent on R_N . Except at Duke where VPD remains unusually constant over the growing season (not shown), VPD is consistently better than T and slightly weaker than R_N over the growing season. The Penman–Monteith model serves as the multivariate model of the primary meteorological variables that drive PET as it provides a structure to incorporate the effects of T , R_N , VPD , and wind speed. Interestingly, based on R^2 values presented in Table III, Penman–Monteith does not appear to provide better estimates of 5-day mean PET than Priestley–Taylor, although both Priestley–Taylor and Penman–Monteith are consistently strong estimators of PET . Also, the ability of the Oudin model to predict 5-day mean PET was very poor across all five sites ($R^2 < 0$), so the results are not included in Table III. This is not unexpected, given that the Oudin model uses the expected solar radiation calculated only from latitude and Julian day, not the actual measured value.

Table IV summarizes the univariate regressions discussed above, but for all years, not just wet years. With the exception of Harvard Forest, the relative ability of different models to predict PET remains consistent with those for wet years. However, as might be expected, suitability of fit values are lower than in Table III because of greater physiological surface controls on ET during moisture limited periods. In Harvard Forest, the predictive ability of R_N sizeably drops, as does that of the Priestley–Taylor equation. From looking at actual plots of the data (not shown), R_N has systematic

structural bias in the relationship with PET but other weak predictors—such as T —simply appear to be scattered in relation to PET .

Finally, it is useful to note that despite the limitations of T in predicting PET , when the growing season and dormant values are not segregated, T appears to be able to track PET over both the dormant and growing seasons. In the case of R_N , the same R_N value may have two possible PET values, depending on whether it is the growing or dormant season. In other words, based on just a qualitative assessment of the plotted data, T appears to be an innate proxy for distinguishing between the growing season and dormant season. This feature may explain some of the value of T -based methods in predicting PET .

Isolating effects of T and R_N

Looking only at the suitability of fit of different PET models can suggest but cannot definitively demonstrate the most physically correct PET model. The correlation between meteorological variables can make it difficult to identify their fundamental physical role in influencing PET . Here we attempt to separate the role of different variables by assessing the relationship between daily mean PET and T (or R_N) when R_N (or T) is held near constant.

Figures 4 and 5 graphically present the results for two select sites, Morgan Monroe and Harvard Forest, respectively (results for all sites are presented in Table V). In Figures 4a and 5a, T is regressed against PET for

Table IV. Suitability of fit (as indicated by Nash–Sutcliffe efficiency R^2 value) of observed 5-day mean vapour flux to different PET models during all available years in the record

	T	VPD	R_N	Hamon	Thornthwaite	P–T	P–M
Harvard Forest (1996–2005)	0.20	0.46	0.45	0.36	0.36	0.32	0.62
Great Mountain (1999–2004)	0.21	0.64	0.72	0.34	0.32	0.73	0.73
Morgan Monroe (1999–2007)	0.48	0.52	0.74	0.57	0.57	0.82	0.74
Duke Forest (2002–2003)	0.52	0.26	0.78	0.61	0.54	0.76	0.56
Walker Branch (1994–1998)	0.27	0.21	0.70	0.35	0.18	0.64	0.57

For T , VPD , and R_N , a linear regression was used. For the Hamon, Thornthwaite, Priestley–Taylor (P–T), and Penman–Monteith (P–M) equations, a best-fit scaling value was applied before the R^2 was calculated. This scaling value was typically around 0.7 and is intended to account for a lack of closure in the energy balance.

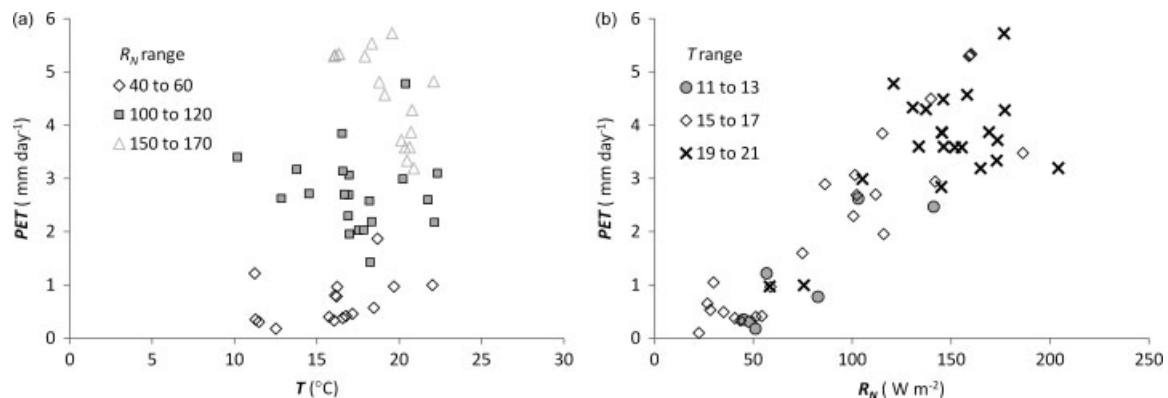


Figure 4. Relation of (a) daily PET to daily T within groupings of similar R_N (in $W m^{-2}$) and (b) daily PET to daily R_N for groupings of similar T (in $^{\circ}C$) for Harvard Forest, MA. Slope, R^2 , and p -values of regression lines for each grouping are summarized in Table V

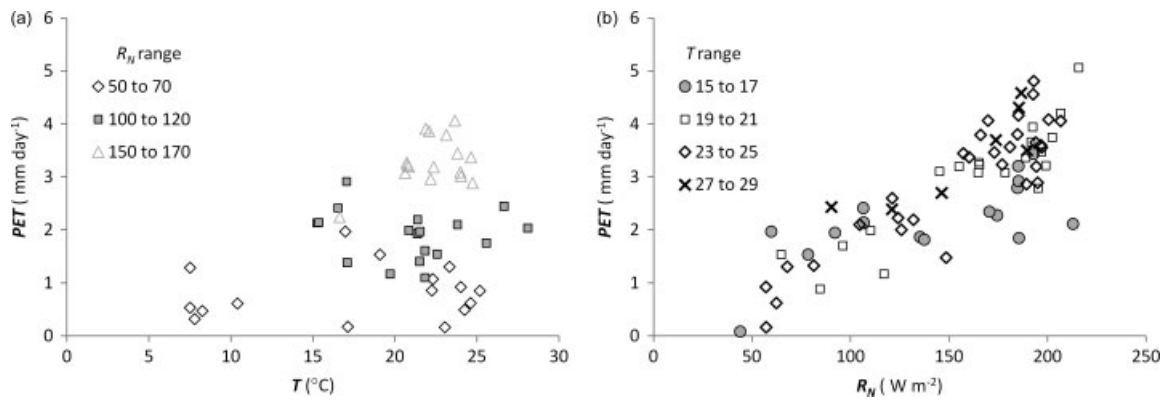


Figure 5. Relation of (a) daily PET to daily T within groupings of similar R_N (in $W m^{-2}$) and (b) daily PET to daily R_N for groupings of similar T (in $^{\circ}C$) for Morgan Monroe State Forest, IN. Slope, R^2 , and p -values of regression lines for each grouping are summarized in Table V

groupings with similar R_N values. In both figures, T has no relationship with PET within the grouping; PET is relatively constant across the grouping. This same outcome is generally repeated across all the sites, as summarized in Table V. Table V reports R^2 , p -value of the slope coefficient, and slope of the regression line if p -value < 0.05 for all the sites. In Figures 4b and 5b, PET is regressed against R_N when similar T -values are grouped. In contrast to Figures 4a and 5a, there is a significant relationship between PET and R_N . Notably, the relationship generally collapses to a single line, no matter what the T . The only discrepancy occurs at low T when presumably full leaf out has yet to occur. As shown in Table V, across all the sites the PET and R_N consistently have a significant slope coefficient.

We are primarily interested in T and R_N as commonly used PET estimators rely only on these variables and not on VPD . However, the assumption is often made that VPD correlates with T . For instance, the Hamon equation is often justified by its attempt to relate T to VPD through the vapour saturation curve. Repeating the above analysis, but now with VPD and T (and only at Harvard Forest and Morgan Monroe), T has no relationship to PET when VPD is near constant. If T is near constant, VPD and PET generally collapse to a single line, no matter what the T . In these cases, the p -value of the slope of the regression between PET and VPD is statistically significant (p -value < 0.05) for all groupings of similar T .

Correlation of T to R_N

Notably, in isolating the effects of R_N from T , we only used daily means while in earlier analyses we used 5-day means. The use of the 5-day means was justified by the length of the averaging window often used in hydrologic studies and the time scale at which PET estimating equations are often applied. Here, we illustrate the impact a changing averaging window has on the correlation between R_N and T .

Figure 6 shows the relationship between R_N and T for four averaging windows: 1-, 5-, 15-, and 60-day. In the figure, the growing season months of June, July, and August are specifically noted. At a 1-day averaging window there is only a very weak correlation between T

and R_N with especially little structure within June, July, or August. By a 5-day averaging window, the correlation appears stronger and more distinct. At 15 days, there is an obvious correlation structure with a hysteresis loop visible, but there remains some scatter. At 60 days, there is limited scatter and distinct hysteresis. Over most of the hysteresis loop, for the same value of R_N , we see two possible values, a lower temperature early in the year and higher temperatures later in the year. Over the year, one would trace around the loop in a clockwise direction.

DISCUSSION

Directly plotting PET models versus observed data (as in Figures 2 and 3) offers some suggestion that T -based models may be insufficient to predict PET , but this approach does not provide an entirely convincing argument. For instance, Figure 3a indicates an imperfect fit, but an R^2 of 0.66 still suggests reasonable predictive power. And, certainly when assessing monthly data or even weekly data (such as our 5-day data), the correlation between R_N and T (as indicated by Figure 6) can permit a reasonable relationship between T and PET .

However, looking only at figures of the suitability of fit (such as Figures 2 and 3) obscures the fundamental causative drivers of PET . T may track R_N through time, but that does not mean T is the primary driver of PET . This is a prime example where correlation does not equal causation. This lack of causation only becomes apparent when the role of T and R_N can be isolated, as illustrated in Figures 4 and 5 and summarized in Table V. Using daily average values from eddy covariance measurements of a hardwood forest in China, Shi *et al.* (2008) also observed limited explanatory power of T in contrast to R_N . But isolating T and R_N does not just mean evaluating one when the other is controlled for; as shown in Figure 6, at an averaging window above 5 days or so, T and R_N will be linked by the fact that they are both systematically changing with large-scale atmospheric and planetary processes.

Relying on a correlation between T and R_N is not entirely unreasonable in a stationary world where

Table V. Summary of regression lines fitted to *PET* versus *T* when R_N is near constant and *PET* versus R_N when *T* is near constant

Site	Control	Range	R ²	<i>p</i> -value	Slope
Harvard Forest	R_N	40–60	0.14	0.14	NA
	R_N	100–120	0.09	0.2	NA
	R_N	150–170	0.42	0.13	NA
	<i>T</i>	11–13	0.73	0.028	0.025
	<i>T</i>	15–17	0.79	<0.001	0.029
Great Mountain	R_N	19–21	0.44	0.003	0.022
	R_N	40–60	0.03	0.59	NA
	R_N	80–100	0.06	0.34	NA
	R_N	110–130	0.07	0.42	NA
	<i>T</i>	11–13	0.17	0.40	NA
Morgan Monroe	<i>T</i>	15–17	0.88	<0.001	0.025
	<i>T</i>	19–21	0.61	0.0028	0.025
	R_N	50–70	0.05	0.42	NA
	R_N	100–120	0.08	0.27	NA
	R_N	150–170	0.08	0.29	NA
Duke Forest	<i>T</i>	15–17	0.47	0.002	0.009
	<i>T</i>	19–21	0.80	<0.001	0.021
	<i>T</i>	23–25	0.80	<0.001	0.022
	<i>T</i>	27–29	0.74	<0.001	0.020
	R_N	100–120	0.05	0.72	NA
Walker Branch	R_N	130–150	0.34	0.07	NA
	R_N	170–190	0.37	0.05	2.95
	<i>T</i>	17–19	0.69	0.02	0.013
	<i>T</i>	22–24	0.90	0.0026	0.02
	<i>T</i>	26–28	0.61	0.068	NA
Walker Branch	R_N	50–70	0.10	0.19	NA
	R_N	100–120	0.02	0.54	NA
	R_N	150–170	0.001	0.84	NA
	<i>T</i>	15–17	0.61	0.0015	0.014
	<i>T</i>	20–22	0.69	<0.001	0.020
	<i>T</i>	25–27	0.33	<0.001	0.017

Control indicates which variable is held constant. The slope is not indicated (NA in table) if the *p*-value is >0.05

climate variables will not change in relation to each other. However, using this correlation between R_N and *T* to predict *PET* in a changing climate is fundamentally flawed because *T* is projected to change much more than R_N . With increasing greenhouse gas emissions, incoming longwave radiation will increase until the land surface temperature reaches a new equilibrium point at which outgoing longwave radiation balances incoming longwave (Trenberth and Fasullo, 2009). Temperature will have increased sizeably, but there will be no appreciable change in R_N as net longwave will remain similar. If the relationship between *T* and R_N is readjusted over time, it is foreseeable that *T*-based *PET* equations could still work, but this seems to eliminate the simplicity of using a *T*-based *PET* equation.

To demonstrate the degree of discrepancy between *T*-based equations and R_N -based *PET* estimates, we calculated the percentage change in *PET* for a location at 42°N latitude and 288°E longitude (approximately at New York State) between the beginning and end of the 21st century using the Hamon equation and an R_N regression equation from our earlier analyses. Monthly output from the GFDL CM2 model with the A2 emission scenario was accessed through the (CMIP-3) web portal (<https://esg.llnl.gov:8443/home/publicHomePage.do>). Surface temperature at 2 m height was used in the

Hamon equation while R_N was determined from the sum of surface downwelling longwave and surface incident shortwave radiation minus the sum of surface upwelling longwave and surface reflected shortwave radiation (all readily downloadable GCM output). We averaged monthly values over the time periods from 2001 to 2020 and 2081 to 2100. To leave out the complication of possible changes in growing season length, we only assess changes in *PET* from June to September, the current primary growing season.

This GCM run indicates that mean growing season temperature in New York will increase 33% (from a mean of 16.5° to 22.0°C) while R_N increases 2.5% (from a mean of 126 to 129 W m⁻²). The Hamon equation predicts a 40% increase in June to September *PET* over the 21st century, while an R_N regression equation (we used one fitted to the Great Mountain site data) predicts a 3.5% increase. If the Priestley–Taylor equation is used to predict future changes, *PET* would increase by 11%. This example is consistent with a simulation study (Davi *et al.*, 2006) at four European eddy flux sites that noted little increase in *ET* from 1960 to 2100 at broadleaf forests despite a 30% increase in temperature (global radiation increases around 5%).

Because of the general success of R_N in predicting *PET*, we have notably not investigated the impact of other

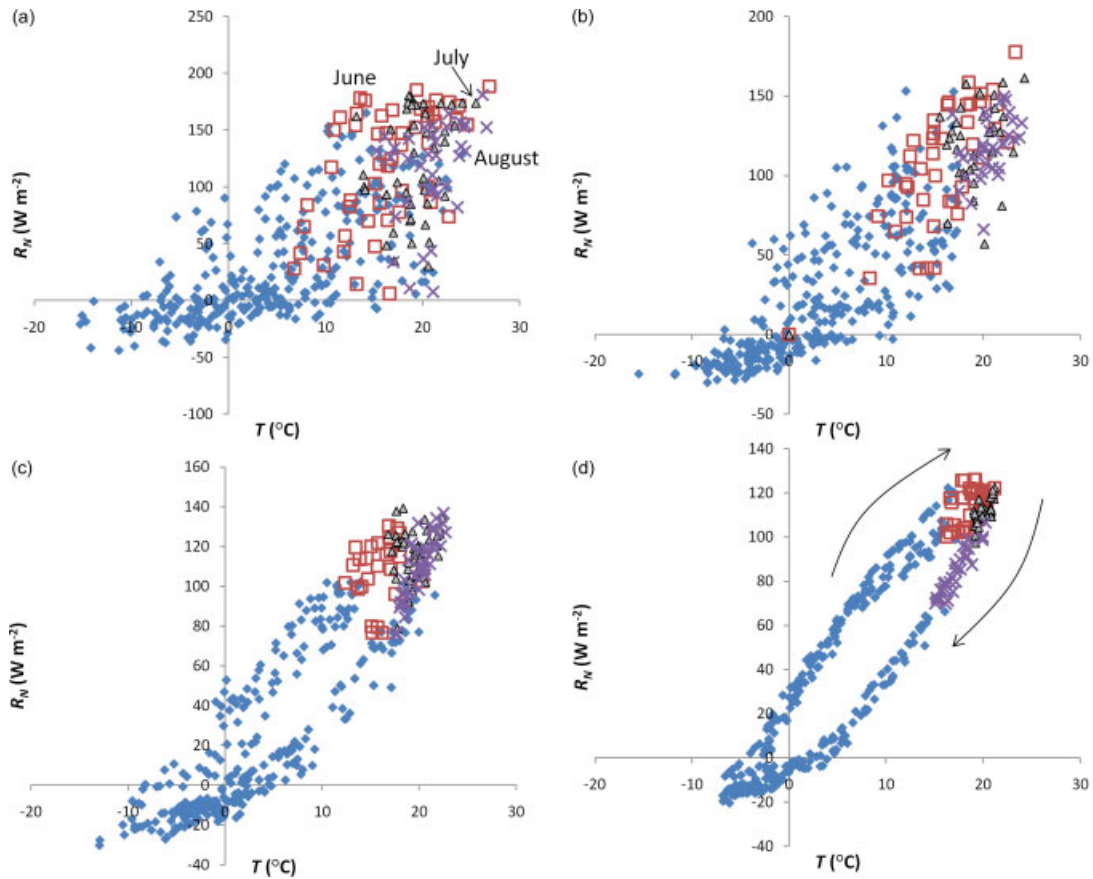


Figure 6. Relation of T to R_N for four different averaging windows: (a) daily, (b) 5-day, (c) 15-day, and (d) 60-day at Harvard Forest, MA, from 2003 to 2009. We use different symbols to indicate different growing season months: squares are June, triangles are July, and crosses are August. In (d), the direction of movement along the hysteresis curve over time is indicated by the arrows

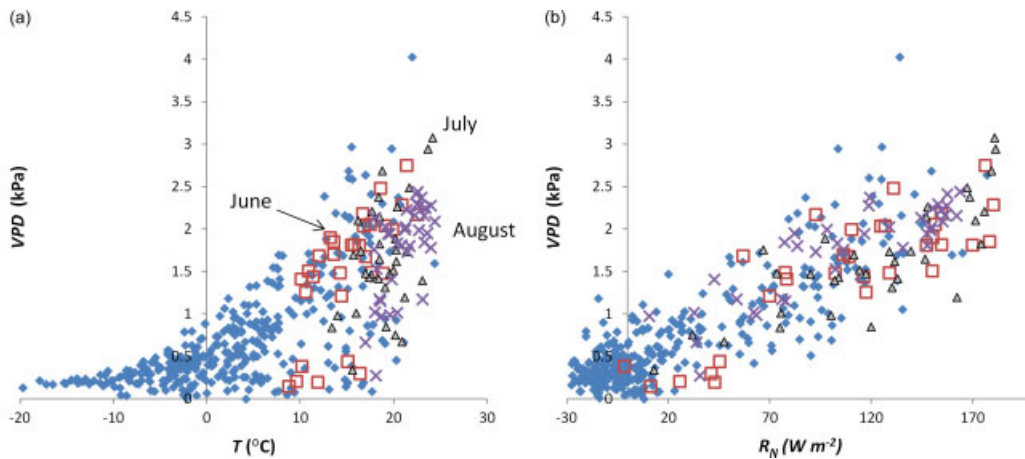


Figure 7. Relationship between 500 randomly selected measurements of (a) daily VPD and daily T and (b) daily VPD and daily R_N at Harvard Forest, MA from 2003 to 2009. Different symbols indicate different growing season months: squares are June, triangles are July, and crosses are August

meteorological variables on PET , in particular VPD . On the basis of the theoretical basis of the Penman–Monteith equation, there would be some expectation that VPD should have a strong influence on PET , especially in forests with rough canopies that lead to reduced aerodynamic resistance. A cursory analysis of AmeriFlux site data seems to suggest that the predictive strength of R_N appears to come from its correlation to VPD . We observed a moderate correlation between VPD and R_N for our five

sites for a 5-day window (median non-parametric Kendall Tau value of 0.58) but also at daily values, as illustrated at Harvard Forest in Figure 7. It seems that T is often intuitively assumed to relate to VPD , but the Harvard Forest data suggests that R_N is instead the better indicator of VPD . Presumably, the intuitive assumption of a correlation between VPD and T arises from looking at hourly data that fluctuate together diurnally or from monthly data that follows seasonal changes.

We conclude the discussion by addressing three specific topics connected to the ideas raised above and of relevance to predicting *PET* in a changing climate.

Implications for using North–South transect data to establish T versus PET relationships

As extensively discussed above, the primary limitation in using T as a proxy for *PET* in a changing climate is that the relationship between T and R_N will shift in the future. However, it is worthwhile to consider other limitations of using previously developed T -based equations. Namely, as alluded to in the introduction, because ET has historically been calculated from catchment water balances, ET can only be reported at an annual scale. As there is relatively little variation in mean annual T at a single location, multiple sites at differing latitudes with differing mean annual T are often used.

For instance, Huntington (2003) established a relationship between mean annual temperature and annual ET (determined from catchment water balances) for sites at a range of latitudes in the eastern United States. Huntington's data can be supplemented with data from Lu *et al.* (2005) for the southeastern United States. Fitting a linear regression equation, both data sets suggest that ET should increase by $\sim 32 \text{ mm year}^{-1}$ with each 1°C increase in mean annual T .

However, it is well established that higher latitudes have a lower net annual radiation than lower latitudes, primarily due to the increasing oblique angle of incoming solar radiation relative to the earth's surface at higher latitudes (Trewartha, 1968 p 34). Taking 11 sites located at nearly the same latitude ($\sim 32^\circ\text{N}$) from Lu *et al.*'s (2005) and Huntington's (2003) data resulted in no relationship between T and ET over a 2°C gradient of mean annual temperatures. We suggest that relationships established from data in which temperature cannot be separated from latitude (i.e. north-south transects) may further overexaggerate the effect of temperature increases due to climate change on ET . Thus, just because mean annual T increases at a location in a more northern latitude does not mean that the location's canopy energy balance is equivalent to a site with historically similar mean annual T at a more southern latitude.

The Hamon and Thornthwaite equations are likely based on data in which latitudinal differences in R_N cannot be separated from T , but the exact data used to establish the Hamon and Thornthwaite relationships is unclear from the original papers (Thornthwaite, 1948; Hamon, 1963). If the equations are based on monthly data, then there could be a sufficient T range from single sites and latitude could possibly be controlled for; if annual water balances were used, multiple sites would almost certainly be needed to span a sufficient wide temperature range. But even if specific sites were used, the relationships may not be transferable. For instance, Thornthwaite shows relationships developed for specific sites (Thornthwaite, 1948 Figure 2). Surprisingly, sites with higher temperature index have a lower *PET* for a given temperature. Kissimmee River Basin, Florida (with

a temperature index value of 117.81), would have 1 cm of *PET* at a monthly mean temperature of 10°C but Coshoc-ton, Ohio (with a temperature index value of 50.89), would have 4 cm of *PET* at a monthly mean temperature of 10°C . This suggests Thornthwaite's relationships are place dependent; presumably, in this example, Kissimmee Florida only reaches 10°C in wintertime when there is lower R_N and less vegetation. Thornthwaite specifically suggest further research into this issue in his original 1948 paper.

Further consideration of the Priestley–Taylor equation

As noted previously, we found that the Priestley–Taylor equation was a strong predictor of the observed trend in *PET*. However, a simple linear relationship of R_N appears to work as well as the Priestley–Taylor equation in explaining the trend. This suggests that certain assumptions behind the Priestley–Taylor equation may not be met at these sites and that modelling of *PET* could be simplified further.

The Priestley–Taylor equation was developed to estimate *PET* over a well-watered surface. The Priestley–Taylor equation scales R_N by a function of temperature (refer Appendix for equation formulation). This scalar ranges from 0.48 to 0.74 over a range from 5 to 25°C . This temperature-dependent scaling term is a function of the vapour saturation—temperature curve slope (Δ), the psychrometric constant (γ), and an adjustment factor (α). Priestley and Taylor (1972) plot the change in H/LE with temperature (from 10 to 30°C) from eight open water and grassed land sites to support their formulation.

In Figure 8, we show the ratio of H/LE (the Bowen ratio) during the growing season over a range of temperatures for the five sites used in this study. We also include the theoretical relationship for the Bowen ratio presumed by the Priestley–Taylor relationship: $(\gamma + \Delta)/(\alpha \cdot \Delta) - 1$. We assume $\alpha = 1.26$. There are two features to note in this figure. First, when looking at sites individually, most sites (with the exception of Walker Branch) do not show

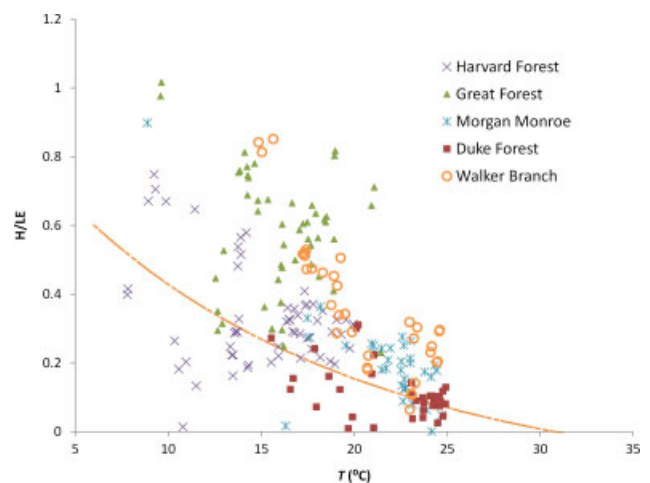


Figure 8. Observed (open) and predicted (dashed line) ratio of H to LE over a range of temperatures at all five sites. The predicted values are estimated from $(\gamma + \Delta)/(\alpha \cdot \Delta) - 1$, a relationship directly related to the assumptions behind the Priestley–Taylor equation

any strong relationship between H/LE and temperature, in opposition to theory. This is consistent with the finding that the simple R_N regression equation appears to do as well as the Priestley–Taylor equation, and that making the temperature adjustment in Priestley–Taylor adds little predictive power for these forested sites. Instead, it appears that at many sites the sensible to latent heat ratio is more near a constant value albeit with some variability unrelated to T . Other researchers have noted variation in α over time (de Bruin, 1983), but we presume that this would just add to the scatter and not lead to a lack of relationship with T . Second, if temperature is considered as a seasonal average (Table I) instead of a 5-day average, there does seem to be a weak correspondence between mean seasonal temperature and H/LE . Previously in the literature, Wilson *et al.* (2002) observed lower Bowen ratios at more southerly latitudes (Walker Branch) and higher Bowen ratios at more northerly latitudes (Harvard Forest), but did not assess distinctions among additional sites. However, this weak correspondence with seasonal temperature is overwhelmed by the variation among sites. For instance, Harvard Forest and Great Mountain generally have higher H/LE values (consistent with their lower mean seasonal temperatures), but Harvard Forest has H/LE values significantly smaller than that of Great Mountain. Similarly, despite having similar seasonal mean temperatures, Duke Forest has a lower H/LE than Morgan Monroe or Walker Branch.

Other considerations of using T-based equations with GCM output

Besides the fact that temperature-based PET equations may be overestimating the role of temperature, temperature-based equations applied externally to a GCM may also possibly exaggerate PET by failing to know when the GCM output is affected by soil moisture deficits. From assessing monthly ET output from 2080 to 2100 for the GFDL CM2 model A2 emission scenario, LE drops from 124 W m^{-2} in June to 107 and 78 W m^{-2} in July and August, respectively. In 2001 to 2020, the July and August LE values are 127 and 91 W m^{-2} , respectively. It appears that greater early season ET in 2081–2100 reduces the moisture availability in the grid cell in the GCM more extensively than in the 2001–2020 period, leading more incoming R_N to be partitioned to H instead of LE . This higher H in part leads to higher GCM-reported T in July and August. Unless the hydrologic model's soil moisture budget corresponds to that in the GCM (highly unlikely given the greatly different scales), the hydrologic model may not be moisture limited and will instead translate the higher T into an increase in ET instead of recognizing that the higher T is actually due to a decrease in ET within the GCM. In such a case, a temperature-based PET model run external to the GCM could be said to 'double count', taking a period when there should be decreased ET and implying that it is a period of increased PET . As all PET models have some temperature dependency, other PET models

besides T -based models would also have some sensitivity to this disconnect between water balances.

Ideally, one could directly use the reported LE from the GCM, but the coarse resolution and lack of local detail in the GCM land surface models introduce their own errors. Further research could focus on ways to assess the degree of congruence between off-line land surface water balances in a hydrologic model and the GCM land surface water balance.

CONCLUSIONS

When daily PET measurements are separated into groups of near constant R_N , regressions of daily T versus PET have little ability to explain variations in PET . Thus, as would be expected given the structure of PET models derived from fundamentals (i.e. the Penman–Monteith or Priestley–Taylor equation), PET has limited direct dependence on T . However, because of the strong correlation between R_N and T for weekly or longer averaging windows, an assessment of T -based models against measured PET values will often show reasonable agreement between model and observations when made at these longer time scales. Furthermore, T -based PET equations have likely appeared especially capable relative to more fundamentally correct models (as noted by Vorosmarty *et al.*, 1998) because of their intrinsic capacity to reflect canopy presence or absence and distinguish among gross intra-annual differences in PET . However, successful use of T -based equations on historical data is not an indicator of future accuracy in a changing climate as the energy balance of the early 20th century under which the temperature-based equations were calibrated will not be the same as that of the late 21st century.

In brief, we suggest that the use of T -based PET equations could overestimate the degree of water deficit in forest region water balances under a changing climate. Most current GCM runs include energy budget components that can provide R_N . We suggest that R_N be considered the primary climate variable driving PET in humid, broadleaf forests in the eastern United States (although T may still be needed to discriminate between dormant and growing seasons using expressions that capture the timing of leaf emergence and leaf senescence). Thus, we suggest that the Priestley–Taylor would be the most suitable approach to estimate future PET if the Penman–Monteith equation is not used. However, differences between Bowen ratios at different AmeriFlux sites need to be better explained to eliminate uncertainty in how the Priestley–Taylor relationship might change with climate. Finally, other equations that also include a primary reliance on radiation (Hargreaves and Samani, 1985; Oudin *et al.*, 2005) could work; but as these equations use the expected solar radiation (as calculated from Julian day and latitude) and are most applicable to looking at cumulative PET over long averaging periods, they have not been extensively assessed in this study.

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APPENDIX

Hamon (1963) method

$$PET = 29.8 H r_{\text{day}} \frac{e_{\text{sat}}(T)}{(T + 273.2)}$$

where PET is in mm day^{-1} ; $H r_{\text{day}}$ is the number of daylight hours; and $e_{\text{sat}}(T)$ is the saturation vapour pressure (kPa) at the air surface temperature T ($^{\circ}\text{C}$).

Thornthwaite (1948) method

$$PET = 1.067 L_d \left(\frac{10T}{I} \right)^a \text{ if } T < 26.5^{\circ}\text{C}$$

and

$$PET = -27.7 + 2.15T - 0.029T^2 \text{ if } T > 26.5^{\circ}\text{C}$$

where PET is in mm day^{-1} (we assume 30 days per month); L_d is mean daytime length in hours divided by 24; T is daily mean air temperature ($^{\circ}\text{C}$); $a = 6.75 \times 10^{-7} I^3 = 7.71 \times 10^{-5} I^2 + 0.0179 I + 0.4921$ and I is annual heat index computed from summing monthly heat indices

$$I = \sum_{j=1}^{12} i_j$$

where i_j is computed as

$$i_j = \left(\frac{T_j}{5} \right)^{1.514}$$

where T_j is the mean historical air temperature for a given month j . While not explicitly stated by Thornthwaite (1948), we presume that if $T_j < 0$, $i_j = 0$.

Priestley and Taylor (1972) equation

$$PET = 1000 \frac{\alpha}{\lambda \rho} \frac{\Delta}{\Delta + \gamma} (R_N - G)$$

where PET is in mm day^{-1} ; λ is the latent heat of vapourization (MJ kg^{-1}); ρ is the density of water (kg m^{-3}); α is a constant reflecting equilibrium with (we use a value of 1.26); γ is the psychrometric constant ($\text{kPa}^{\circ}\text{C}^{-1}$); Δ is the slope of the saturation vapour pressure temperature curve ($\text{kPa}^{\circ}\text{C}^{-1}$); and R_N and G are in units of $\text{MJ m}^{-2} \text{d}^{-1}$.

Penman–Monteith (Penman, 1948; Monteith, 1965)

$$PET = \frac{1}{\lambda} \left[\frac{\Delta(R_N - G) + k \cdot \rho \cdot c_p VPD / r_a}{\Delta + \gamma(1 + r_s / r_a)} \right]$$

where PET is in mm day^{-1} , k is a unit conversion ($3.6 \times 24 \text{ s d}^{-1}$), c_p is the specific heat of moist air ($\text{kJ kg}^{-1}\text{C}^{-1}$), r_a is the aerodynamic resistance (s m^{-1}), and r_s is the surface resistance of the canopy (s m^{-1}). r_a is calculated as a function of wind speed and measurement height (Shuttleworth, 1993, Eqn. 4.2.25). r_s is calculated using a Jarvis–Stuart type model where resistance increases with increasing VPD and R_N (Whitley *et al.*, 2009).

*Oudin *et al.* (2005)*

$$PET = \frac{R_s}{\rho \lambda} \left[\frac{T + 5}{100} \right]$$

where PET is in mm day^{-1} and R_s is solar radiation predicted as a function of latitude and Julian day.