

Uncertainty in the estimation of potential evapotranspiration under climate change

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Received 27 July 2009; revised 8 September 2009; accepted 15 September 2009; published 31 October 2009.

[1] 21st century climate change is projected to result in an intensification of the global hydrological cycle, but there is substantial uncertainty in how this will impact freshwater availability. A relatively overlooked aspect of this uncertainty pertains to how different methods of estimating potential evapotranspiration (PET) respond to changing climate. Here we investigate the global response of six different PET methods to a 2°C rise in global mean temperature. All methods suggest an increase in PET associated with a warming climate. However, differences in PET climate change signal of over 100% are found between methods. Analysis of a precipitation/PET aridity index and regional water surplus indicates that for certain regions and GCMs, choice of PET method can actually determine the direction of projections of future water resources. As such, method dependence of the PET climate change signal is an important source of uncertainty in projections of future freshwater availability. **Citation:** Kingston, D. G., M. C. Todd, R. G. Taylor, J. R. Thompson, and N. W. Arnell (2009), Uncertainty in the estimation of potential evapotranspiration under climate change, *Geophys. Res. Lett.*, *36*, L20403, doi:10.1029/2009GL040267.

1. Introduction

[2] Robust estimates of the terrestrial water balance form the basis of sustainable and equitable water management. These estimates will be of increasing importance as effects of climate change become more pronounced [Bates *et al.*, 2008]. Central to water-balance calculations are reliable estimates of evapotranspiration (ET), as these typically represent a substantial source of uncertainty. Most global [e.g., Arnell, 1999] and catchment-scale hydrological models [e.g., Arnold *et al.*, 1998], as well as offline GCM land-surface schemes [e.g., Gerten *et al.*, 2004], estimate ET using a conceptual variable, potential ET (PET), constrained by available soil moisture. As such, clear understanding of PET dynamics is vital for the assessment of hydrological change and subsequent implications for sectors such as ecosystem functioning and terrestrial carbon storage.

[3] More than 50 different methods exist by which PET can be estimated [Lu *et al.*, 2005]. The Food and Agricultural Organisation of the United Nations (FAO) recom-

mends use of the Penman-Monteith equation [Allen *et al.*, 1998] as it directly incorporates the relevant meteorological variables which control ET. In many locations, however, insufficient data prevent use of Penman-Monteith and compel application of simplified, empirical methods requiring fewer input data. PET method intercomparisons [e.g., Vörösmarty *et al.*, 1998; Lu *et al.*, 2005] confirm that Penman-Monteith is the most reliable where sufficient meteorological data exist, but that in certain climatological environments and where empirical calibrations are robust, less data-intensive methods can also provide reliable approximations of PET.

[4] Given the strong likelihood of future change in the global hydrological cycle [Bates *et al.*, 2008], there is a need to understand the response of PET to climate change. In climate change scenario studies, empirical PET methods may be applied to climate settings where they are essentially uncalibrated, adding uncertainty to water balance estimations. In consequence, different PET methods can produce different climate change signals (shown locally by McKenney and Rosenbergl [1993], Arnell [1999], and Kay and Davies [2008]). There is, however, little understanding at the global scale of the impact of applying different PET methods on future estimates of the terrestrial water balance. This paper addresses this research gap by comparing the global climate change signal in PET from a 2°C rise in global mean temperature (relative to a 1961–1990 baseline) from six commonly used PET methods. Two further analyses are performed to indicate the implications of different rates of change in PET for global and regional water resources: an aridity index, and regional precipitation minus PET water surplus.

2. Data

[5] To calculate PET, global land-surface gridded climate data (at 0.5° × 0.5° resolution) comprising monthly temperature, precipitation, vapour pressure and cloud cover were obtained from the CRU TS 3.0 data set [Mitchell and Jones, 2005] for a baseline period (1961–1990). Future climate scenarios were produced for each variable using the ClimGen pattern-scaling approach [Arnell and Osborn, 2006]. By scaling the spatial pattern of global climate change by the change in global mean temperature, this approach enables the climate change signal associated with any change in global mean temperature to be derived. Here, changes associated with a 2°C rise in global mean temperature were simulated using five different GCMs: UKMO HadCM3, CCCMA CGCM31, IPSL CM4, MPI ECHAM5, and NCAR CCSM30. These GCMs have been selected from the CMIP-3 database [Meehl *et al.*, 2007] as exemplar

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GCMs representing different future representations of key global climate system features.

[6] The 2°C rise in global mean temperature scenario is used to gain understanding of the uncertainty in PET response to a given magnitude of climate change (thereby removing the uncertainty associated with GCM climate sensitivity). Different GCMs are used to explore uncertainty associated with differences in the spatial patterns of change in climate between GCMs, and of different GCM relationships between the scaling factor (i.e., temperature) and other climate variables. The set of projected patterns of climate change was interpolated to a $0.5^\circ \times 0.5^\circ$ grid and imposed upon the 30-year historical baseline CRU TS 3.0 data for each grid cell.

3. Methods

[7] Six different PET methods have been investigated: Penman-Monteith, Hamon, Hargreaves, Priestley-Taylor, Blaney-Criddle and Jensen-Haise. They have been selected to represent a sample of PET schemes commonly used within hydrological models. Penman-Monteith (based on net radiation, temperature, wind-speed and vapour pressure) is used in the MacPDM global hydrological model [Arnell, 1999]. Priestley-Taylor is a widely used simplification of Penman-Monteith based on net radiation and temperature [Priestley and Taylor, 1972], and is used in the WaterGAP global hydrological model [Alcamo et al., 2007]. Jensen-Haise is another radiation-based method (using net short-wave radiation and temperature) [Jensen and Haise, 1963]. Hargreaves is based on mean, minimum and maximum temperature and extra-terrestrial solar radiation, and is the method recommended by the FAO in the absence of sufficient data to calculate Penman-Monteith [Allen et al., 1998]. Hamon and Blaney-Criddle are both based on temperature and day-length. Hamon is used in the WBM global hydrological model [Vörösmarty et al., 1998], whilst Blaney-Criddle is a simple, 'rough estimate' method that is nevertheless frequently used.

[8] The monthly version of Penman-Monteith was calculated according to FAO-56 guidelines [Allen et al., 1998], with three exceptions: (1) cloud cover was used to derive sunshine hours [Hulme et al., 1995] and then short-wave radiation following FAO-56; (2) surface albedo from the Earth Radiation Budget Experiment (ERBE) satellite data set [Barkstrom, 1984] was used in the calculation of net short-wave radiation; and (3) climatological wind-speed values from CRU CL 1.0 [New et al., 1999] were used for both baseline and scenario calculations. Hargreaves, Priestley-Taylor, and Hamon were calculated according to Lu et al. [2005], Jensen-Haise according to Vörösmarty et al. [1998], and Blaney-Criddle following Brouwer and Heibloem [1986]. The radiation terms in Priestley-Taylor and Jensen-Haise were derived as per Penman-Monteith. PET for all methods was calculated on a monthly basis, where mean monthly temperature $>0^\circ\text{C}$, and for 60°S – 60°N . Given the brevity of this paper, annual latitudinal averages are used to provide overall representation of the large scale sensitivity to PET method.

[9] To explore the impact of uncertainty in PET on water availability, two measures are applied. Firstly, a global annual aridity index is calculated. Following the *United*

Nations Environment Program [1992], this is defined as mean annual precipitation (P) divided by PET (on a grid cell basis). Grid cells are defined as arid if P/PET is <1.0 and humid where P/PET is ≥ 1.0 . Secondly, the annual water surplus is calculated as annual P-PET, from months in which $P > \text{PET}$. This was derived for regions highlighted by the IPCC AR4 report [Christensen et al., 2007] as having coherent precipitation change signals (i.e., in the distribution of precipitation response between the 21 AR4 GCMs, where the middle half of the distribution is of the same sign), specifically the Mediterranean (drying), East Africa and Southeast Asia (wetting).

4. Results

[10] The latitudinal structure of baseline (1961–90) PET (Figure 1a) for all methods consists of a primary (secondary) peak in the northern (southern) subtropics as a result of seasonal maxima in temperature and solar radiation. However, the magnitude of PET differs substantially between methods (by up to 600 mm), with differences between methods not consistent across latitudes. For example, Jensen-Haise provides the highest estimate of PET at 20°N , but the lowest PET between 50 – 60°S and N.

[11] For the 2°C climate scenario PET increases at all latitudes in all GCMs and for all PET methods (Figures 1 and 2). PET changes broadly follow the temperature climate change signal (i.e., peaks at approximately 25°S and N). However, differences of over 100% (>200 mm in the tropics) exist in the PET climate change signal between methods in all GCMs (Figures 1b–1f). Maximum absolute differences occur at the same latitude as the peak PET climate change signal; these are unrelated to differences in baseline PET. At most latitudes Hamon produces the largest climate change signal, followed closely by Jensen-Haise. Hargreaves, Penman-Monteith and Priestley-Taylor are generally closely grouped, but still exhibit differences of over 60 mm in places. Whilst the Blaney-Criddle climate change signal is of a similar magnitude to the other methods, its latitudinal variation is remarkably constant in comparison.

[12] The absolute magnitude of the PET climate change signal varies between GCMs (Figure 2), but the relative differences between methods are similar for each GCM (Figure 1). For all methods except Jensen-Haise, the uncertainty between GCMs is lower than the uncertainty between methods within each individual GCM. The NCAR (HadCM3) GCM generally produces the lowest (highest) PET climate change signal.

[13] Results from the aridity index show different levels of change in humid and arid land-surface areas between PET methods (Figure 3). Differences also occur between GCMs (reflecting substantial differences in precipitation response between GCMs), but similar relative patterns are present between PET methods in each GCM (following Figures 1 and 2). As such, Hamon and Jensen-Haise generally give the greatest changes in humid and arid land surface areas (up to 13.3 million km^2); Penman-Monteith and Priestley-Taylor frequently show the smallest changes. Penman-Monteith, Priestley-Taylor and Hargreaves again give relatively similar results, although differences between these methods remain large (e.g., for the IPSL GCM, changes differ by 4.25 million km^2).

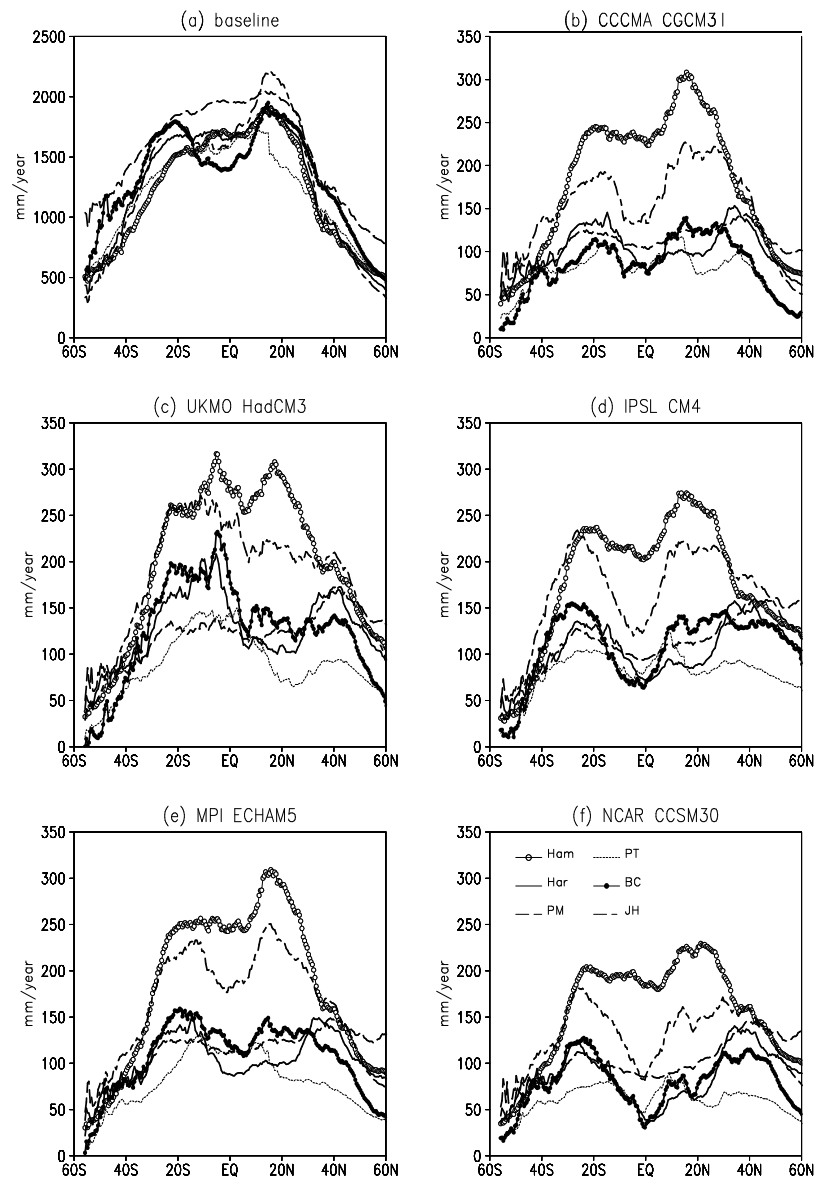


Figure 1. (a) Latitudinally averaged annual PET for 1961–1990 baseline and (b–f) 2°C climate change signal (scenario minus baseline for each method), grouped by GCMs (Ham, Hamon; Har, Hargreaves; PM, Penman-Monteith; PT, Priestley-Taylor; BC, Blaney-Criddle; and JH, Jensen-Haise).

[14] Estimates of regional water surpluses (Table 1) further confirm the influence of PET method on projections of water availability. In each region the projected mean water surplus change is consistent with the mean precipitation change documented in the IPCC AR4 report (drying for the Mediterranean, wetting in East Africa and Southeast Asia). Crucially, however, the uncertainty in water surplus between PET methods from each GCM is of comparable magnitude to the uncertainty between GCMs for a given PET method, resulting in substantially increased overall uncertainty.

5. Discussion

[15] This paper has shown that clear differences exist in the global PET climate change signal produced by different PET methods (following the findings produced by more

limited localised studies [Arnell, 1999; Kay and Davies, 2008]). Similar differences between methods occur for each GCM. Furthermore, calculation of an annual aridity index and regional water surpluses have indicated that different rates of change in PET have comparable impacts on water balances at global and regional scales.

[16] The method dependence of the PET climate change signal can be attributed to two factors: (1) inclusion of different meteorological variables in each method and (2) different empirical formulation of each method. The first factor is exemplified by comparison of Penman-Monteith and Priestley-Taylor climate change signals. Although these methods yield similar values at certain latitudes, they strongly diverge at latitudes encompassing large arid or semi-arid zones (e.g., 10–30°N). This suggests that the absence of humidity data in Priestley-Taylor is important, and follows previous work showing that this method often per-

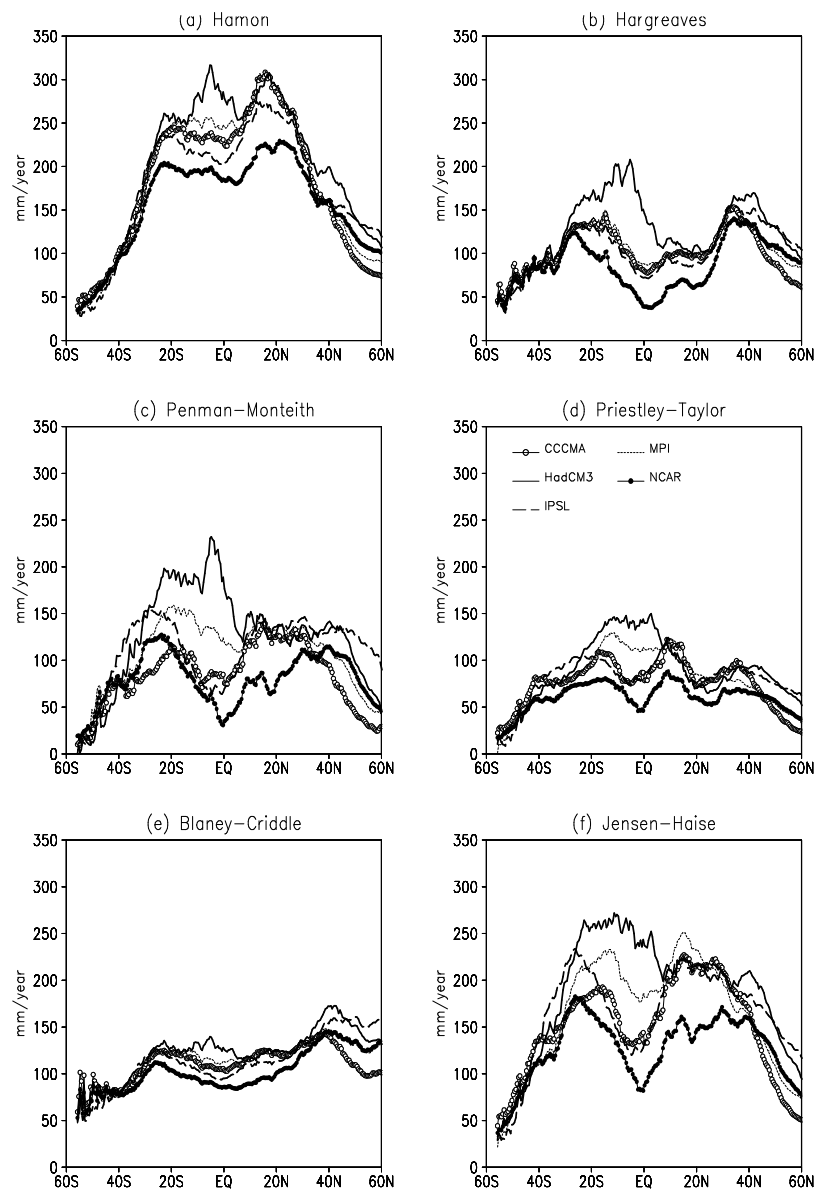


Figure 2. Latitudinally averaged PET 2°C climate change signal (scenario minus baseline for each method), grouped by PET method.

forms poorly in moisture limited environments [McAneney and Itier, 1996].

[17] The role of empirical formulation is demonstrated by comparison of Hamon and Blaney-Cridle. Both methods are based on mean monthly temperature and daylength, yet have markedly different climate change signals. Further comparison with Hargreaves, and the similarity of Hargreaves to Penman-Monteith and Priestley-Taylor, suggests that the empirical approximation of humidity may be the cause of these differences. Hargreaves is also based on temperature and an equivalent variable to daylength, but importantly, also includes minimum and maximum monthly temperature (the difference between these variables is a good indicator of humidity [Allen et al., 1998]).

[18] It is difficult to state here which method is most reliable for assessing climate change impacts on water resources. Penman-Monteith has the strongest physical basis, and is the only method to directly include all relevant

meteorological variables. Whilst Penman-Monteith is subject to non-meteorological uncertainties such as specification of canopy conductance, it should be the most reliable method. It follows that methods with similar results (Priestley-Taylor and Hargreaves) should be reliable alternatives. However, this assertion is dependent on the reliability of input climate data. For instance, whilst relatively high confidence can be placed in gridded-observed and GCM-simulated temperature [New et al., 1999; Randall et al., 2007], less confidence can be placed in cloud cover and vapour pressure. The empirical conversion from cloud cover to sunshine hours is also subject to bias [Hulme et al., 1995]. This poses the important question of whether more reliable estimation of changes in PET can be obtained from physically-based methods (e.g., Penman-Monteith) with uncertain data quality, or more empirical methods (e.g., Hargreaves) with more reliable input data.

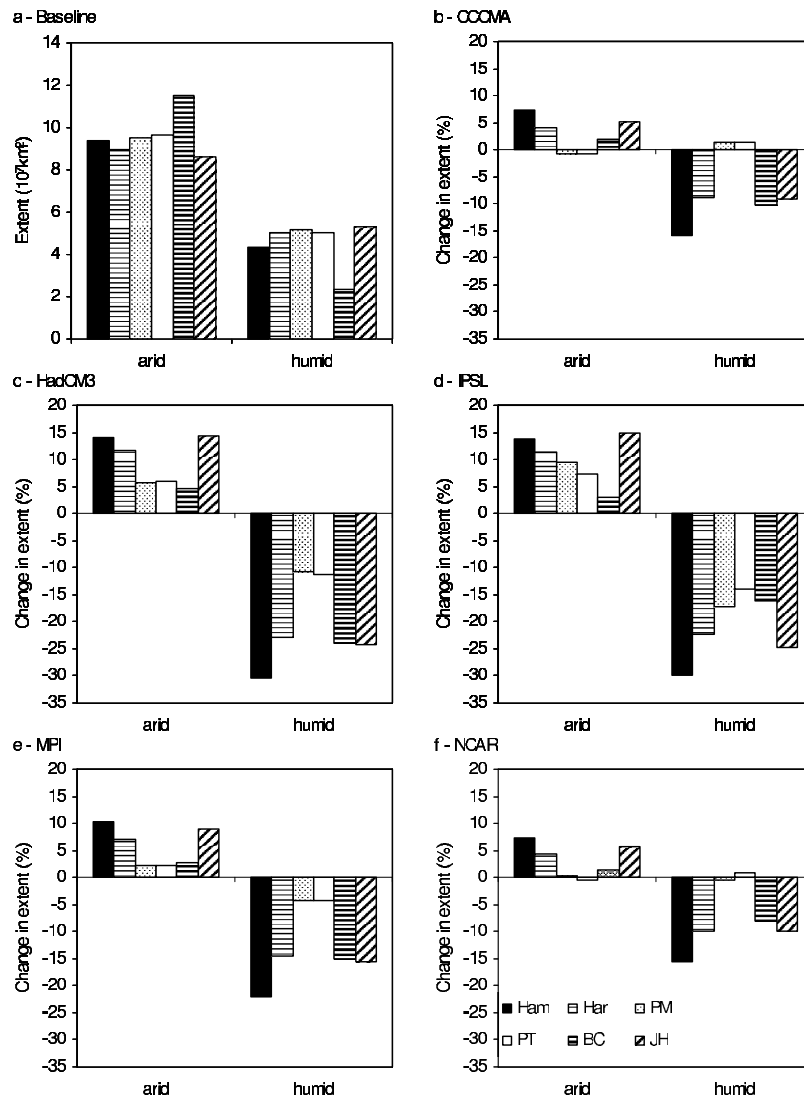


Figure 3. (a) Baseline global land coverage of arid and humid areas and (b–f) percent change in extent of arid and humid areas from the baseline to the 2°C scenario, using different GCMs (Ham, Hamon; Har, Hargreaves; PM, Penman-Montieth; PT, Priestly-Taylor; BC, Blaney-Criddle; and JH, Jensen-Haise).

[19] The occurrence of method-dependence in both humid and arid categories of the aridity index climate change signal suggests that differences between PET methods are not simply a function of different PET estimates in moisture-limited environments (i.e., where no actual ET occurs). As such, these results have important implications for assessment of changes in the overall terrestrial water budget (e.g.,

WaterMIP, http://www.eu-watch.org/nl/25222736-Global_Modelling.html, accessed 07/2009). This is further demonstrated by analysis of regional water surpluses. In each case the choice of PET method adds substantial uncertainty to the existing uncertainty associated with the climate change signal between GCMs. Indeed, in the case of East Africa and Southeast Asia the choice of PET method for certain

Table 1. Statistics of Percentage Changes in Water Surplus for Selected Regions

	Mean Range Between PET Methods ^a	Mean Range Between GCMs ^b	Absolute Minimum and Maximum Change
Mediterranean (30°N, 10°W to 48°N, 40°E)	14.1	9.7	−4.2, −27.6
East Africa (12°S, 22°E to 18°N, 52°E)	15.4	23.3	−12.4, 25.5
Southeast Asia (11°S, 95°E to 20°N, 115°E)	7.9	12.8	−1.1, 20.9

^aUncertainty associated with PET methods (i.e., mean over all GCMs of the range from different PET methods).

^bUncertainty associated with GCMs (i.e., mean over all PET methods of the range from different GCMs).

GCMs can actually determine the direction of projected change in water surplus. As such, the apparent coherence in projected changes in water availability identified in these (and other) regions [e.g., Bates *et al.*, 2008] may not be as strong as previously suggested.

6. Conclusions

[20] Considerable uncertainty remains in projections of global freshwater availability under conditions of climate change and rapidly growing demand, limiting capacity to develop robust and equitable water management strategies [Bates *et al.*, 2008]. Results presented here demonstrate that characterisation of the PET climate change signal, a previously under-researched topic, is an important contributor to this uncertainty, particularly in regions where precipitation is closely in balance with PET. As such, these results have important implications for how future assessments of changes in the hydrological cycle are undertaken, and also for the interpretation of previous studies. Further work is required to more fully integrate the uncertainty in the PET climate change signal into projections of future freshwater availability. Although many other sources of uncertainty exist in relation to the projection of future freshwater availability, improving understanding of changes in PET is an important step in the process of improving confidence in such projections.

[21] **Acknowledgments.** This work was supported by a grant from the UK Natural and Environmental Research Council (NERC), under the QUEST programme (grant NE/E001890/1). Tim Osborn (Climatic Research Unit, University of East Anglia) produced the climate scenarios.

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