Hydrol. Earth Syst. Sci.
hess-2019-103

Response to editor's comments

Dear Editor,

Thank you very much for your detailed comments. Following please find our point-by-point response to your questions and suggestions. The editor's comments are in regular font and our response is in bold. The page and line numbers refer to the revised manuscript that will be submitted with this response (with "all mark up" display for review).

The authors present a study where they investigated the effects of spatial averaging on modelled evaporation (ET) estimates at the global scale. They make use of the Budyko framework to model ET and use this same framework to spatially 'average' ET and to determine the heterogeneity bias. This method was already presented in a previous paper (Rouholahnejad Freund & Kirchner, 2017), but is now applied at the global scale. Only applying a method to the global scale without adding new insights (or very limited) is not enough for a new publication. As also mentioned by reviewer #1, this should be improved. Clearly show the added value of this study above the previous one.

- **Our previous work showed mathematically that averaging over spatially heterogeneous P and PET results in overestimation of ET within the Budyko framework. We did not, however, determine where around the globe, and under what conditions, this heterogeneity bias is likely to be most important. In this work, we examine the global distribution of this bias, its scale dependence, and its sensitivity to variations in P versus PET.**
- **Our goal is to identify where, under what conditions, and at what spatial scales averaging over heterogeneities in P and PET could be most important to estimates of evapotranspiration, but not to quantify the absolute magnitude of these averaging effects.**
- **Our work outlines a strategy for quantifying heterogeneity biases and potentially correcting for them, and highlights regions where more detailed mechanistic modeling is needed.**
- **Our analysis of percent variability of P and PET products shows that percent variabilities of precipitation products are in general larger than PET products and hence contribute more to heterogeneity bias.**
- **Our analyses show that mountainous terrain, regions with temperate climates and dry summers, and landscapes where spatial variations in precipitation and potential evapotranspiration are inversely correlated exhibit greater heterogeneity bias in ET estimates.**
- **Our analysis of scale dependence shows that heterogeneity bias increases almost exponentially as gird cell sizes increase.**
- **The second order Taylor expansion of a function around its mean is a powerful quantifiable approach that can be practically used in estimating biases in ET calculations due to spatial averaging over heterogeneous inputs. We use Budyko relations as ET functions for purposes of demonstration, but discuss that the approach is expandable and quantifiable in any other ET function at large scales (global, continental, and regional scales). We used Budyko as an**

example "see-through" case to show the applicability of the proposed mathematical method at scales that are relevant to large-scale land surface models.

- **One can use this approach to correct for averaging bias without explicitly representing finer-scale processes within the modeling framework. The same approach can potentially be used in more mechanistic ET models with time varying inputs at each modeling time step (daily or sub-daily).**

We have revised the manuscript to point out the added value of this paper more clearly.

In the abstract (L40-41) it is promised to proved insights in the underlying mechanisms, but these can not (or limited) be found in the manuscript.

We revised the manuscript in way that it doesn't emphasize the underlying mechanisms (because of the inherent characteristics of Budyko Framework used in this paper). The discussion about the sensitivity of heterogeneity bias to climatic variability (variability in P and PET) is now added to the revised manuscript (P14, L326-339). We now no longer mention underlying mechanisms.

Furthermore, I have some doubts on your methodology. You frame your study in such way, that it will help to quantify errors in ET due to spatial averaging for ESMs. To investigate this, you don't use a ESM, but you choose for the Budyko framework for simplicity reasons. However, the Budyko framework is a first order estimate, meant for large catchments under steady-state (see also comment reviewer #1). I wonder if the gridcells can be considered as mini-catchments under steady state.

In response to reviewer #1's comments, we made it clearer in the manuscript that the current heterogeneity bias rates are not applicable to correct for this bias in ESMs because ESMs use different algorithms to calculate ET at daily or sub-daily temporal resolution, which goes beyond the steady-state assumptions of Budyko curves. We nonetheless think the current manuscript is useful because it demonstrates, at global scale, an overall framework for estimating how averaging over heterogeneity in atmospheric forcing at the land surface affects evapotranspiration estimates. We state in the paper that the current results can not be directly exploited by ESMs to correct for averaging bias, although the proposed methodology sheds light on the potential ways one can account for this bias (depending on the specific ET algorithms ESMs use and the scales at which they average over sub-grid heterogeneities) (P21, L394-402). We made the revised paper even more explicit on this point. Our paper highlights a general methodology that can be used to estimate the systematic bias due to averaging, but not the precise magnitude of this bias because it will change significantly depending on ET formulation used.

Regarding Budyko's steady sate assumptions: here we used long-term averages of P and PET to get long-term averages of ET at grid scales. Over long periods of time, changes in storage are commonly neglected in water balance calculations. Besides, current large-scale physically

based models overlook changes in deep groundwater storage and lateral transfers of water among their vertical columns at any given modeling time step, so they force grid cells to behave like catchments, whether they do so in reality or not.

We agree that on shorter time steps, Budyko curves cannot be used over individual grid cells. The temporal variations in climatic variables and the effect of their averaging on ET estimates is indeed an open question but cannot be addressed within Budyko framework.

We revised the manuscript to include these points more clearly (P21, L394-402 and P22, line440-450).

What is the effect of lateral flow, irrigation, advected energy (dry gridcell next to wet gridcell) etc.? This should be more discussed in detail.

We treated lateral transfers in some detail in our 2017 paper and we currently have nothing to add on this subject. Lateral transfers may of course be important, but unless and until we have reliable quantitative estimates of how big lateral transfer fluxes actually are (and where they are), it will be difficult to estimate their impact on ET heterogeneity biases. These shortcomings are stated in the discussion part of the manuscript (P22, L440-443).

Furthermore, I wonder if the study shows the real ET-heterogeneity bias (as far as you can at all), or that I am looking at uncertainties in rainfall products? Because looking at figure 1b, the bias is largest once P/PET deviates most between 2 locations. This is the case when either P or PET differs most between locations. Often PET differs less than P, so the bias is dominated by differences in P (as shown in figure 4). Hence I am not surprised to see that the bias is related to topography, because it is well known that P changes significantly with altitude (and also becomes more uncertain).

Equations 4 of the revised manuscript shows that averaging biases in Budyko ET estimates are equally sensitive to the same <u>percentage</u> variability in P and PET. Thus we do not try to explain the different degree of sensitivity, per se, between P and PET (because, at least in percentage terms, these sensitivities are the same). If P is more variable than PET (in percentage terms) across landscapes, as is often the case, then the variability in P will make a larger contribution to the averaging bias. (At least in the Budyko approach; whether this is true for more physically based ET estimates remains to be seen, and we are working on this question.)

As a practical matter, it is difficult to know whether rainfall products overestimate the spatial variability in P (due to errors or uncertainties), or underestimate it (by leaving out mechanisms that cause real-world variability in P). We agree that it is an interesting question (how variability in real-world P relates to variability in rainfall product P), but that is well beyond the scope of this paper.

Figure 4a is the boxplot of two products of P and PET for the entire US. It is the spatial (and temporal) variability in each calculation unit (grid cells) that contributes to the heterogeneity bias in ET estimate on that grid cell. The purpose of the figure was to show the difference in mean and variability of the data products. We have revised the manuscript to more clearly

> **explain that the key variables are the fractional variability in P and PET, and that the fractional variability in P will usually be the dominant variable (P14, L326-339).**

In relation to this, I wonder if figure 5b would not look similar once you plot climate zone against the standard deviation in P?

> **The derived heterogeneity bias term (Eq. 3) is a direct function of percentage standard deviations in P and PET (see Eq. 4). Standard deviations of P and PET at 1-degree grid scale show similar patterns (figure 3 a and b). We expanded Fig. 5 to show how the distributions of P and PET change as a function of climate zones, both in absolute terms (Figs. 5c and 5d) and in percentage terms (Fig. 5e). This was one of the concerns of the first reviewer too. We made changes in the manuscript to make sure these points are stated more clearly (P14, L326-339 and Figure 5c-e).**

Based on these concerns, plus the 2 critical recommendations by the reviewers I advise to do a major revision of your manuscript and emphasize what we can learn from this study in addition to the previous study (what are the new insights). Hereafter, I will send out the manuscript for a new review round. Please also have a careful look at the comments of reviewer #1. They will help to improve the quality of the paper.

> **The added values of this work are reviewed in page one and two of the current document in response to the Editor's first comment.**

Specific comments:

- P1L23: what do you mean by "landscapes where P is inversely related with PET"?

> **landscape in which spatial variations in P are inversely related to spatial variations in PET. This is corrected in the revised manuscript.**

- P3L78: in my view ET and LH are synomyms.

> **We corrected this in the revised manuscript.**

- P5L151-153: the hypotheses miss link with previous text. Please make the connection clearer.

> **The strongest link is actually with the analysis that follows in Section 2, and we have added that linkage explicitly to this sentence (P6, L172-176).**

- fig 1b: Please change this figure to the common way Budyko curves are drawn, i.e.: aridity on x-asis (aridity=PET/P) and not the wetness index

> **Budyko curves are drawn both ways (either PET/P and ET/P on the x and y axes, or as we have done it here and in our previous paper, P/PET and ET/PET on the x and y axes). We agree with you that the official UN/FAO definition of P/PET as the "aridity index" is a source of confusion, but that train left the station years ago and none of us can solve it now. We clearly refer to**

the "aridity index" and not "aridity". While in theory one could plot the curves the other way, that would create a lot of confusion with respect to our original paper – among other things, it would require entirely different equations to connect the heterogeneity bias to the Budyko plot, and readers would not understand why the equations are different between the two papers. So we really think it is essential to keep the axes the way they are. Besides, for the same reason you pointed out above – that P is more variable than PET – we think it is much more intuitive to have the main "driving variable", P, on only one axis rather than redundantly on both the x and y axes.

- P7L208: P/PET is not aridity, become once P/PET becomes larger the index becomes wetter instead of dryer

We did not say "aridity", we said "aridity index", and the distinction is important. As mentioned above, AI=P/PET became a widely used international definition of the "aridity index" (not aridity) years ago, and that can't be reversed now. (We agree that it is confusing to have an "aridity index" that is really a wetness index, but that's not a problem we created and for the reasons explained above, P/PET is really the correct x-axis variable for our problem. Given that the figures and text are written based on this definition (AI=P/PET) and the index has been defined several times throughout the text, we would like to keep the definition as it is.

- P11L262-264: this line somehow suggest that you prefer prism P, because you then have larger biases? Why?

Our intention in this section is not to suggest any particular data product merely because it gives a larger bias. Our point was that we can't show explicitly that Prism P gives a larger heterogeneity bias at global scale, because the data set is not available globally without paying a substantial fee. We see that the phrasing was unclear and we have clarified it.

- Fig 4: I would swop a) and b)

Figure 4 is revised as suggested.

- Fig 5b: would be nice to also make this graph for standard deviation of P and PET. Likely it's similar.

Three panels are added to figure 5 as requested.

- P15L314: add comma after e.g.

Revised as suggested.

Global assessment of how averaging over spatial ~~land-surface~~ heterogeneity ~~of~~in precipitation and potential evapotranspiration affects modeled evapotranspiration rates

Elham Rouholahnejad Freund[1,2], Ying Fan[3], James W. Kirchner[2,4,5]

[1]Laboratory of Hydrology and Water Management, Ghent University, Ghent, Belgium
[2]Department of Environmental Systems Science, ETH Zurich, 8092, Zurich, Switzerland
[3]Department of Earth and Planetary Sciences, Rutgers University, New Brunswick, NJ, United States
[4]Swiss Federal Research Institute WSL, Birmensdorf, 8903, Switzerland
[5]Dept. of Earth and Planetary Science, University of California, Berkeley, CA 94720, United States

Correspondence to: Elham Rouholahnejad Freund, elham.rouholahnejad@gmail.com

~~Key point~~Short summary~~s~~

- ~~Evapotranspiration (ET) rates and the properties that regulate them are spatially heterogeneous at scales orders of magnitude smaller than typical Earth System Models (ESMs) grid cells. Averaging over this spatial heterogeneity may lead to biased estimates of energy and water fluxes in ESMs.~~
- ~~We showed that because Tthe relationships driving ET are nonlinear,. Hence, averaging over sub-grid heterogeneity of drivers of ET, namely precipitation (P) and potential evapotranspiration (PET), leads to overestimation of average ET.~~
- ~~We quantified tThe effects of averaging over spatial heterogeneity on grid-cell-averaged evapotranspiration (ET)ET rates are quantifiable when the finer resolution variations of the driving forces are known. over heterogeneous landscapes across the globe and highlighted the locations where the heterogeneity bias matters. We showed that because the relationships driving ET are nonlinear, averaging over sub-grid heterogeneity of drivers of ET, namely precipitation (P) and potential evapotranspiration (PET), leads to overestimation of average ET.~~

Evapotranspiration (ET) rates and the properties that regulate them are spatially heterogeneous. Averaging over spatial heterogeneity in precipitation and potential evapotranspiration as main drivers of ET may lead to biased estimates of energy and water fluxes from the land surface to the atmosphere. Here we show that this ~~Our analysis showed that this "heterogeneity~~” bias~~"~~ ~~is~~ will be largest in mountainous terrain, ~~most pronounced~~ in ~~n~~ regions with temperate climates and dry summers, ~~-~~and ~~in mountainous terrains,~~ in landscapes where spatial variations in precipitation~~P~~ and potential evapotranspiration are inversely correlated.~~is are inversely correlated with to spatial variations in PET, and in regions with temperate climates and dry summers.~~

~~- We showed that theThe magnitude of this heterogeneity bias grows on average, and expands over larger areas, as the sub-grid heterogeneities are averaged over size of the coarser grid cells increases.~~

Abstract

The major goal of large-scale Earth System Models (ESMs) is to understand and predict global change. However, computational constraints require ESMs to operate on relatively large spatial grids (typically ~1 degree or ~100 km in size), with the result that the heterogeneity in land surface properties and processes at smaller spatial scales cannot be explicitly represented. Averaging over this spatial heterogeneity may lead to biased estimates of energy and water fluxes. ~~in ESMs. For example, evapotranspiration rates and the properties that regulate them are spatially heterogeneous at scales orders of magnitude smaller than typical ESM grid cells.~~ Here we ~~quantify~~ estimate how averaging over spatial heterogeneity in precipitation (P) and potential evapotranspiration (PET) may affect ~~the effects of spatial heterogeneity on~~ grid-cell-averaged evapotranspiration (ET) rates, as seen from the atmosphere over heterogeneous landscapes across the globe. Our goal is to identify where, under what conditions, and at what scales this heterogeneity bias could be most important, but not to quantify its absolute magnitude. ~~I~~W~~n an earlier study, w~~e use~~d~~ ~~a~~ Budyko curves ~~framework to~~as ~~a~~ simple functions that ~~estimator of ET that functionally~~ relate~~s~~ ET to precipitation (P) and potential evapotranspiration (PET)~~, and used a sub-grid closure relation to quantify the effects of sub-grid heterogeneity on average ET at 1° by 1° grid cells- the scale of typical ESM~~. ~~We showed that b~~Because the relationships driving ET are nonlinear, averaging over sub-grid heterogeneity in P and PET ~~leads to overestimation~~will lead to biased estimates of average ET. ~~In this study, we~~ We ~~extend that work to the globe and~~ examine the global distribution of this bias, its scale dependence, ~~and the underlying mechanisms~~and its sensitivity to variations in P versus PET ~~as the heterogeneous inputs are averaged at 1° by 1° grid cells, the scale of typical ESMs~~. Our analysis shows that this "heterogeneity bias" is more pronounced in mountainous terrain~~s~~, in landscapes where spatial variations in P and PET are inversely correlated, ~~is are inversely correlated with to spatial variations in PET,~~ and in regions with temperate climates and dry summers. We also show that ~~that the magnitude of~~ this heterogeneity bias ~~grows~~ increases on average, and expands over larger areas, as the ~~size of the~~ grid cell size increases. ~~Correcting for this overestimation of ET in ESMs is important for modeling the water cycle, as well as for future temperature predictions, since current overestimations of ET rates imply smaller sensible heat fluxes, and potential underestimation of dry and warm conditions in the context of climate change.~~ Our work outlines a strategy for quantifying heterogeneity biases and potentially correcting for them, ~~provides a basis for translating the estimates of heterogeneity bias into correction factors in large-scale ESMs,~~ and highlights ~~the~~ regions where more detailed mechanistic modeling is needed.

1. Introduction

Earth System Models (ESMs) are designed to understand interactions between the land surface, atmosphere, and oceans and to predict global environmental changes. However, the Earth system and its underlying physical processes are highly heterogeneous across orders of magnitude in scale below the scale of typical ESM grids (e.g., 1° by 1°). Despite increasing recognition of the need to mechanistically represent physical processes in ESMs, currently even the most disaggregated large-scale ESMs cannot explicitly represent the spatial heterogeneity of land surface hydrological properties at scales that are important to atmospheric fluxes. ~~Overlooking this spatial heterogeneity and instead a~~Averaging over land surface properties at the scale of ESM model grid cells may have important implications for water and energy flux estimates ~~in large-scale ESMs~~ (Avissar and Pielke, 1989; Giorgi and Avissar, 1997; Ershadi et al., 2013; Lu et al., 2014).

Estimates of evapotranspiration (ET) fluxes have significant implications for future temperature predictions. Smaller ET fluxes imply greater sensible heat fluxes and, therefore, ~~amplified dry and warm~~drier and warmer conditions in the context of climate change (Seneviratne et al., 2010). Surface evaporative fluxes (and thus energy partitioning over land surfaces) are nonlinear functions of available water and energy, and thus are coupled to spatially heterogeneous surface characteristics (e.g., soil type, vegetation, topography) and meteorological inputs (e.g., radiative flux, wind, and precipitation~~) (~~; Kalma et al., 2008; Shahraeeni and Or, 2010; Holland et al., 2013). These characteristics are spatially variable on length scales of <1 m to many kilometers, well below typical ESM grid scales of ~100 km. ESMs calculate grid-averaged surface and atmospheric fluxes ~~from grid-averaged land surface~~ using parameterizations that correspond~~s~~ to grid-averaged properties of the land surface~~parameterizations~~ (Sato et al., 1989; Koster et al., 2006; Santanello and Peters-Lidard, 2011). Thus ET estimates that are derived from spatially-averaged land surface properties do not capture ET variations driven by the underlying surface heterogeneity (McCabe and Wood, 2006). Because the relationships driving ET are nonlinear, the average ET flux from a heterogeneous landscape may be different from an ET estimate calculated from spatially averaged inputs (Rouholahnejad Freund and Kirchner, 2017).

Several studies have quantified the effects of land surface heterogeneity on ~~ET,~~ potential evapotranspiration (PET)~~,~~ and latent heat (LH) fluxes, and have found that averaging over land surface heterogeneity can potentially bias ET estimates either positively or negatively. For example, Boone and Wetzel (1998) studied the effects of soil texture variability within each pixel in the Land-Atmosphere-Cloud Exchange (PLACE) model, which has a spatial resolution of approximately 100 by 100 km. They reported that accounting for sub-grid variability in soil texture reduced global ET by 17%, increased total runoff by 48%, and increased soil wetness by 19%, compared to using a homogenous soil texture to describe the entire grid cell. Kollet (2009) found that heterogeneity in soil hydraulic conductivity had a strong influence on evapotranspiration during the dry months of the year, but not during months with sufficient moisture availability. Hong et al. (2009) reported that aggregating radiance data from 30 m to 60, 120, 250, 500, and 1000 m resolution (input upscaling) and then calculating ET from these aggregated inputs at these grid scales using Surface Energy Balance Algorithm for Land (SEBAL, Bastiaanssen et al., 1998a) yields slightly larger ET estimates as compared to ET calculated with finer resolution inputs and then aggregated at the desired grid scales (output upscaling). The discrepancy between ET estimated with the output upscaling method and the input upscaling method grows as the size of the grid~~-~~ cell increases (the difference between ET calculated from the input and output upscaling methods is ~20% more at a grid scale of 1 km by 1 km compared to a grid scale of 120 m by 120 m). Aminzadeh et al. (2017) investigated the effects of averaging surface heterogeneity and soil moisture availability on potential evaporation from a heterogeneous land surface including bare soil and vegetation patches. They found that if the heterogeneity length scale is smaller than the convective atmospheric boundary layer (ABL) thickness, averaging over heterogeneous land surfaces has only a small effect on average potential evaporation rates. Averaging over larger-scale heterogeneities, however, led to overestimates of potential evaporation.

Heterogeneity biases have also been identified in ~~Another example of overestimation bias as surface and sub-surface heterogeneities are averaged are manifested with~~ ET calculation algorithms that use remote sensing data as inputs. McCabe and Wood (2006) found that remote sensing retrievals of ET are larger than the corresponding in-situ flux estimates and characterized the roles of land surface heterogeneity and remote sensing resolution in the retrieval of evaporative flux. McCabe and Wood (2006) used Landsat (60 m), Advanced Space borne Thermal Emission and Reflection Radiometer (ASTER) (90 m), and MODIS (1020 m) independently to estimate ET over the Walnut Creek watershed in Iowa. They compared these remote sensing estimates to eddy covariance flux measurements and reported that Landsat and ASTER ET estimates had a higher degree of consistency with one another and correlated better to the ground measurements (0.87 and 0.81, respectively) than MODIS- based ET estimates did. All three remote sensing products overestimated ET as compared to ground measurements (at 12 out of 14 tower sites). Upon aggregation of Landsat and ASTER retrievals to MODIS scale (1 km), the correlation with the ground measurements decreased to 0.75 and 0.63 for Landsat and ASTER, respectively.

Contrary to overestimation bias, many remotely sensed ET estimates that include parameters related to aerodynamic resistance are significantly affected by heterogeneity, and underestimate ET as the scale increases (Ershadi et al., 2013). Because aerodynamic resistance is significantly affected by land surface properties (e.g., vegetation height, roughness length, and displacement height), decreases in aerodynamic resistance at coarser resolutions could lead to smaller estimates of evapotranspiration. Ershadi et al. (2013) showed that input aggregation from 120m to 960 m in Surface Energy Balance System (SEBS, Su, 2002) leads to up to 15 % underestimation of ET at the ~~aggregated~~ larger grid resolution in a~~n~~ study area in the south-east of Australia. Rouholahnejad Freund and Kirchner (2017) quantified the impact of sub-grid heterogeneity on grid-average ET using a simple Budyko curve (Turc, 1954; Mezentsev, 1955) in which long-term average ET is a non-linear function of long-term averages of precipitation (P) and potential evaporation (PET). They showed mathematically that averaging over spatially heterogeneous P and PET results in overestimation of ET within the Budyko framework (Fig.

1). Their analysis implies that large-scale ESMs that overlook land surface heterogeneity will also yield biased evapotranspiration estimates due to the inherent nonlinearity in ET processes. They did not, however, ~~estimate the likely actual magnitude of this heterogeneity bias beyond a few example grid cells~~determine where around the globe, and under what conditions, this heterogeneity bias is likely to be most important.

The recognition that spatial averaging can potentially lead to biased flux estimates has prompted methods for representing sub-grid-scale heterogeneities and processes within ESMs. Accounting for land surface heterogeneity in large-scale ESMs is not merely constrained by limitations in both computational power (Baker et al. 2017) and the availability of high-resolution forcing data, but also by the fact that the atmospheric and land surface components of some ESMs operate at different resolutions. There have been several attempts to integrate sub-grid heterogeneity in ESMs while ~~maintaining~~ keeping the computational costs affordable. In "mosaic" approaches, the model is run separately for each surface type in a grid cell, and then the ~~surface~~ surface-specific fluxes are area-weighted to calculate the grid-cell average fluxes (e.g., Avissar and Pielke, 1989; Koster and Suarez, 1992). The "effective parameter" approach (e.g., Wood and Mason, 1991; Mahrt et al., 1992), by contrast, seeks to estimate effective parameter values at the grid cell scale that subsume the effects of sub-grid heterogeneity. Estimating these effective parameters can be challenging because the relevant land-surface processes typically depend nonlinearly on multiple interacting parameters, and land-surface signals at different scales are propagated and diffused differently in the atmosphere. Alternatively, the "correction factor" approach (e.g., Maayar and Chen, 2006) uses sub-grid information on spatially heterogeneous land-surface processes and properties to estimate multiplicative correction factors for fluxes that are originally calculated from spatially averaged inputs at the grid-cell scale. All three approaches try to reduce the heterogeneous problem to a homogeneous one that has equivalent effects on the atmosphere at the grid-cell scale.

There is a growing need to understand how sub-grid heterogeneity (and the atmosphere's integration of it)~~,~~ affect grid-scale water and energy fluxes, and to develop effective methods to incorporate these effects in ESMs (Clark et al., 2015, Fan et al., 2019). ~~The above-mentioned studies present the potential effects of spatial heterogeneity on water and energy flux estimates in land surface models at several scales, but are deficient i~~In a previous study, we proposed ~~n proposing~~ a general framework for quantifying systematic biases in ET estimates due to averaging over heterogeneities (Rouholahnejad Freund and Kirchner, 2017). W~~In a previous study, w~~e used the Budyko framework as a simple estimator of ET, and demonstrated theoretically how averaging over heterogeneous precipitation and potential evapotranspiration ~~at the grid scale of a typical ESM (e.g., 1° by 1°)~~ can lead to systematic overestimation of long-term average ET fluxes from heterogeneous landscapes. In the present study, we apply this~~at~~ analysis across the globe and highlight the locations where the heterogeneity bias ~~matters~~is largest. Our hypotheses, derived from the Budyko framework as summarized in Eq. (4) below, are that~~,~~ (1) strongly heterogeneous landscapes, such as mountainous terrain, will exhibit ~~higher~~ greater ~~bias due to averaging~~heterogeneity bias, (2) this~~e~~ bias will be ~~higher~~ larger in climates where P and PET are inversely correlated in space, and (3) heterogeneity bias will decrease as the spatial scales of averaging decrease.

2. Effects of sub-grid heterogeneity on ET estimates in the Budyko framework

Budyko (1974) showed that ~~the~~ long-term annual average evapotranspiration is a function of both the supply of water (precipitation, P) and the evaporative demand (potential evapotranspiration, PET) under steady-state conditions and in catchments with negligible changes in storage (Eq. 1; Turc, 1954; Mezentsev, 1955~~).~~):

$$ET = f(P, PET) = \frac{P}{\left(\left(\frac{P}{PET}\right)^{n} + 1\right)^{1/n}}. \qquad (1)$$

where ET is actual evapotranspiration, P is precipitation, PET is potential evaporation, and n (dimensionless) is a catchment-specific parameter that modifies the partitioning of P between ET and discharge.

Evapotranspiration rates are inherently bounded by energy and water limits. Under arid conditions ET is limited by the available supply of water (the water limit line in Fig. 1b), while under humid conditions ET is limited by atmospheric demand (PET) and converges toward PET (the energy limit line in Fig. 1b). Budyko showed that over a long period and under steady-state conditions, hydrological systems function close to their energy or water limits. These intrinsic water and energy constraints make the Budyko curve downward-curving.

In a heterogeneous landscape, like the simple example of two ~~ESM~~ model columns in Fig. 1a, P and PET vary spatially. The two columns with heterogeneous P and PET are represented by the two solid black circles on the Budyko curve in Fig. 1b. In this hypothetical two-column example, the true average of ET values calculated from individual heterogeneous inputs (the solid black circles) lies below the curve (the grey circle, labeled “true average”). However, if we aggregate the two columns and consider the system as one column with average properties, the function of average inputs (averaged P and PET over the two columns) lies on the Budyko curve (the open circle) which is larger than the true average of the two columns. In short, in any downward curving function, the function of the average inputs (the open circle) will always be larger than the average of the individual function values (the true average; grey circle). The difference between the two can be termed the "heterogeneity bias".

In a previous study (Rouholahnejad Freund and Kirchner, ~~(~~2017) we showed that when nonlinear underlying relationships are used to predict average behaviour from averaged properties, the magnitude of the resulting heterogeneity bias can be estimated from the degree of the curvature in the underlying function and the range spanned by the individual data being averaged. Here we summarize theses findings as building blocks of the current study. The second-order, second-moment Taylor expansion of the ET function f(P,PET) (Eq. 1) around its mean directly yields:

$$\bar{f}(P,PET)=\overline{ET}\approx f(\bar{P},\overline{PET})+\frac{1}{2}\frac{\partial^2 f}{\partial P^2}\,var(P)+\frac{1}{2}\frac{\partial^2 f}{\partial PET^2}\,var(PET)+\frac{\partial^2 f}{\partial P\,\partial PET}cov(P,PET)\quad, \tag{2}$$

where $\bar{f}(P,PET)$ is the true average of the spatially heterogeneous ET function, $f(\bar{P},\overline{PET})$ is the ET function evaluated at its average inputs $\bar{P}$ and $\overline{PET}$, and ~~where~~ the derivatives are ~~quantified~~ calculated at $\bar{P}$ and $\overline{PET}$. Evaluating the derivatives using Eq. (1) and reshuffling the terms, Rouholahnejad Freund and Kirchner (2017) obtained the following expression for the heterogeneity bias, the difference between the average ET, $\bar{f}(P,PET)$, and the ET function evaluated at the mean of its inputs, $f(\bar{P},\overline{PET})$:

$$f(\bar{P},\overline{PET})-\bar{f}(P,PET)\approx(n+1)\frac{\bar{P}^{n+1}\overline{PET}^{n+1}}{(\bar{P}^n+\overline{PET}^n)^{2+1/n}}\left[\frac{1}{2}\frac{var(P)}{\bar{P}^2}+\frac{1}{2}\frac{var(PET)}{\overline{PET}^2}-\frac{cov(P,PET)}{\bar{P}\,\overline{PET}}\right]. \tag{3}$$

To more clearly show the effects of variations in P and PET, Eq. (3) can be reformulated as follows:

$$f(\bar{P},\overline{PET})-\bar{f}(P,PET)\approx$$
$$(n+1)\frac{\bar{P}^{n+1}\overline{PET}^{n+1}}{(\bar{P}^n+\overline{PET}^n)^{2+1/n}}\left[\frac{1}{2}\left(\frac{SD(P)}{\bar{P}}\right)^2+\frac{1}{2}\left(\frac{SD(PET)}{\overline{PET}}\right)^2-r_{P,PET}\left(\frac{SD(P)}{\bar{P}}\right)\left(\frac{SD(PET)}{\overline{PET}}\right)\right]\quad. \tag{4}$$

Equation (4) shows that the heterogeneity bias depends on only four quantities: the fractional variation (i.e., the coefficient of variation) in precipitation $\left(\frac{SD(P)}{\bar{P}}\right)$ and in potential ET $\left(\frac{SD(PET)}{\overline{PET}}\right)$, the correlation between precipitation and potential ET ($r_{P,PET}$), and the function $(n+1)\frac{\bar{P}^{n+1}\overline{PET}^{n+1}}{(\bar{P}^n+\overline{PET}^n)^{2+1/n}}$, which quantifies the curvature in the ET function in Budyko space. As shown by Fig. 1b and Eq. (2), the discrepancy between average of the ET function and the ET function of the average inputs (the heterogeneity bias) is proportional to both the degree of nonlinearity in the function, as defined by its second derivatives, and the ~~and the range of variation in its input~~ variability of P and PET.~~variables, as defined by their variances.~~ Equation~~.~~ (~~3~~4) allows one to estimate how much the curvature of ~~a nonlinear relationship~~the ET function and the fractional variability (standard deviation divided by mean) of P and PET ~~variance of its inputs at any desired scale~~ will affect estimates of ~~the true mean~~ET. However, to the best of our knowledge, the consequences of these nonlinearities for global evaporative flux estimates have not previously been quantified.

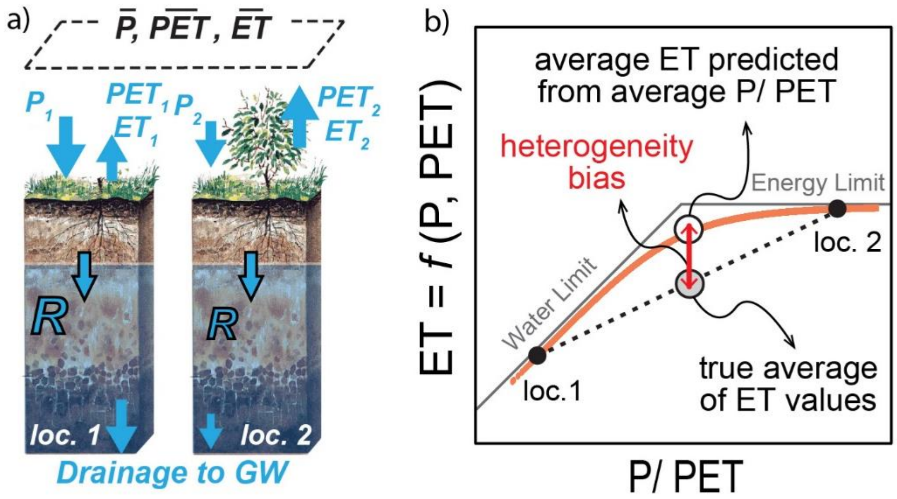


Figure 1. Heterogeneity bias in a hypothetical two-column model in the Budyko framework. The true average ET of the columns (gray circle) lies below the curve and is less than the average ET estimated from the average P/PET of the two columns (open circle). The heterogeneity bias depends on the curvature of the function and the spread of its inputs. Both panels are~~(b) is~~ adapted from Rouholahnejad Freund and Kirchner (2017).

3. Effects of sub-grid heterogeneity on ET estimates at 1° by 1° grid scale across the globe

Across a landscape of ~~size~~ similar size to a typical ESM grid cell (1° by 1°), soil moisture, atmospheric demand (PET) and precipitation (P) will vary with topographic position; hillslopes will typically be drier, and riparian regions will be wetter. To map the spatial pattern in the heterogeneity bias that results from ~~quantify the likely biases introduced by~~ averaging over this land surface heterogeneity, we ~~used~~ applied the approach outlined in section 2 to the global land surface area at 1° by 1° grid scale. Within each 1° by 1° grid cell, we used 30 arc-second values of P (WorldClim; Hijmans et al., 2005) and PET (WorldClim; Hijmans et al., 2005) to examine the variations in small-scale climatic drivers of ET. Because 30 arc-seconds is nearly 1 km, hereafter we refer to the 30 arc-second data as 1km values for simplicity. The spatial distribution of long-term annual averages (1960-1990) of P and PET values at 1 km resolution, along with ~~and~~ 1km values of the aridity index (AI=P/PET), are shown in Fig 2a-c. ET values ~~estimated~~ calculated from these 1km P and PET values using Eq. (1) are then averaged at 1° by 1° scale (“true average”, Fig. 2e). ~~To mimic the averaging that takes place within ESMs, w~~We also averaged the 1km values of P and PET within each grid cell and then modeled ET using the Budyko curve (Eq. 1) applied to these averaged input values. The difference between these two ET estimates is the heterogeneity bias.

We also calculated the heterogeneity bias using Eq. (4~~3~~), which describes how the nonlinearity in the governing equation and the heterogeneity in P and PET jointly contribute to the heterogeneity bias. The heterogeneity bias estimates obtained by Eq. (4) were functionally equivalent (R^2=0.97, root mean square error of 0.17%) to those obtained by ~~y~~ direct calculation using Eq. (1) as described above. ~~and by Eq. (3) were functionally equivalent (R^2=0.97, root mean square error of 0.17%).~~

Fig. 3a-d illustrates the variability (quantified by standard deviation) of 1km values of P, PET, aridity index, and altitude at the 1° by 1° grid scale. The heterogeneity bias in long-term average ET fluxes at the 1° by 1° grid scale (Fig. 3e) highlights regions around the globe where ET fluxes are likely to be systematically overestimated. The spatial distribution of the heterogeneity bias calculated using Eq. ~~3~~4 (Fig. 3e) closely coincides with locations ~~with~~ where the aridity index is highly variable ~~large variability in the aridity index~~ (Fig. 3c), which is driven in turn by topographic variability (Fig. 3d). Strongly heterogeneous landscapes exhibit significant heterogeneity biases in long-term average ET fluxes. A~~, a~~lthough the global average heterogeneity bias is small (<1%),~~ . P~~physically based ET calculations may exhibit larger heterogeneity biases than the modest values we calculate here, because the Budyko approach already subsumes spatial heterogeneity effects at the catchment scale (and also temporal heterogeneity effects due to its steady-~~-~~state assumptions). The heterogeneity biases in ET estimates shown in Fig. 3e correspond~~s~~ to long-term average ET estimates. Given the fact that P and PET can vary temporally (i.e., seasonality), the ~~estimated~~ actual bias could be much larger, particularly where P and PET are inversely correlated (see the last term of Eq. ~~3~~4).

Our results show that the topographic gradient, and hence the variability in the aridity index across a ~~desired~~ given grid ~~size~~ scale, ~~exhibit~~ drives consistent, predictable patterns of ~~associated prediction~~heterogeneity bias in evapotranspiration estimates at that scale. Equation ~~.~~4~~3~~ shows that this bias is equally sensitive to ~~percentage~~fractional variability in P and PET (~~variability~~standard deviation divided by mean~~ in Eq. 3~~). However, because~~if~~ P is typically more variable (in percentage terms) than PET- across landscapes~~ (in percentage terms), then~~ the variability in P will usually make a larger contribution to the heterogeneity bias.

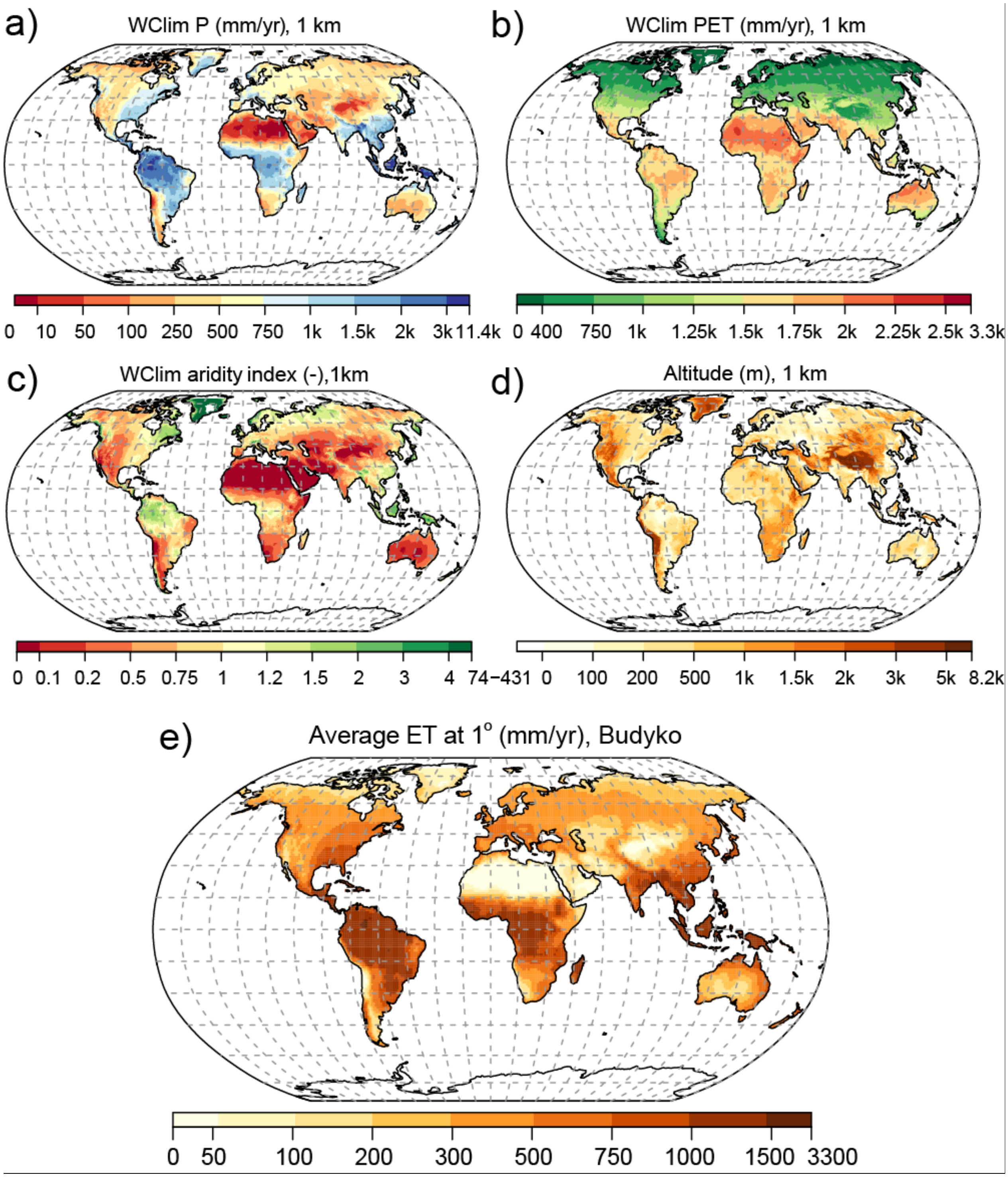

a)
WClim P (mm/yr), 1 km
0 10 50 100 250 500 750 1k 1.5k 2k 3k 11.4k
b)
WClim PET (mm/yr), 1 km
0 400 750 1k 1.25k 1.5k 1.75k 2k 2.25k 2.5k 3.3k
c)
WClim aridity index (-),1km
0 0.1 0.2 0.5 0.75 1 1.2 1.5 2 3 4 74−431
d)
Altitude (m), 1 km
0 100 200 500 1k 1.5k 2k 3k 5k 8.2k
e)
Average ET at 1° (mm/yr), Budyko
0 50 100 200 300 500 750 1000 1500 3300

Figure 2. Global distribution of one-kilometer resolution annual mean precipitation (a: P; WorldClim; Hijmans et al., 2005), potential evapotranspiration (b: PET; WorldClim; Hijmans et al., 2005), aridity index (c: AI=P/PET; WorldClim; Hijmans et al., 2005), and topography (d: SRTM; Jarvis et al., 2008), along with ~~and~~ (e) evapotranspiration (ET) at 1° by 1° scale by averaging 1km values of ET calculated using the Budyko function (Eq. 1).

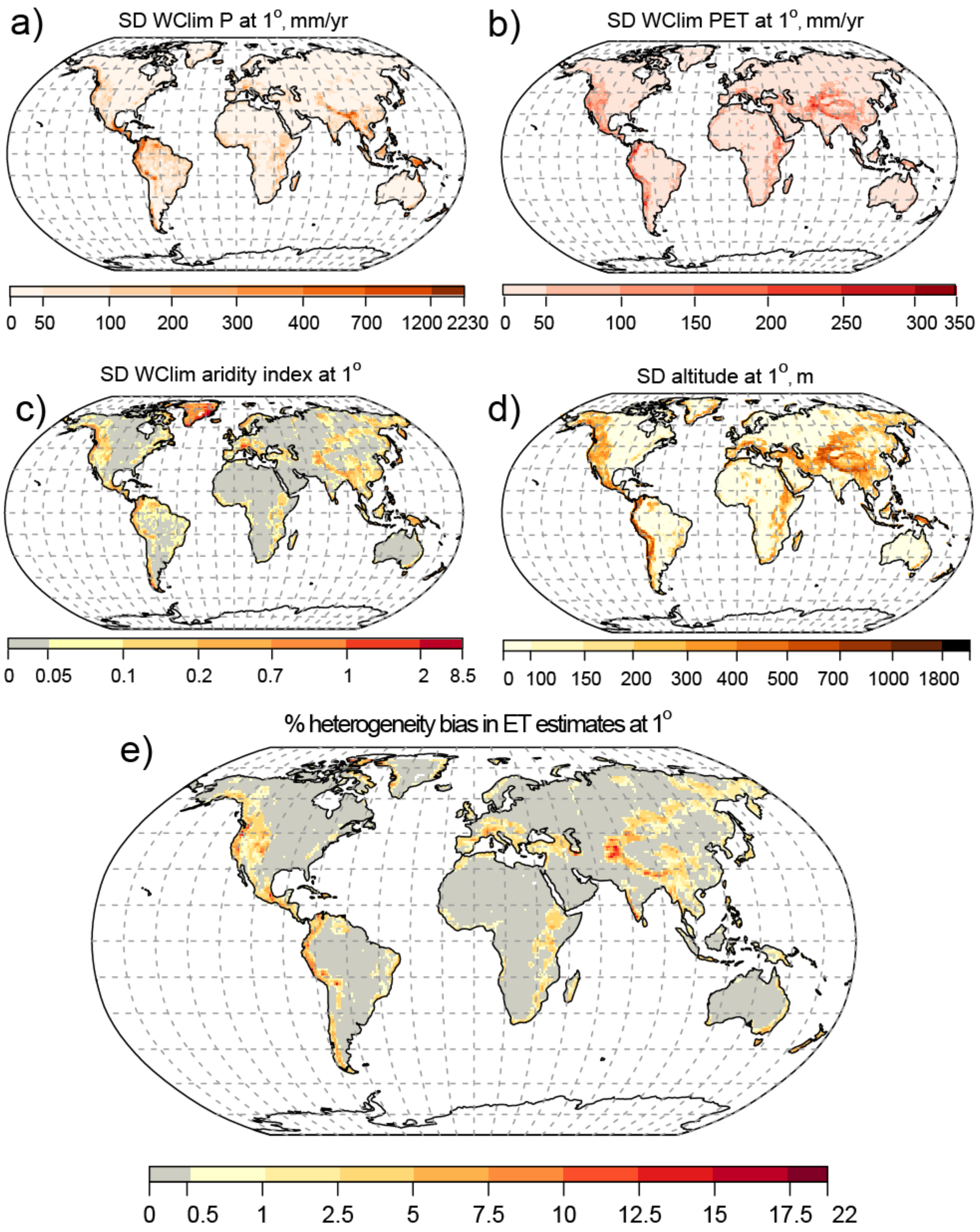


Figure 3. Global spatial distribution of variability (standard deviation) of one-kilometer values of a) precipitation (P), b) potential evapotranspiration (PET), c) aridity index (AI=P/PET), and d) altitude at 1° by 1° grid cell. The ~~approximated~~ ~~averaging~~heterogeneity bias in ET estimates (e) is calculated using Eq. (4~~3~~). Grid cells with larger

standard deviation in altitude and aridity index ~~encounter higher percentage of~~have larger ~~averaging~~ heterogeneity bias.

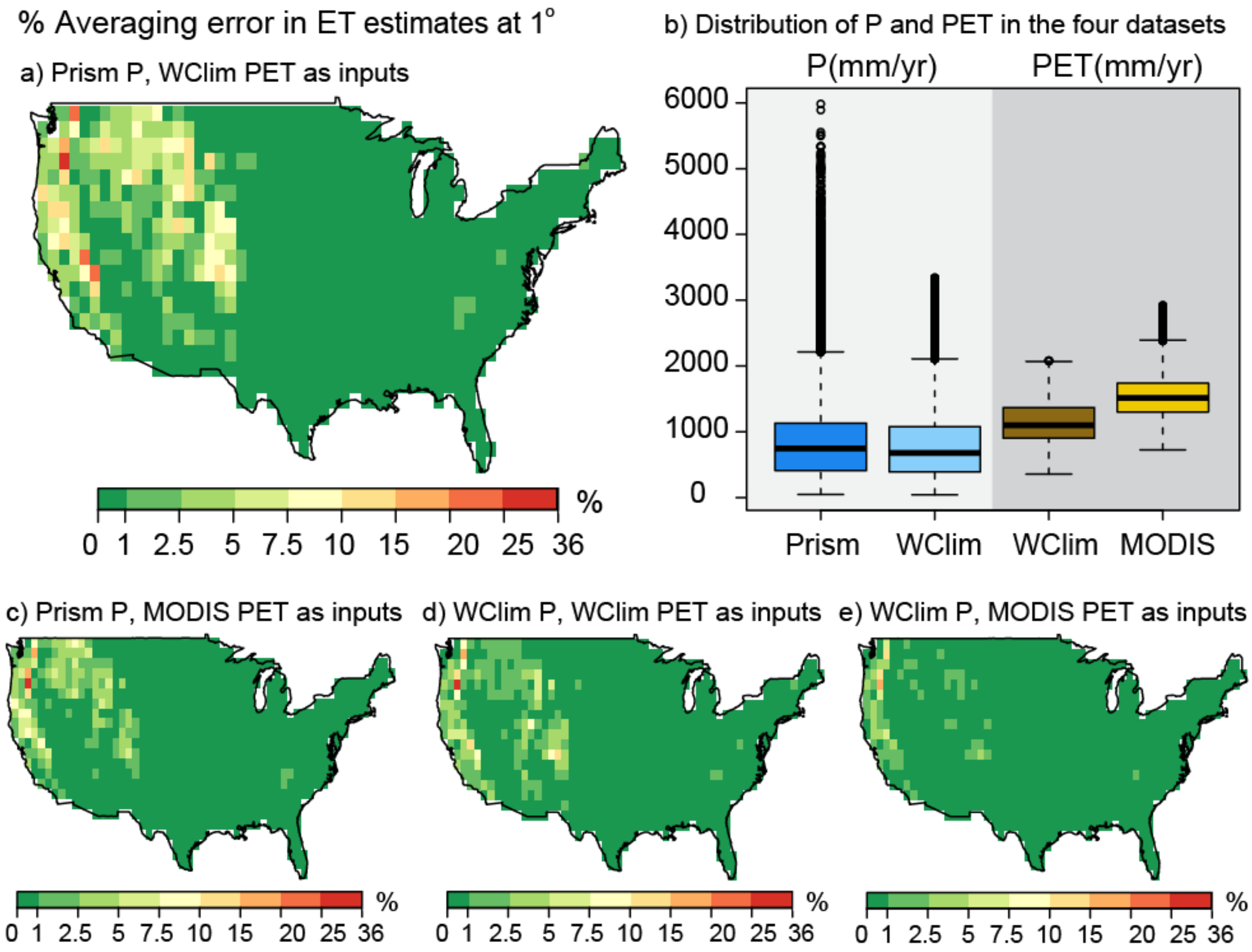
4. Variation in heterogeneity bias across climate zones, data sources, and grid scales

With increased availability of spatial data, it is becoming standard practice to assess input data uncertainties and their propagated impacts on water and energy flux estimates in land surface models. To quantify how choices among alternative input data products could affect the heterogeneity bias in ET estimates, we calculated the heterogeneity bias at 1 ° by 1° grid cell resolution across the contiguous US using four different pairs of P and PET data products. Two precipitation data sets, Prism (http://prism.oregonstate.edu) and WorldClim (Hijmans et al., 2005), along with two PET data sets, MODIS (Mu et al., 2007) and WorldClim (Hijmans et al., 2005), all at 1 km resolution, were combined in all possible pairs. The WorldClim PET dataset (Hijmans et al., 2005) is based on the Hargreaves method (Hargreaves and Samani 1985) while the MODIS PET product (Mu et al, 2007) is based on the Penman–Monteith equation (Monteith, 1965). The heterogeneity bias in ET estimates (Eq. ~~3~~4), as outlined in S~~s~~ect.~~ion~~ 2, was evaluated from 1km values of P, PET, and the estimated average ET using the Budyko relationship (Eq. 1) for each of the four input data pairs. Figure~~.~~ 4a-e compares the spatial distributions of heterogeneity bias across the contiguous US for the four pairs of P and PET data products. The heterogeneity bias in ET estimates reached as high as 36 % in the western US using Prism P and WorldClim PET as input to the ET model (Fig. ~~4a~~4b). A visual comparison of Figs. ~~4a~~4b and Fig. 4~~, c,~~ d ~~, and e~~ shows that the choice of P data source (Prism vs. WorldClim) had a bigger effect on the heterogeneity bias than the choice of PET data source (MODIS vs. WorldClim), meaning that the~~a~~ fractional variability ~~(variability divided by mean)~~ in P is the dominant variable.~~.~~ In all cases, data sources that were more variable in relation to their means (Prism for P and WorldClim for PET; Fig. 4b) led to larger heterogeneity biases, as expected from Eq. (~~3~~4). Thus we infer that we would have obtained larger heterogeneity biases if~~If~~ we had conducted our global analysis (Fig. 3) with Prism P and either WorldClim or MODIS PET~~ we would have obtained larger heterogeneity biases~~, but we cannot show that result explicitly at global scale because Prism P is not freely available globally.

If we ~~divide~~ separate the heterogeneity biases shown in Fig. 4 ~~by~~ according to Köppen-Geiger climate zones (Peel et al., 2007; Fig. 5a), we see that ~~the heterogeneity bias~~they are~~ is~~ distinctly higher in particular climate-terrain combinations. H~~The h~~eterogeneity biases are~~ is~~ higher in regions with temperate climates and dry summers (climate zone Cs) and in regions with cold, dry summers (climate zone Ds), ~~perhaps~~ most likely due to the sharp spatial gradient in their water and energy sources for evapotranspiration (Fig. 5b). These areas typically have high topographic relief, combined with seasonal climate. The heterogeneity effects on ET estimates in these regions are expected to be even ~~higher~~ larger when a mechanistic model of ET is used. We expect that averaging over temporal variations of drivers of ET, especially in places with strong seasonality, could substantially bias the ET estimates, but this cannot ~~but can not~~ be quantified in the Budyko framework due to its underlying steady-state assumptions. Figure 5b also illustrates the relative magnitudes of the heterogeneity biases obtained with the four pairs of P and

PET data sources. The heterogeneity bias is the highest when the Prism P and WorldClim PET datasets are ~~utilized~~used, followed by the combination of Prism P and MODIS PET, ~~that~~which resulted in the second~~-~~-highest heterogeneity bias across different climate zones. Equation~~s 2 and 3~~ 4 shows that ~~averaging biases~~heterogeneity biases in Budyko estimates ~~when Budyko is used as an estimator~~ of ET~~,~~ are equally sensitive to the same percentage variability in P and PET~~ and their means~~. Thus the degree of sensitivity, per se, ~~between~~to P and PET variations ~~, when~~ expressed in percentage terms is the same. Although Figs. 5c and 5d give the visual impression that PET is more variable than P across climate zones and between data sources, Fig. 5e shows that the fractional variability in P is systematically higher than PET, and it also varies more across the climate zones and between the two data sets. ~~, are not different in the Budyko approach. In the Budyko approach, if~~Because P is typically more variable than PET (in percentage terms) across landscapes, ~~then~~ the variability in P will make a larger contribution to the heterogeneity bias (Fig. 5e) in the Budyko approach. Whether this is true for more physically based ET estimates remains to be seen. Analysis of percent variability of P and PET products shows that percent variabilities of precipitation products are in general larger than PET products and hence contribute more to heterogeneity (Fig 5e). While the percent variabilities of the two PET products are in the same range, the percent variability in Prism precipitation is slightly larger than in WorldClim precipitation, in regions with dry summers (Cs and Ds climate zones in Fig. 5a).

~~The heterogeneity bias generally decreases in the order: Prism P-WorldClim PET >> Prism P-MODIS PET >> WorldClim P-WorldClim PET >> WorldClim P-MODIS PET.~~


% Averaging error in ET estimates at 1°
a) Prism P, WClim PET as inputs
0
1
2.5
5
7.5
10
15
20
25
36
%
b) Distribution of P and PET in the four datasets
P(mm/yr)
PET(mm/yr)
6000
5000
4000
3000
2000
1000
0
Prism
WClim
WClim
MODIS
c) Prism P, MODIS PET as inputs
d) WClim P, WClim PET as inputs
e) WClim P, MODIS PET as inputs

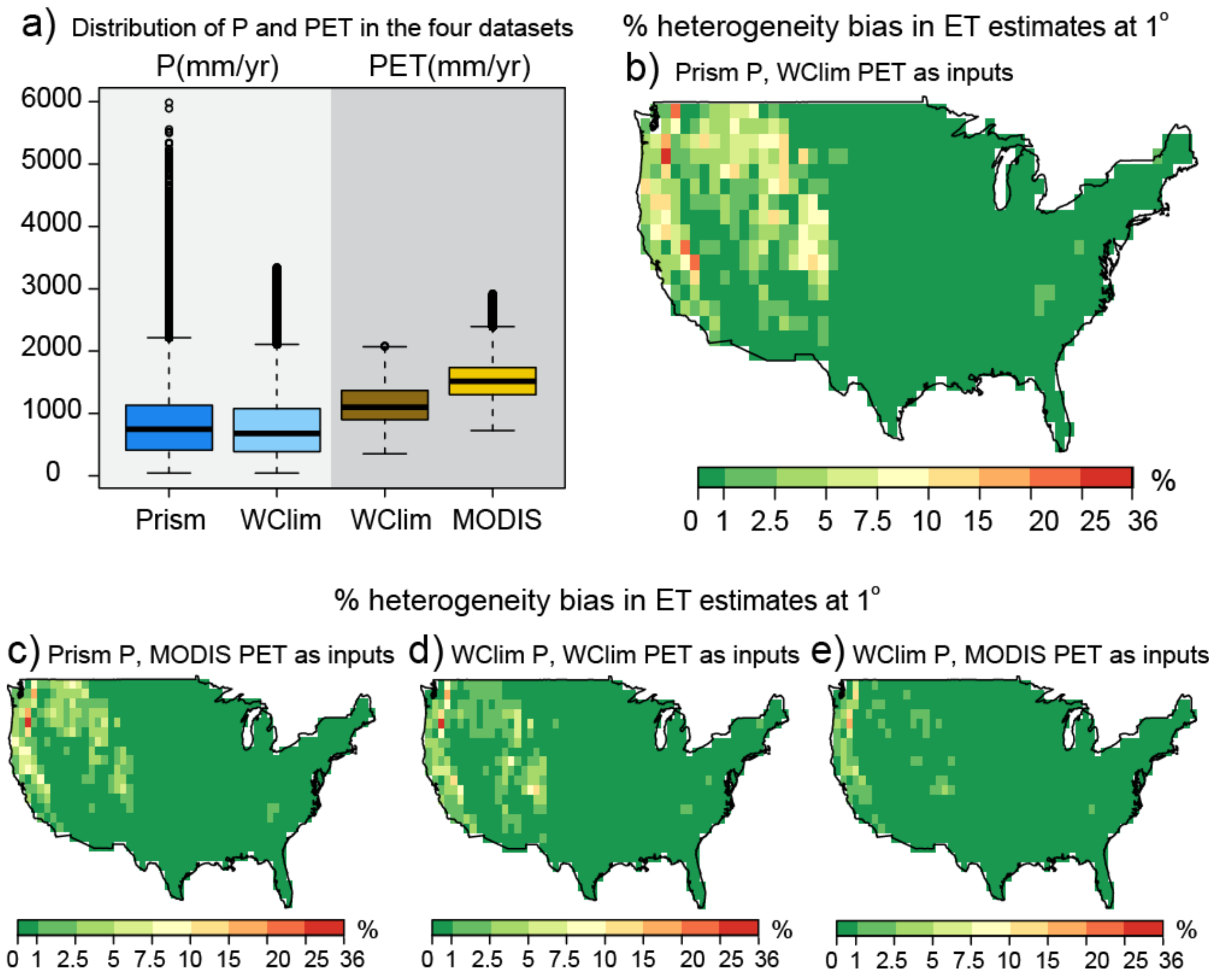
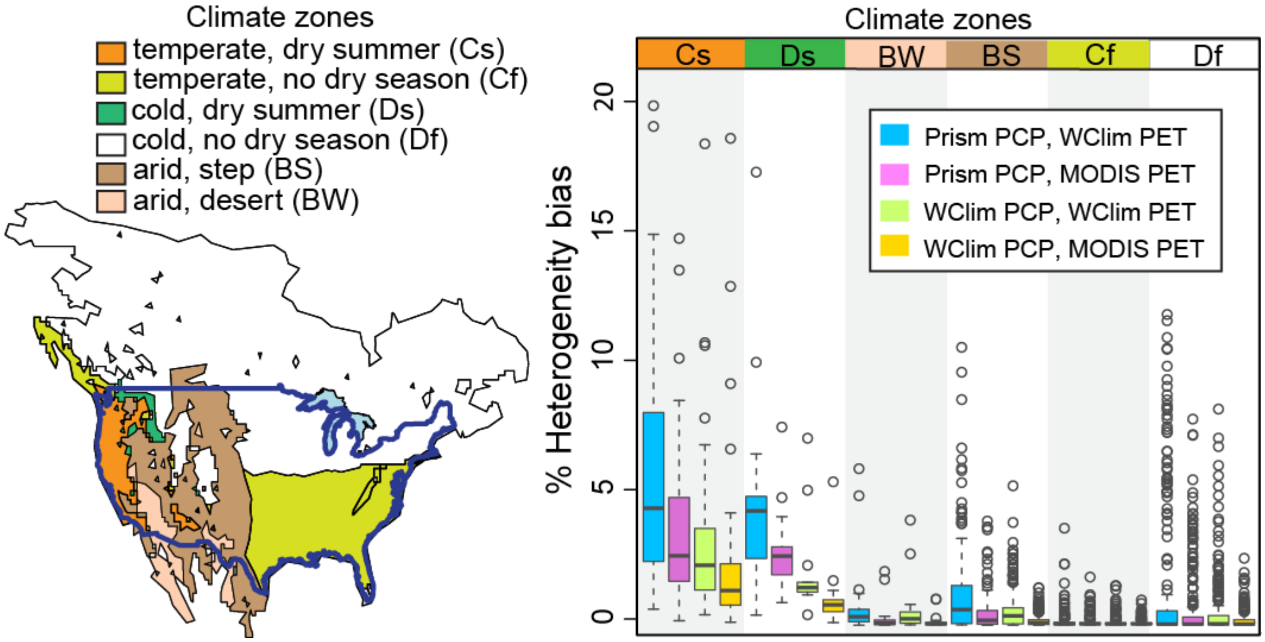


Figure 4. The distribution of P and PET in the four datasets is shown in a). Estimated ~~averaging~~ heterogeneity bias (Eq. 4~~3~~) across the contiguous US using one-kilometer values of ~~a~~b) Prism P and WorldClim PET c) Prism P and MODIS PET d) WorldClim P and WorldClim PET, and e) WorldClim P and MODIS PET as inputs. ~~The distribution of P and PET in the four datasets is shown in b).~~


Climate zones
🟧 temperate, dry summer (Cs)
🟨 temperate, no dry season (Cf)
🟩 cold, dry summer (Ds)
□ cold, no dry season (Df)
🟫 arid, step (BS)
🟫 arid, desert (BW)
Climate zones
Cs
Ds
BW
BS
Cf
Df
% Heterogeneity bias
0
5
10
15
20
Prism PCP, WClim PET
Prism PCP, MODIS PET
WClim PCP, WClim PET
WClim PCP, MODIS PET

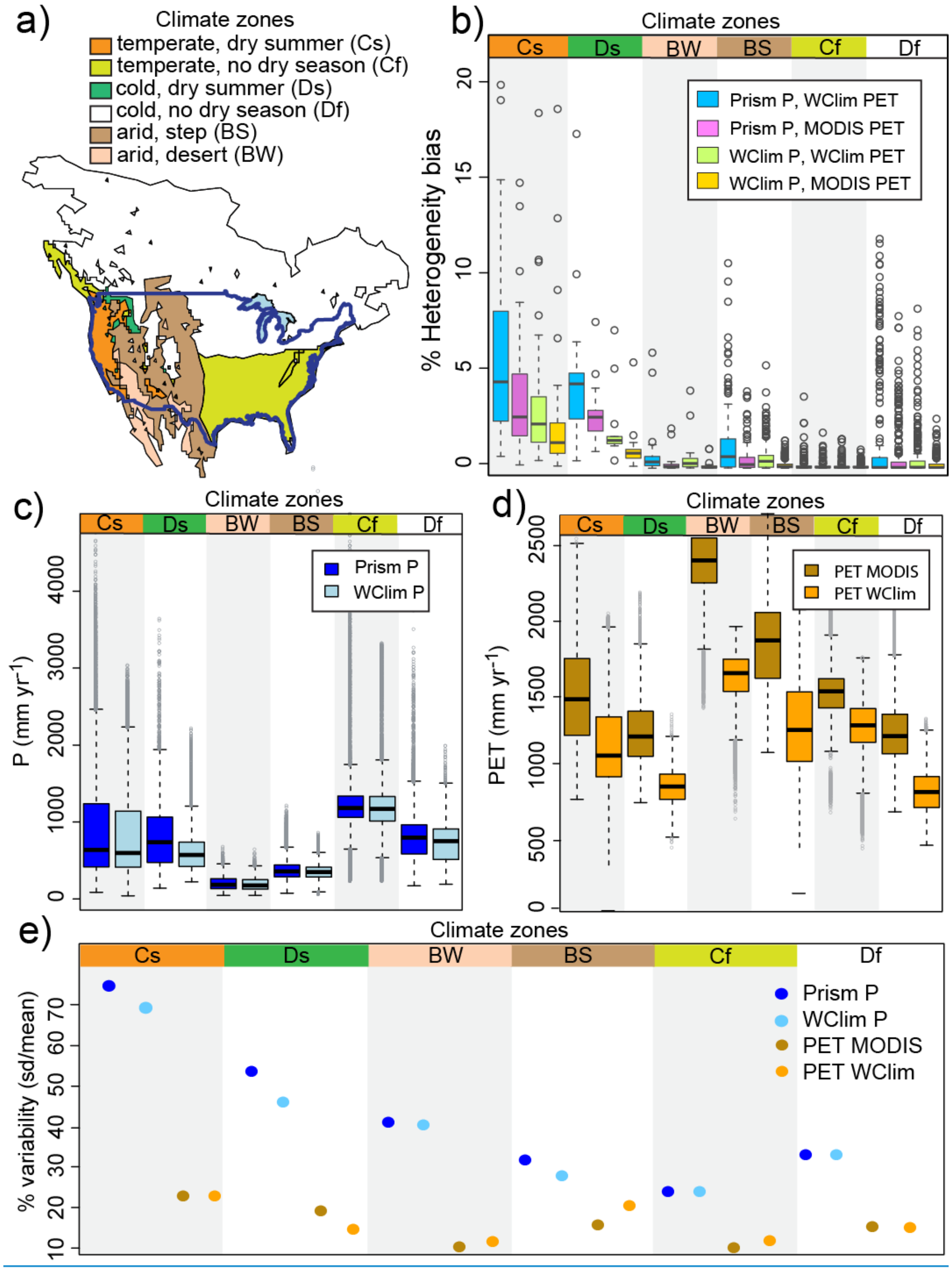
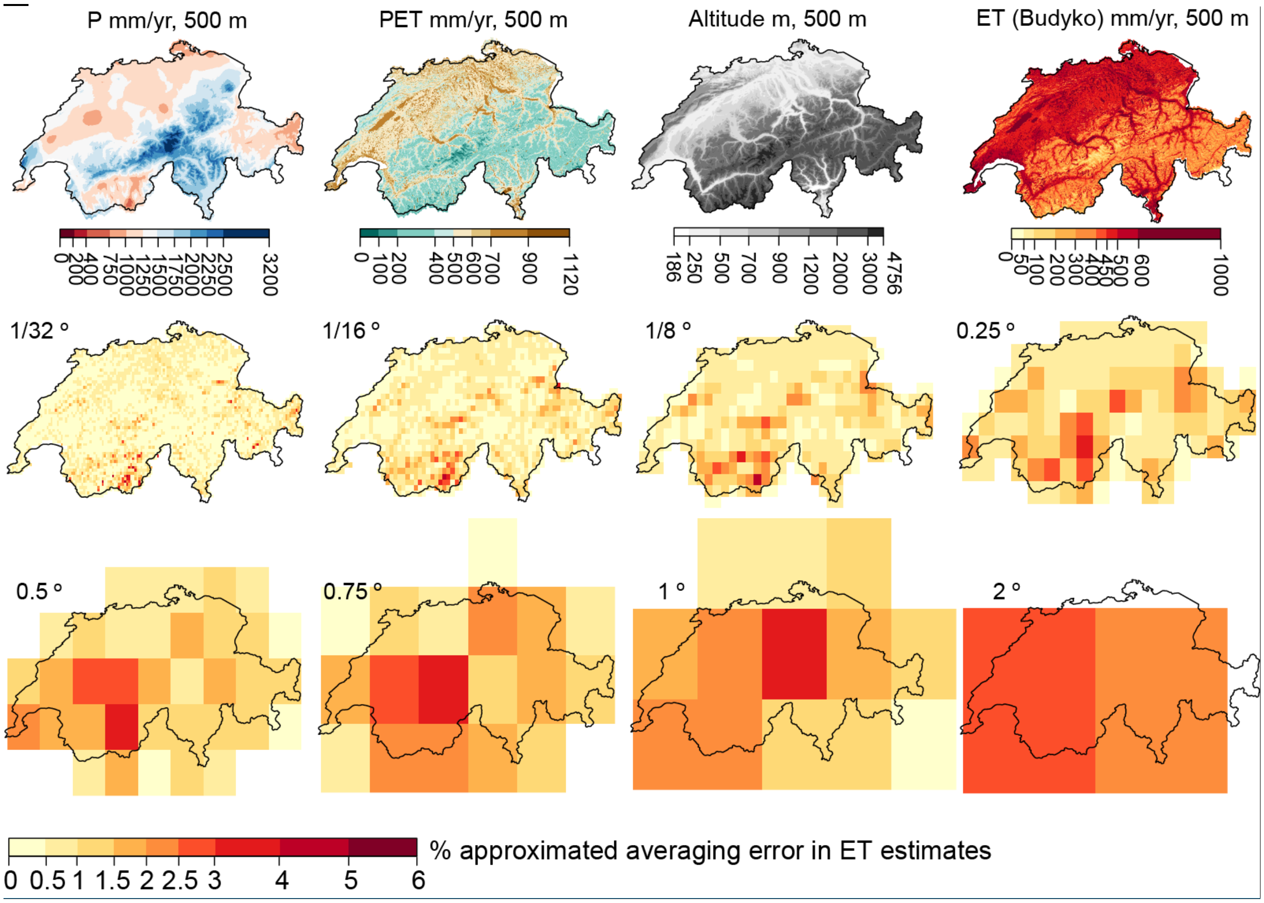


Figure 5. a) Köppen-Geiger climate classification (Peel et al., 2007 in Beck et al. 2013) across the contiguous US, b) ~~and~~ the distribution of ~~corresponding~~ calculated ~~averaging~~ heterogeneity bias in ET estimates (Eq. 4~~3~~) at 1° by 1° grid cell ~~at~~ in individual climate zones, shown by boxplot (three data points with heterogeneity biases of over 20% are off-scale). ~~The background panels top color coded in the box plotb, c, and d corresponds to the climate zones in aon the left. In panel b, Tthree data points with heterogeneity biases of over 20% are off-scale.~~ Pan~~n~~els c and d show the distribution of precipitation products (Prism and WorldClim) and potential evaporation products (MODIS and WorldClim) at individual climate zones, respectively. The color-coded climate zones at the tops of panels b, c, and d correspond to the climate zones mapped in panel a. Panel e compares the percentage variability of the two P and PET data products across climate zones, showing that the percentage variability in P is markedly higher than in

PET, and the percentage variability in Prism P is somewhat higher than in WorldClim P, particularly in climate zones with dry summers.

~~One may expect that~~Because future increases in computing power will lead to ESMs with smaller grid cells, ~~than those in common usage today. It is therefore~~it is useful to ask how changes in ~~ESM~~ grid resolution ~~are likely to~~ affect the heterogeneity biases that we have estimated in this paper. To quantify the heterogeneity bias in ET estimates as a function of grid scale, we repeated our analysis at various grid resolutions using Switzerland as a test case. We started with high-resolution (500m) maps of long-term average annual precipitation and PET across the Swiss landscape (Fig. 6), and then used Eq. 4~~3~~ to estimate the heterogeneity bias at grid scales ranging from 1/32° to 2° (~3 km to ~200 km). As Fig. 6 shows, aggregating P and PET over larger scales leads to larger, and more widespread, overestimates in ET. Conversely, at finer grid resolutions, the average heterogeneity bias is smaller, and the locations with large biases are more localized. On average, the heterogeneity bias across ~~the entire~~ Switzerland as a whole grows exponentially as the inputs are averaged over larger grids (as shown in the lower-right panel in Fig. 6~~, inset~~).



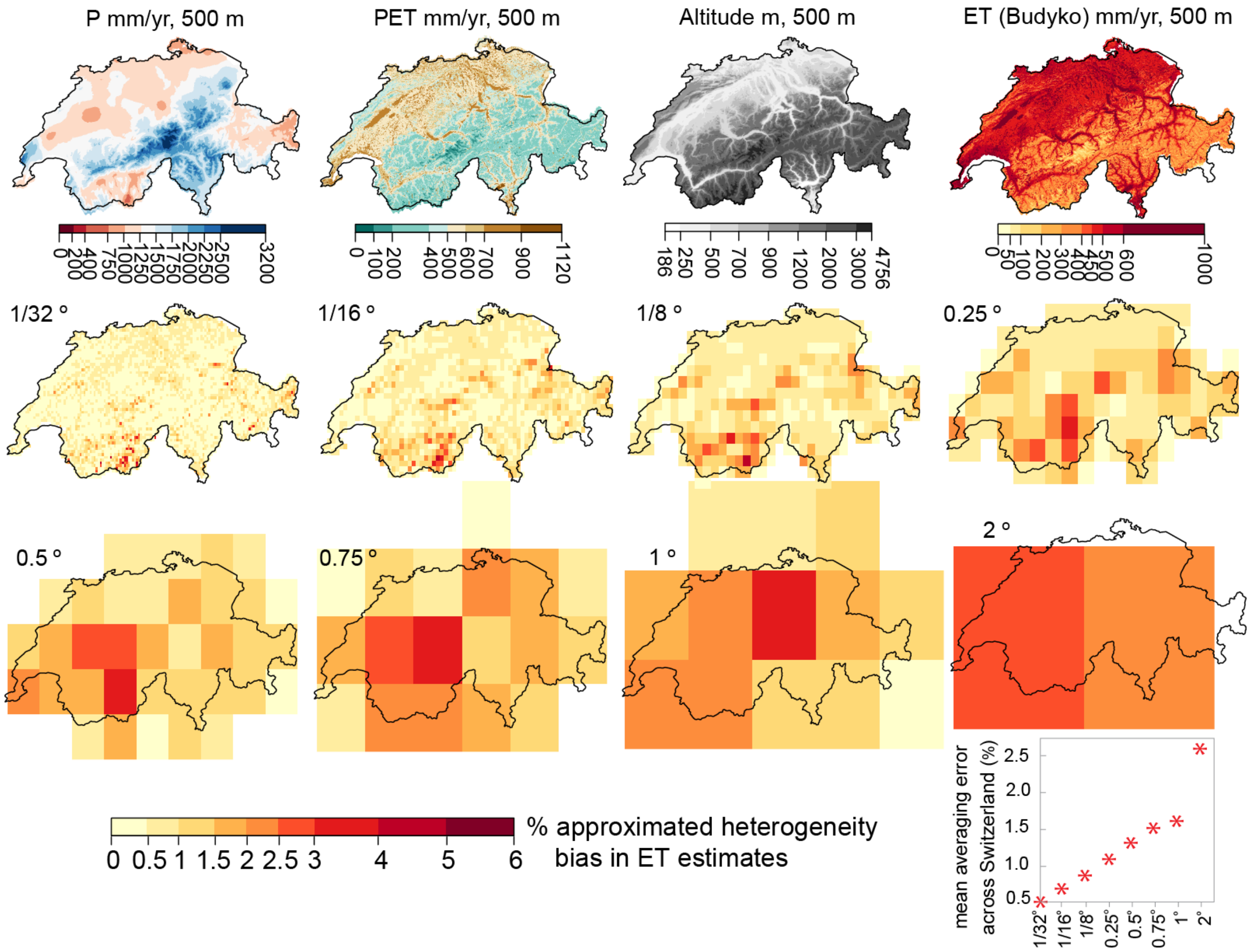


Figure 6. Heterogeneity bias in ET estimates at various scales across Switzerland, estimated from 500m climate data. ET is calculated using the Budyko relationship (Eq. 1). Heterogeneity bias was estimated from 500m precipitation (P) and potential evapotranspiration (PET), and their variances at each grid scale, using Eq. 4~~3~~. At finer grid resolutions, the heterogeneity bias is more localized, and smaller on average.

5. Summary and discussion

Because evapotranspiration (ET) processes are inherently bounded by water and energy constraints, over the long term, ET is always a nonlinear function of available water and PET, whether this function is expressed as a Budyko curve or another ET model. These nonlinearities imply that spatial heterogeneity will not simply average out in predictions of land surface water and energy fluxes in ESMs. Overlooking ~~the~~ sub-grid spatial heterogeneity in ~~large~~ large-scale ESMs could lead to biases in estimated water and energy fluxes (e.g., ET rates). Here we have shown that, across several scales, averaging over spatially heterogeneous land surface properties and processes leads to biases in evapotranspiration estimates. Our analysis does not quantify the heterogeneity biases in ESMs, owing to the many differences between these mechanistic models and the simple empirical Budyko curve. But if the heterogeneity biases in ESMs can be quantified, they~~These biases can be estimated, and these estimates~~ can ~~potentially~~ be used as correction factors to improve ESM estimates ~~calculations~~ of surface-atmosphere water and energy fluxes across landscapes~~ in large scale models~~. ~~We use Budyko framework as a simple "see through" test case for quantifying these biases although Budyko is not actually used in ESM's.~~ Our paper highlights a general methodology that can be used to estimate ~~the systematic bias due to averaging~~heterogeneity biases and to map their spatial patterns, ~~,~~but not to calculate their ~~precise~~absolute magnitudes because those ~~of this bias because the latter~~ will change significantly depending on the ET formulation that is used.

In this study, we used Budyko curves as simple models of ET, in which long-term average ET rates are functionally related to long-term averages of P and PET. We used an approach outlined by Rouholahnejad Freund and Kirchner (2017) to estimate the heterogeneity bias in modeled ET at 1-degree grid scale across the globe (Fig. 3), and also at multiple grid scales across Switzerland (Fig. 6), using finer-resolution P and PET values as drivers of ET. We showed how the heterogeneity effects on ET estimates vary with the nonlinearity in the governing equations and with the variability in land surface properties. Our analysis shows that heterogeneity effects on ET fluxes matter the most in areas with sharp gradients in the aridity index, which are in turn controlled by topographic gradients, and not merely in areas that are either arid or humid (e.g., compare Fig. 3e with Fig. 2c).

According to our analysis, regions within the U.S. that have temperate climates and dry summers exhibit greater heterogeneity bias in ET estimates (Fig. 5). We show that the heterogeneity bias in ET estimates at each grid scale depends on the variance in the drivers of ET at that scale (Fig. 4), and on the choice of data sources used to estimate ET. Heterogeneity bias was significantly larger across the contiguous United States when P and PET data sources with larger variances were used (Fig. 4).

We also explored the magnitude and spatial distribution of heterogeneity bias in ET estimates as a function of the scale at which the climatic drivers of ET are averaged. We found that as heterogeneous climatic variables are aggregated to larger scales, the heterogeneity biases in ET estimates become greater on average, and extend over larger areas (Fig. 6). At smaller grid scales, the heterogeneity bias does not completely disappear, but instead becomes more localized around areas with sharp topographic gradients. Finding an effective scale at which one can average over the heterogeneity of land surface properties and processes has been a longstanding problem in Earth science. Our analysis shows that at smaller resolutions the average heterogeneity bias as seen from the atmosphere becomes smaller, but there is no characteristic scale at which it vanishes entirely (Fig. 6). The magnitude and spatial distribution of this bias depend strongly on the scale of the averaging and degree of the nonlinearity in the underlying processes. The ~~averaging~~ heterogeneity bias concept is general and extendable to any convex or concave function (Rouholahnejad Freund and Kirchner 2017), meaning that in any nonlinear process, averaging over spatial and temporal heterogeneity can potentially lead to bias.

One should keep in mind that the true mechanistic equations that determine point-scale ET as a function of point-scale water availability and PET (if such data were available) may be much more nonlinear than Budyko's empirical curves, because these curves already average over ~~the~~ significant spatial and temporal heterogeneity. ~~spatial heterogeneities across spatial and temporal scales.~~ Thus, we expect that the real-world effects of sub-grid heterogeneity are probably larger than those we have estimated in Sects. 3 and 4 of this study. In addition, the 1km P and PET values that are used in our global analysis might be still too coarse to represent small-scale heterogeneity that is important to evapotranspiration processes.

Budyko curves are empirical relationships that functionally relate evaporation processes to the supply of water and energy under steady-state conditions in closed catchments with no changes in storage. Our analysis likewise assumes no changes in storage, nor any lateral transfer between the model grid cells, although both lateral transfers and changes in storage may be important, both in the real world and in models. Unlike the Budyko framework, ET fluxes in most ESMs are often physically based (not merely functions of P and PET) and are calculated at much smaller time steps (seconds to minutes). These models often represent more processes that are important to evapotranspiration (such as storage variations) and include their dynamics to the extent that is computationally feasible. Because these relationships may be much more nonlinear than Budyko curves, there may also be significant ~~averaging~~ heterogeneity biases when complex physically based models are used to estimate ET from spatially aggregated data. Therefore, we are now working to quantify ~~aggregation~~ heterogeneity bias in ET fluxes using a more mechanistic land surface model.

~~Our results have further implications for representing sub-grid heterogeneity in hydrological parameterizations of large scale ESMs, for example as sets of correction factors. However, the estimated bias shown in this study is for long-term average ET estimates using a conceptual model that uses long-term annual averages and hence can not be directly exploited by ESMs to correct for averaging bias. Average ET could be substantially affected by temporal heterogeneity in water and energy fluxes, particularly in climates with strong seasonally and shifts between water-limited and energy-limited conditions. The temporal variations in the drivers of ET fluxes have not been addressed in the current study but can potentially be a source of bias for ET flux estimates but have not been addressed in the~~

~~current study because Budyko curves cannot be used over individual grid cells in short time steps. Estimating aggregation bias in ET fluxes at time scales that are relevant to ESMs is therefore needed. Once such bias estimations are quantified at daily or sub-daily time scales, they can be used as correction factors to account for the aggregation bias in ET flux estimates.~~

Acknowledgements

E.R.F. acknowledges support from the Swiss National Science Foundation (SNSF) under Grant No. P2EZP2_162279. The authors thank Massimiliano Zappa of the Swiss Federal Research Institute WSL for providing the 500m resolution data that enabled the analysis shown in Fig. 6.

References

Aminzadeh M., and D. Or: The complementary relationship between actual and potential evaporation for spatially heterogeneous surfaces, Water Resour. Res., 53, 580–601, doi:10.1002/2016WR019759, 2017.

Avissar, R., R. A. Pielke: A Parameterization of Heterogeneous Land Surfaces for Atmospheric Numerical Models and Its Impact on Regional Meteorology, Monthly Weather Review, vol. 117, issue 10, p. 2113, doi:10.1175/1520-0493(1989)117<2113:APOHLS>2.0.CO;2, 1989.

Baker I. T. , P. J. Sellers , A. S. Denning, I. Medina , P. Kraus, K. D. Haynes , and S. C. Biraud: Closing the scale gap between land surface parameterizations and GCMs with a new scheme, SiB3-Bins, Journal of Advances in Modeling Earth Systems, J. Adv. Model. Earth Syst., 9, 691–711, doi:10.1002/2016MS000764, 2017.

Bastiaanssen, W. G. M., M. Menenti, R. A. Feddes, and A. A. M. Holtslag: A remote sensing surface energy balance algorithm for land (SEBAL): 1. Formulation, Journal of Hydrology, 212-213, 198–212, 1998.

Beck H. E., A. I. J. M. van Dijk, D. G. Miralles, R. A. M. de Jeu, L. A. Bruijnzeel, T. R. McVicar, and J. Schellekens: Global patterns in base flow index and recession based on streamflow observations from 3394 catchments, Water Resour. Res., 49, 7843–7863, doi:10.1002/2013WR013918, 2013.

Boone, A., and O. J. Wetzel: A simple scheme for modeling sub-grid soil texture variability for use in an atmospheric climate model. Journal of the Meteorological Society of Japan, 77(1), 317−333, 1998.

Budyko, M. l.: Climate and life, Academic, New York, 1974.

Clark, M. P., Y. Fan, D. M. Lawrence, J. C. Adam, D. Bolster, D. J. Gochis, R. P. Hooper, M. Kumar, L. R. Leung, D. S. Mackay, R. M. Maxwell, C. Shen, S. C. Swenson, and X. Zeng: Improving the representation of hydrologic processes in Earth System Models, Water Resour. Res., 51, 5929–5956, doi:10.1002/2015WR017096, 2015.

Ershadi A., M. F. McCabe, J. P. Evans, J. P. Walker: Effects of spatial aggregation on the multi-scale estimation of evapotranspiration, Remote Sensing of Environment 131, 51–62, http://dx.doi.org/10.1016/j.rse.2012.12.007, 2013.

Fan, Y., M. Clark, D. M. Lawrence, S. Swenson, L. E. Band, S. L. Brantley, P. D. Brooks, W. E. Dietrich, A. Flores, G. Grant, J. W. Kirchner, D. S. Mackay, J. J. McDonnell, P. C. D. Milly, P. L. Sullivan, C. Tague, H. Ajami, N. Chaney, A. Hartmann, P. Hazenberg, J. McNamara, J. Pelletier, J. Perket, E. Rouholahnejad-Freund, T. Wagener, X. Zeng, E. Beighley, J. Buzan, M. Huang, B. Livneh, B. P. Mohanty, B. Nijssen, M. Safeeq, C. Shen, W. van Verseveld, J. Volk, D. Yamazaki: Hillslope hydrology in global change research and Earth system modeling, Water Resources Research, 55, doi:10.1029/2018WR023903, 2019.

Giorgi, F., and R. Avissar: Representation of heterogeneity effects in Earth system modeling: Experience from land surface modeling, Rev. Geophys., 35, 413–437, doi:10.1029/97RG01754, 1997.

Hargreaves, G. H., and Z. A. Samani: Reference crop evaporation from temperature, Appl. Eng. Agric., 1(2), 96-99, 1985.

Hijmans, R. J., S. E. Cameron, J. L. Parra, P. G. Jones, and A. Jarvis: Very high resolution interpolated climate surfaces for global land areas, Int. J. Climatol., 25, 1965–1978, doi:10.1002/joc.1276, 2005.

Holland, S., J. L. Heitman, A. Howard, T. J. Sauer, W. Giese, A. Ben-Gal, N. Agam, D. Kool, and J. Havlin: Micro Bowen ratio system for measuring evapotranspiration in a vineyard interrow, Agric. For. Meteorol., 177, 93–100, 2013.

Hong, S. H., J. M. H. Hendrickx, and B. Borchers: Up-scaling of SEBAL derived evapotranspiration maps from Landsat (30 m) to MODIS (250 m) scale, Journal of Hydrology, 370, 122–138, 2009.

Jarvis, A., Reuter, H. I., Nelson, A., and Guevara, E.: Hole-filled SRTM for the globe Version 4, available from the CGIARCSI SRTM 90m Database, http://srtm.csi.cgiar.org (last access: 26 February 2016), 2008.

Kalma, J. D., T. R. McVicar, and M. F. McCabe: Estimating land surface evaporation: A review of methods using remotely sensed surface temperature data, Surv. Geophys., 29, 421–469, doi:10.1007/s10712-008-9037-z, 2008.

Kollet S. J.: Influence of soil heterogeneity on evapotranspiration under shallow water table conditions: transient, stochastic simulations, Environmental Research Letters, 4, 35007, doi:10.1088/1748-9326/4/3/035007, 2009.

Koster R. D. et al.: GLACE: The Global Land– Atmosphere Coupling Experiment. Part I: Overview. J. Hydrometeor., 7, 590–610, 2006.

Koster R. D., and M. Suarez: Modeling the land surface boundary in climate models as a composite of independent vegetation stands, J. Geophysical Research, 97 (D3), 26-97-2715, 1992.

Lu, H., T., Liu, Y. Yang, D. Yao: A hybrid dual-Source model of estimating evapotranspiration over different ecosystems and implications for satellite-based approaches, Remote Sens. 6, 8359–8386, 2014.

Maayar, M. E., J. M. Chen: Spatial scaling of evapotranspiration as affected by heterogeneities in vegetation, topography, and soil texture, Remote Sensing of Environment, 102, 33–51,2006.

Mahrt, L., J. Sun, D. Vickers, J. I. MacPherson, J. R. Perderson, and R. L. Desjardins: Observations of fluxes and inland breezes over a heterogeneous surface, J. Atmos. Sci. 51, 2165e2178, 1992.

McCabe M., and E. Wood: Scale influences on the remote estimation of evapotranspiration using multiple satellite sensors, Remote Sensing of Environment 105 (2006) 271–285, 2006.

Mezentsev, V. S.: More on the calculation of average total evaporation, Meteorol. Gidrol., 5, 24–26, 1955.

Montheith, J. L.: Evaporation and environment, the state of and movement of water in living organisms, Proceeding of Soc. for Exp. Biol., 19, 205-234, doi:10.1002/qj.49710745102, 1965.

Mu, Q., F. A. Heinsch, M. Zhao, and S. W. Running: Development of a global evapotranspiration algorithm based on MODIS and global meteorology data, Remote Sens. Environ., 111, 519–536, doi:10.1016/j.rse.2007.04.015, ~~(~~2007.

Peel, M. C., B. L. Finlayson, and T. A. McMahon: Updated world map of the Köppen-Geiger climate classification, Hydrol. Earth Syst. Sci., 11, 1633-1644, https://doi.org/10.5194/hess-11-1633-2007, 2007.

PRISM Climate Group, Oregon State University, http://prism.oregonstate.edu, created 22 Feb 2017.

Rouholahnejad Freund, E., and J. W. Kirchner: A Budyko framework for estimating how spatial heterogeneity and lateral moisture redistribution affect average evapotranspiration rates as seen from the atmosphere, Hydrology and Earth System Sciences, 21(1), 217-233, 2017.

Santanello J. R., and C. D. Peters-Lidard: Diagnosing the Sensitivity of Local Land–Atmosphere Coupling via the Soil Moisture–Boundary Layer Interaction, J. Hydrometeporology, 12, 766-786, doi: 10.1175/JHM-D-10-05014.1, 2011.

Sato N., P. J. Sellers, D. A. Randall, E. K. Schneider, J. Shukla, J. L. Kinter III, Y. T. Hou, and E. Albertazzi: Effects of Implementing the Simple Biosphere Model in a General Circulation Model, J. Atmospheric Sciences, 46(18), 2757-2782, 1989.

Seneviratne, S. I., T. Corti, E. L. Davin, M. Hirschi, E. B. Jaeger, I. Lehner, B. Orlowsky, and A. J. Teuling: Investigating soil moisture–climate interactions in a changing climate: A review, Earth-Science Reviews, 99(3–4), 125-161, 2010.

Shahraeeni, E., and D. Or: Thermo-evaporative fluxes from heterogeneous porous surfaces resolved by infrared thermography, Water Resour. Res., 46, W09511, doi:10.1029/2009WR008455, 2010.

Su, Z.: The Surface Energy Balance System (SEBS) for estimation of turbulent heat fluxes. Hydrology and Earth System Sciences, 6, 85–100, 2002.

Turc, L.: Le bilan d’eau des sols: relation entre la precipitations, l’evaporation et l’ecoulement, Ann. Agron. A, 5, 491–569, 1954.

Wood, N., and P. J. Mason: The influence of static stability on the effective roughness length for momentum and heat transfer, Quart. J. Roy. Meteor. Soc. 117, 1025e1056, 1991.