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Large-Scale Controls of the Surface Water Balance Over Land: Insights From a Systematic Review and Meta-Analysis

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Key Points:

- Newly assembled global observational data set for partitioning of long-term mean precipitation (P) into evapotranspiration (ET) and runoff
- Reassessment of 26 previously proposed hypotheses on controlling factors of the ratio ET/P in regions with different climates
- Both the long-term mean ratio of potential ET and P, as well as land cover, have a smaller effect on ET/P than commonly hypothesized

Supporting Information:

- Supporting Information S1
- Data Set S1
- Figure S1
- Figure S2
- Figure S3
- Figure S4

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Abstract The long-term surface water balance over land is described by the partitioning of precipitation (P) into runoff and evapotranspiration (ET), and is commonly characterized by the ratio ET/P. The ratio between potential evapotranspiration (PET) and P is explicitly considered to be the primary control of ET/P within the Budyko framework, whereas all other controls are often integrated into a single parameter, ω. Although the joint effect of these additional controlling factors of ET/P can be significant, a detailed understanding of them is yet to be achieved. This study therefore introduces a new global data set for the long-term mean partitioning of P into ET and runoff in 2,733 catchments, which is based on in situ observations and assembled from a systematic examination of peer-reviewed studies. A total of 26 controls of ET/P that are proposed in the literature are assessed using the new data set. Results reveal that: (i) factors controlling ET/P vary between regions with different climate types; (ii) controls other than PET/P explain at least 35% of the ET/P variance in all regions, and up to $\sim$90% in arid climates; (iii) among these, climate factors and catchment slope dominate over other landscape characteristics; and (iv) despite the high attention that vegetation-related indices receive as controls of ET/P, they are found to play a minor and often nonsignificant role. Overall, this study provides a comprehensive picture on factors controlling the partitioning of P, with valuable insights for model development, watershed management, and the assessment of water resources around the globe.

Plain Language Summary Precipitation over long time periods (several years or longer) is partitioned into water leaving a river catchment as runoff, and water that is evaporated or transpired by plants. Different factors have been suggested to directly and indirectly influence how much of the precipitation turns into runoff, and how much is evaporated or transpired. To further assess the relevance of these factors, we gathered observational information about the water balance from numerous previous studies, obtaining a dataset with unprecedented global coverage. Results reveal a similar importance of long-term average evaporative demand (the amount of water that would evaporate under conditions of sufficient water supply) relative to precipitation, and the net effect of all other influencing factors. Among these additional factors we find that the average slope of a catchment and climate-related variables, such as the fraction of precipitation falling as snow and the relative timing of rainfall and evaporative demand during the year, influence the partitioning of precipitation more than other landscape characteristics. Surprisingly, vegetation-related factors are found to play a minor role despite the high attention they have previously received. Overall this study provides valuable insights on processes controlling freshwater resources globally.

1. Introduction

The partitioning of precipitation (P) into evapotranspiration (ET) and runoff (R) characterizes the surface water balance over land on climatological scales (e.g., Budyko, 1956, 1974; Roderick & Farquhar, 2011; Williams et al., 2012; Zhang et al., 2001, 2004), and is commonly represented by the ratio between long-term actual evapotranspiration and precipitation (ET/P). Society, climate, ecology, agriculture, and economy are affected by the partitioning of P as it influences the coupling between the water, energy, and carbon cycles (e.g., Adler et al., 2003; Célleri & Feyen, 2009; Laio et al., 2001; Mooney et al., 2005). More specifically, surface temperature and plant productivity are linked to ET/P (e.g., Ambrose & Sterling, 2014; Baldocchi et al., 2001;

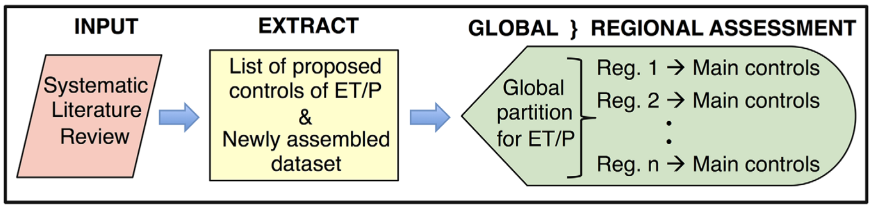

Figure 1. Schematic of the approach employed to advance our understanding of factors controlling the surface water balance (ET/P) over land.

Beer et al., 2010; Seneviratne et al., 2010). Thus, understanding the controls of the partitioning is an important aspect of Earth system sciences. For example, it is relevant for climate and land surface modeling (e.g., Arora, 2002; Kumar et al., 2016; Sun et al., 2013), as well as for water resources planning and adaptation (e.g., Destouni et al., 2013; Gao et al., 2016; Hamel & Guswa, 2015; Jaramillo & Destouni, 2014).

The ratio between measures of long-term potential evapotranspiration (PET) and precipitation, denoted as $\phi = \text{PET/P}$ and often referred to as the "aridity index," is well established as a factor controlling the partitioning of P (e.g., Budyko, 1974; Milly, 1994; Zhang et al., 2004). In addition to ϕ, several global studies have suggested that factors such as climate type, land cover, and human water management can influence both the spatial and temporal variability of ET/P (Jaramillo & Destouni, 2014, 2015; Li et al., 2013; Sterling et al., 2013; Williams et al., 2012; Xu et al., 2013). Furthermore, numerous regional studies have also examined these and other possible controls of ET/P, including, e.g., topography, soil, and precipitation characteristics (e.g., Berghuijs et al., 2014; Brown et al., 2015; Dean et al., 2016; Donohue et al., 2012; Shao et al., 2012; van der Velde et al., 2013; Yang et al., 2007; Yokoo et al., 2008; Yuan et al., 2010; Zhang et al., 2004). However, the combined evidence on the effects of factors other than ϕ is inconclusive, in most cases regionally constrained, and sometimes apparently contradictory. Consequently, our understanding of the most relevant controls of the long-term surface water balance around the world remains unclear.

Our goal in this study is to deepen our observations-based knowledge on the controls of long-term mean ET/P around the world. To achieve this, we review readily available literature to extract relevant observational data, which are further used to test several hypotheses on factors controlling ET/P (Figure 1). More specifically we obtain: (i) a comprehensive list of previously proposed controls of the partitioning (section 2), and (ii) a newly assembled data set by merging published values of long-term mean hydrometeorological variables through a systematic review of the literature (sections 3 and 4). Subsequently, we partition the world into regions with possibly different controls and distributions of ET/P. For each of these regions, we then quantify the relative contributions of ϕ and other controls for explaining the variance in ET/P. Finally, we test the significance of each of the previously proposed factors controlling ET/P by region through a correlation analysis.

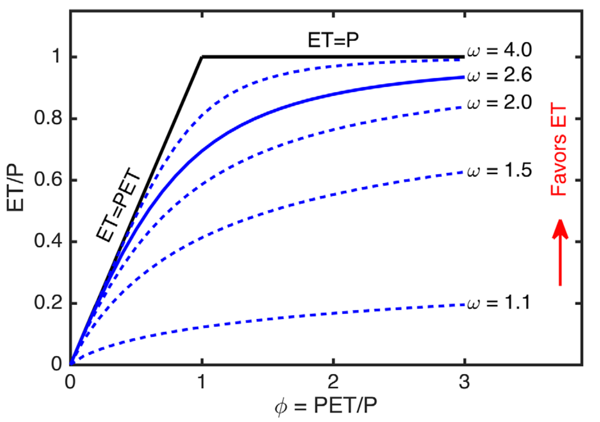

Figure 2. The original Budyko curve representing ET/P as a function of $\phi = \text{PET/P}$ (continuous line). Solutions to Fu's equation for different values of ω are shown as dashed lines. Note that higher values of ω result in higher ET/P, and thus favor ET over R.

2. Previously Proposed Controls of the Long-Term Mean Surface Water Balance

The Budyko framework is a widely used approach for studying the partitioning of long-term mean precipitation into evapotranspiration and runoff (e.g., Berghuijs et al., 2014; Budyko, 1974; Gentine et al., 2012; Greve et al., 2014; Gudmundsson et al., 2016, 2017; Jiang et al., 2015; Li et al., 2013; Shao et al., 2012; Xu et al., 2013; Yokoo et al., 2008; Zhang et al., 2001). The framework describes ET/P primarily as a function of $\phi = \text{PET/P}$ under the assumption that long-term mean changes in terrestrial water storage are negligible (Figure 2). Thus, this relation is constrained by the physical limits of atmospheric water supply (i.e., ET cannot be larger than P), and water demand (i.e., ET cannot be larger than PET). Originally, Budyko (1956, 1974) proposed that, on climatological time scales, ET is predominantly determined by P and net radiation. The net radiation water flux equivalent (i.e., Rn/λ, where λ is the latent heat of vaporization) is a well-defined absolute physical limit to ET; however, for consistency with many previous studies we instead use PET, which attempts to also account for factors such as relative humidity or the buildup of atmospheric turbulence, to represent the atmospheric water demand (e.g., Li et al., 2013; Milly, 1994; Potter et al., 2005; Xu et al., 2013; Zhang et al., 2004).

Already Budyko (1974) recognized that there is variability around his original deterministic curve. Consequently, several empirical and theoretical extensions of the Budyko framework have been developed to account for this by introducing one or more additional parameters (e.g., Choudhury, 1999; Fu, 1981; Gerrits et al., 2009; Greve et al., 2015, 2016; Milly & Dunne, 2002; Porporato et al., 2004; Wang & Tang, 2014; Yang

Table 1
Previously Proposed Climate Controls of ET/P

Subcategory	Acronym	Effect	Description
Climate Type	KG	0	*Koeppen-Geiger Class*. Corresponds to a categorical classification of climate (Kottek et al., 2006). Williams et al. (2012) found a significant relation between KG and ω.
Precipitation	MAP	0	*Mean Annual Precipitation*. Tested as a control of ω for the Weihe River basin in China (Jiang et al., 2015). No relation was found.
	ASD	−	*Average Storm Depth*. Computed as the mean precipitation depth from rainy days. Milly (1994) and Zhang et al. (2004) suggested ASD to be a significant control of ω. For Australian data, Donohue et al. (2012) and Shao et al. (2012) found that an increase in ASD favored runoff (lower ET/P).
	SAR	+, 0, −	*Storm Arrival Rate*. Calculated as the average number of rainy days in a year. Milly (1994) and Zhang et al. (2004) proposed SAR as a significant control, but its individual effect on ω was not explicitly discussed. The INVEST model (Hamel & Guswa, 2015; Redhead et al., 2016; Sharp et al., 2015), as well as Donohue et al. (2012), suggest that higher values of SAR lead to higher ω and hence favor ET. On the other hand, opposite results have been found in ephemeral catchments in Australia (Dean et al., 2016).
Snow and Temperature	MAT	+	*Mean Annual Temperature*. Jiang et al. (2015) found a positive relation between MAT and ω for the Weihe River in China.
	FSNOW	−, 0	*Fraction of Precipitation Falling as Snow*. Computed as the annual mean of the ratio between the amount of P that falls in months with average surface air temperature $\leq 2\,^{\circ}$C, and total annual P. Berghuijs et al. (2014) proposed this index, and showed for catchments in the USA that more snow favors runoff over ET. Previously, Williams et al. (2012) concluded from their data that there was no evidence of larger fractions of frozen P favoring R. Milly (1994) had suggested that the snow fraction of precipitation should not have a major influence in annual ET/P, but it could favor R.
Seasonality	Seas P, Seas SAR, & Seas PET	0	*Relative Amplitude of the Seasonal Cycle of P, SAR, and PET*. Computed as the multiyear average of: the seasonal cycle amplitude (monthly max-monthly min) divided by the annual mean. The model of Milly (1994) used these indices to represent the runoff caused by differing seasonality of P and PET, and by the interaction of storminess and seasonality. Potter et al. (2005) also used Seas P and Seas PET, but rather as an initial step to distinguish between catchments with wet winter and wet summer regimes.
P–PET accumulation	PS P&PET	−, +	*Phase Shift of the Seasonal Cycles of P and PET*. Computed as the negative Pearson correlation coefficient between the monthly climatology of P and PET (Beck et al., 2015; Petersen et al., 2012). A value of 1 (correlation = −1) implies that higher P is present when PET is lower, leading to accumulation. On the other hand, a value of −1 (correlation = 1) indicates that the shape of the seasonal cycles is identical and that they are in phase, i.e., higher values of P always cooccur with higher values of PET. Yokoo et al. (2008) and Shao et al. (2012) used the number of months between peak P and peak PET to represent the phase shift in their seasonal cycles, finding a general tendency for a stronger phase shift favoring R over ET. However, for catchments in Australia with summer-dominant rainfall regimes—i.e., no phase shift—R is also favored over ET (Potter et al., 2005).
	MAMS	−	*Maximum Accumulation Monthly Surplus*. Defined as the maximum accumulation from consecutive months with a positive value for the difference between the climatology of P and PET. Williams et al. (2012) found a weak negative relation between MAMS and ω, i.e., higher MAMS favors R. In a similar manner, Hickel and Zhang (2006) used P–PET for a storage recharge period in their model for mean annual water balance.
	SSI	−	*Seasonal Surplus Index*. Defined as the difference between MAMS and the long-term annual mean hydrological surplus (annual P–annual PET). Williams et al. (2012) found that higher values of SSI favored R over ET, especially for Mediterranean climate types.
	SM	0	*Soil Moisture*. Computed as the weighted average of the four layers (total depth = 2.68 m) defined in the ERA-Interim-Land data (Balsamo et al., 2015). In a theoretical assessment Porporato et al. (2004) discussed the effect of soil moisture on the terrestrial water balance. Carmona et al. (2016) found no significant influence of the climatological mean water table depth on ET/P.

Note. The reported effect is positive (+) if an increase of the index led to an increase in ω and ET/P, and negative (−) if it led to a decrease. A value of 0 indicates that no effect was found or that the direction of the effect was not reported et al., 2008; Zhang et al., 2001, 2004). In this study, we focus on the analytical solution to the framework from Fu (1981), which was introduced to the international literature by Zhang et al. (2004), and is derived by combining dimensional analysis and mathematical reasoning:

$$\frac{ET}{P} = 1+\phi-(1+\phi^{\omega})^{\frac{1}{\omega}} \tag{1}$$

In this equation, ω is a free parameter that integrates the net effect of all controls other than ϕ, on the partitioning of P into ET and runoff. When comparing catchments with equal ϕ, those with a higher value of ω have higher ET/P—i.e., they favor ET over R (Figure 2). Note that the sensitivity of a relative change in ET/P to ω is maximum for values of $\phi = 1$, and decreases toward extreme conditions—i.e., very low or high ϕ (see Zhang et al., 2004). Additionally, Gudmundsson et al. (2016, 2017) showed that a small change in ω has likely a larger effect on ET/P than an equal relative change in ϕ for transitional and arid climate regions.

In addition to Fu's widely used solution (e.g., Greve et al., 2014, 2015; Gudmundsson et al., 2016, 2017; Li et al., 2013; Shao et al., 2012; Xu et al., 2013; Zhang et al., 2004), Choudhury (1999) introduced another popular one-parameter (n) formulation of the Budyko framework. Nonetheless, Yang et al. (2008) showed that both formulations are approximately equivalent with $\omega = n + 0.72$.

Several other indices, in addition to ϕ, have been suggested to represent physical controls of long-term mean ET/P. In general, they attempt to represent direct and indirect constraints on water supply, demand, and storage (Milly, 1994), and can be categorized into indices representing additional climate factors and indices representing landscape characteristics. Whereas climate controls attempt to summarize relevant climate conditions not captured by ϕ, landscape controls summarize on-the-ground conditions such as topography or land cover. Tables 1 (climate controls) and 2 (landscape controls) show a comprehensive overview of previously suggested indices, including their definition, relevant references, as well as their reported effect on ET/P after accounting for ϕ. Within Fu's solution to the Budyko framework the effect of an index on ET/P, after accounting for ϕ, is mediated through ω: an increase in ω leads to an increase in ET/P by favoring ET over runoff (Figure 2).

3. Data Compilation and Processing

3.1. Collecting Observational Evidence of the Surface Water Balance Through a Systematic Literature Review

Observational evidence is required to test the plausibility of previously proposed factors controlling ET/P. Although there is currently a lack of readily available global data that would be suitable for such an analysis, systematic literature reviews have proven to be a valuable option to overcome this issue in similar cases. In the words of Webb et al. (2013), "systematic reviews explicitly treat the literature as data and conduct analyses to test hypotheses." Prespecified search and eligibility criteria aim at guaranteeing reproducibility of the research and at minimizing literature search bias (CEE, 2013). This type of approach has been used in medical sciences for more than two decades (Higgins & Green, 2011), and has been adapted in recent years to other fields of study, such as environmental science and management (CEE, 2013). Therefore, a systematic review is deemed appropriate to address open questions about factors controlling the partitioning of precipitation into ET and runoff. Below we summarize how we assemble a new hydrometeorological data set focused on Fu's ω parameter (equation (1)), following the guidelines from CEE (2013).

3.1.1. Search Criteria

Zhang et al. (2004) brought Fu's solution of the Budyko framework (Fu, 1981) (originally published in Chinese) to the attention of the worldwide scientific community. We therefore screened all articles that cite the work of Zhang et al. (2004) and are included in the core collection of the Web of Science search engine (http://apps.webofknowledge.com). The final search was performed in November 2016. It resulted in a total of 170 studies, with Redhead et al. (2016) being the most recent one to that date. Numerous publications that focused on alternative formulations for ET/P, instead of Fu's solution, were also among the resulting list of reviewed studies. This is an argument in favor of the comprehensiveness of the performed literature search.

3.1.2. Study Inclusion Criteria

Any study that explicitly provides at least values of mean annual precipitation, ET or runoff, and PET for individual catchments is included in a first stage. This is the information required to determine a value of ω for

Table 2
Previously Proposed Landscape Controls of ET/P

Subcategory	Acronym	Effect	Description
Vegetation	NDVI	+, −	*Normalized Difference Vegetation Index (NDVI)*. A remote-sensing index that provides indirect information on vegetation coverage. Higher values of long-term average NDVI imply higher vegetation coverage. In some cases a positive linear relation between NDVI and the ω parameter has been found (Li et al., 2013; Xu et al., 2013), whereas contradicting results have also been obtained by other studies (e.g., Teuling et al., 2010; Williams et al., 2012). Moreover, Yang et al. (2009) found that vegetation favored R for one group of catchments, whereas it favored ET for a second group located in a different climatic zone in China. Donohue et al. (2010) found a positive relation between ω and vegetation for Australian catchments, and that its magnitude increases with decreasing spatial scales. Carmona et al. (2016) also found a positive effect of increasing NDVI on ET/P through the parameters of their power law equation.
	Tree Cov	+, −	*Tree Coverage*. A positive relation between forested area and the ω parameter has been found (Zhang et al., 2001, 2004; Zhou et al., 2015). Williams et al. (2012) found that grasslands have higher ET/P than forests. Oudin et al. (2008) found a small but significant effect of land cover on the partitioning; however, forests were the least informative land cover type.
	Grass Cov	+, −	*Grassland Coverage*. Studies have not analyzed its direct relation with ω. Zhang et al. (2004) and Williams et al. (2012) compared the effect of forests versus grasslands on ET/P obtaining contradicting results. The conversion of forests and wetlands to grasslands has been suggested to decrease ET in a modeling study (Sterling et al., 2013).
	PESWC	+	*Plant Extractable Soil Water Capacity*. Mainly related to rooting depth and soil porosity. It has been considered to have a positive relation with ω and ET/P (e.g., Zhang et al., 2001, 2004; Yang et al., 2007; Donohue et al., 2012).
Soil	PSWST	0	*Potential Storage of Water Derived from Soil Texture*. Williams et al. (2012) suggested that soil characteristics could be a relevant control, however they did not test this due to lack of data. Others have also suggested the relevance of soil characteristics (e.g., Donohue et al., 2012; Porporato et al., 2004; Potter et al., 2005; Yang et al., 2007; Yokoo et al., 2008).
Topography	SLOPE	−	*Average Slope*. The value is measured in degrees from 0° (flat) to 90° (vertical). Similar indices, like relief ratio have also been used (Shao et al., 2012; Zhang et al., 2004). Catchments with steeper slopes have been shown to favor R over ET (Xu et al., 2013; Yang et al., 2007; Zhou et al., 2015).
	CTI	+	*Compound Topographic Index*. CTI is a function of the upstream drainage area and the slope. Higher values of CTI represent more water accumulation in the soil, and are thus proposed to favor ET over R (Xu et al., 2013).
	SIZE	+, 0	*Catchment Size*. A positive correlation with ω has been found, indicating that ET is favored in larger catchments (Xu et al., 2013; Zhou et al., 2015). On the other hand, no influence of catchment area was found in a multiple regression model for ω with data from large basins only (Xu et al., 2013). Choudhury (1999) suggested that size could affect ω through the spatial variability of factors controlling ET/P.
	ASPECT	0	*Average Aspect*. This index represents the direction of the slope. The angle is measured clockwise from 0° (north) to 360°. For the analysis we compute it as the cosine of the direction angle in the northern hemisphere, whereas for the southern hemisphere the sign is changed—south facing slopes in the North have the same sign as north facing slopes in the South. Xu et al. (2013) found no significant relation between ASPECT and ω.
Human	Urban Cov	−	*Urban Land Coverage*. A positive coefficient of determination ($R^2 = 0.39$) was found between the percentage of urban land and the change in mean annual runoff not attributable to a change in ϕ for catchments in the contiguous United States (Wang & Hejazi, 2011). This suggests a negative relation of urban land coverage with ω and ET/P.
	Pop Dens	0, −	*Population Density*. It has been proposed as a proxy for human influence in a catchment, especially in terms of land use and land cover. Jiang et al. (2015) tested as a predictor of ω for a catchment in China, but no significant effect was identified. On the other hand, the results of Wang and Hejazi (2011) suggest a negative relation of population density with ω and ET/P.
	Dam Cap	+	*Dam Capacity*. The total reservoir capacity of dams relative to the catchment area is an index to estimate flow regulation. It has been found that higher regulation increases ET/P in the USA (Wang & Hejazi, 2011), Sweden (Destouni et al., 2013), the Balkans (Levi et al., 2015), and at the global scale (Jaramillo & Destouni, 2015). Note that all of these studies analyzed temporal changes in long-term ET/P, as opposed to spatial variability.
	Irrg Crop, Irrg Cap	+	*Irrigated Cropland Coverage (Irrg Crop) and Area Equipped for Irrigation (Irrg Cap)*. Studies in the USA (Wang & Hejazi, 2011), China (Jiang et al., 2015), and at the global scale (Jaramillo & Destouni, 2015) have found that an increase in irrigation between two multiyear time periods led to higher values of ω and ET/P. In another study in China, Han et al. (2011) extended Budyko's framework by adding an irrigation term to the water balance. A negative relation between nonirrigated cropland and ET has been suggested (Schilling et al, 2008; Sterling et al., 2013), although the opposite was found by another study in Sweden (Destouni et al., 2013).

Note. The reported effect is positive (+) if an increase of the index led to an increase in ω and ET/P, and negative (−) if it led to a decrease. A value of 0 indicates that no effect was found or that the direction of the effect was not reported.

each catchment by numerically solving equation (1). If the required information is shown in graphs/plots, and not as numeric values, the studies are disregarded. If a data set is cited within one of the studies, only one additional search is done to access it. In no case, an author is contacted to request data. As a result, five large data sets are included (Andréassian et al., 2016; Cheng et al., 2011; Peel et al., 2010; Schaake et al., 2006; Zhou et al., 2015).

3.1.3. Possible Reasons for Inconsistencies When Replicating the Review

Some studies identify periods with major changes of landscape characteristics or climate, and thus provide more than one value for the required long-term mean annual data. Our approach is to only include the values of the most recent period. Nonetheless, this issue is relevant for less than 5% of all included catchments. Duplicated catchment information from the various sources could be an issue; however, this was simply addressed in our case by checking catchment name and size for duplicates. We do not consider nested catchments as duplicated information.

3.1.4. Study Quality Assessment

In all studies ground-based measurements are used, and in a few cases they are complemented with remote-sensing data and other products. Long-term ET is computed as the difference between long-term precipitation and runoff for the vast majority of catchments (i.e., $ET = P - R$). We omit all catchment data that does not fulfill the physical constraints of $ET \leq P$ and $ET \leq PET$ required within the Budyko framework.

A wide range of interpolation methods for estimating areal P and PET are used in the different studies. Likewise, the methods used for estimating PET also vary across studies. We are aware that the different methodologies will likely affect any analysis of the data. Nonetheless, no data are excluded because of this.

3.1.5. Data Extraction Strategy

Numerical values from the selected studies are transcribed (copied/pasted) to fill in the corresponding fields of the newly assembled data set. The original reference is also stored in the data set. Additional relevant information, especially geolocation (latitude and longitude), and catchment size are also extracted into the newly assembled data set. If geolocation data are only provided as a map, a visual approximation is done to obtain first order estimates for latitude and longitude. In some cases, the coordinate information corresponds to the catchment outlet, whereas in others to the center of the area, and in many cases it is unclear.

3.1.6. Data Synthesis and Presentation

The full data set is made available in the supporting information. An overview of the data, focused on the ω parameter, is presented in section 4.

3.2. Gridded Data for Deriving Indices of Proposed Controls of ET/P

To analyze the controls of the partitioning of precipitation different than ϕ, additional climatic data and landscape characteristics are required. Table 3 lists the considered gridded data sets that were used for computing the indices described in Tables 1 and 2. In all cases, the considered data are regridded to a regular latitude-longitude grid with a 1° resolution. This resolution is a compromise that relates to both the original resolution of many of the considered gridded data sets and the area of most considered catchments. Furthermore, considering a coarser resolution would imply a higher heterogeneity in the conditions within the grid cell, making it more difficult to disentangle the effect of local factors on ET/P. Note that values for MAP and SIZE are from the newly assembled data set, and not from any gridded product.

3.3. Combining Catchment-Scale Observations With Gridded Data

The values of ω from our newly assembled data set need to be linked to the indices characterizing additional controls of ET/P (Tables 1 and 2). This is not straightforward since values for the indices are available on a 1° grid, whereas data related to ω represent catchment-scale information. Unfortunately, the low precision of the geolocation information (section 3.1.5) prevents us from a reliable delineation of catchment boundaries. In addition, many of the considered catchments are smaller than the resolution of the data sets used to compute the indices. In a first step, we therefore assign each catchment to its corresponding grid cell using the latitude/longitude information from the assembled data set. When there is only one assigned catchment in any given grid cell ($\sim$40% of the cases), the value of ω is assumed to represent the entire grid cell. For cases with multiple catchments assigned to a grid cell, ω is recomputed with equation (1) from the weighted average of P, PET, and ET. The employed weights are proportional to catchment size. Grid cell estimates of MAP and SIZE are obtained with the same averaging procedure to be consistent with all other indices in the analysis.

A mismatch between the areas represented by ω (catchments) and the controls (1° grid cells) will likely affect the accuracy of the results. This is especially relevant for cases where the catchment size is much

Table 3
Gridded Data for Computing Indices of Proposed Climate (Top) and Landscape (Bottom) Controls of ET/P

Variable	Proposed Control	Time Period	Data Set	Reference
Climate Controls				
Koeppen-Geiger Climate Type	KG	1951–2000	Koeppen-Geiger Classification	Kottek et al. (2006)
Monthly P, PET, and Temperature	Seas P, Seas PET, PS P&PET, MAMS, SSI, MAT, FSNOW	1966–2015	CRU TS v. 4.00	Harris et al. (2014)
Daily Precipitation	ASD, SAR, Seas SAR	1979–2015	CPC-Global-rt	Chen et al. (2008)
Soil Moisture	SM	1979–2010	ERA-Interim/Land	Balsamo et al. (2015)
Landscape Controls				
Monthly NDVI	NDVI	1981–2006	GIMMS	Tucker et al. (2005)
Land Cover	Tree Cov, Grass Cov, Urban Cov, Irrg Cov	1998–2012	ESA-CCI-LC v.1.6.1	[a]
Plant Extractable Soil Water Capacity	PESWC	1996	Global Distribution of PESWC	Dunne and Willmott (2000)
Potential Storage of Water Derived From Soil Texture	PSWST	1950–1996	Global Soil Texture and Water-Holding Capacities	Webb et al. (2000)
Slope, Elevation, CTI, and Aspect	SLOPE, CTI, ASPECT	Time-invariant	HYDRO1k	Verdin (2011)
Population Density	Pop Dens	2000	GPW	CIESIN (2005)
Dam Capacity	Dam Cap	Until 2011	GRanD	Lehner et al. (2011)
Area equipped for irrigation	Irrg Cap	1970–2005	Hid-v1	Siebert et al. (2015)

[a]Project URL: www.esa-landcover-cci.org.

larger or much smaller than the grid cell area. Therefore, following previous studies (Beck et al., 2016; Gudmundsson & Seneviratne, 2016), we omit data from all catchments with size greater than 12,000 km^2 ($\sim$area of a 1° grid cell) or less than 12 km^2 ($\sim$0.1% of area of a 1° grid cell) from the analysis. Despite this, there can be remaining cases where catchment location is near the edge of its corresponding grid cell, whereas most of the catchment area is in a neighboring grid cell.

Table 4
Peer-Reviewed Studies That Contributed to our Newly Assembled Data Set

Reference	Number of catchments	Geolocation	Reference	Number of catchments	Geolocation
Wang and Zhou (2016)	6	Map	Zhan et al. (2012)	1	Explicit: outlet
Wang et al. (2016)	30	Explicit: outlet	Renner et al. (2012)	3	Basin name: not usable
Gao et al. (2016)	15	Map	Zhang et al. (2011)	8	Map
Alemayehu et al. (2016)	1	Map	Rao et al. (2011)	2	Map
Du et al. (2016)	2	Map	Yang and Liu (2011)	1	Map
Zhang et al. (2015a)	1	Explicit	Roderick and Farquhar (2011)	1	Basin name: not usable
Liu and Liang (2015)	1	Map	Kumar and Merwade (2011)	1	Map: not usable
Zhang et al. (2015b)	17	Explicit: latitude	Tekleab et al. (2011)	20	Map
Adamovic et al. (2015)	3	Map	Zhang et al. (2010)	24	Explicit
Hamel and Guswa (2015)	10	Map	Liu and Yang (2010)	4	Map
Cong et al. (2015)	5	Map	Wang et al. (2009)	34	Map
Zhao et al. (2014)	12	Map	Tilahun and Merkel (2009)	1	Explicit: range
Tekleab et al. (2014)	1	Map	Shao et al. (2012)	3	Catchment name: not usable
Xiong et al. (2014)	40	Map	Elshamy et al. (2009)	1	Explicit: range
Smettem and Callow (2014)	11	Map	Ma et al. (2008)	12	Explicit: range. Map
Wang et al. (2014)	1	Explicit: centroid	Batelaan and De Smedt (2007)	3	Map
Zhao et al. (2013)	2	Map	Yang et al. (2007)	108	Map
Pan et al. (2013)	1	Map	Schaake et al. (2006) (MOPEX)	423	Explicit
Li et al. (2013)	26	Map: not usable	Peel et al. (2010)	699	Explicit
Chen et al. (2013)	1	Explicit: range	Andréassian et al. (2016)	402	Explicit: outlet
Zhan et al. (2013)	1	Explicit	Cheng et al. (2011)	501	Map: not usable
Donohue et al. (2012)	1	Map	Zhou et al. (2015)	291	Catchment name: not usable
Peña-Arancibia et al. (2012)	2	Map			

Note. The column Geolocation indicates how each reference provides this information about the catchments (explicit: 14, estimated from map: 24, not usable in our study: 7).

4. A Newly Assembled Data Set for Analyzing the Controls of the Long-Term Mean Surface Water Balance

The newly assembled data set comprises information from 45 peer-reviewed studies (Table 4), resulting in data for 2,733 catchments (Figure 3). However, around one-third of these studies did not explicitly report the geographical location of the catchments, and had to be omitted from the analysis. Only two references (Peel et al., 2010; Schaake et al., 2006) provided more than half of the data with geolocation.

The assembled data set has a relatively good global coverage (Figure 4), with clusters of information in Europe (28.5% of the number of catchments with geolocation), USA (28.1%), China (13.6%), and Australia (8.5%). The final data used for the analysis includes 1,604 catchments with information on geographical location that are assigned to 786 1° grid cells in accordance with section 3.3—very small or large catchments, representing 16% of those with geolocation, are omitted from the analysis. The selected subset of catchments is explicitly indicated in the data set provided in the supporting information.

Additional information that is available for each catchment includes the time period covered by the data and the method used for estimating PET. The median timespan is 33 years, whereas the minimum is 5 years and the maximum 95 years for the subset of catchments used in the analysis. We recall that for the vast majority of catchments ET is estimated as the difference between P and R, although changes in water storage may not be negligible especially for short time periods. This situation can cause shifts in the Budyko relationships (Condon & Maxwell, 2017) and may hence be a confounding factor of our investigation. However, an exploratory analysis showed no obvious relation between the values of ω and the number of years of data used for computing long-term mean annual values of PET/P and ET/P (supporting information Figure S1). Furthermore, 82.6% of the catchments used in the analysis have a data timespan of at least 15 years and observations ending in 1980 or later, leading to a relatively good temporal overlap with most of the of the data used to compute indices on proposed controls of ET/P. Only approximately 7% of the catchments covered a period prior to 1970. A total of eight different methods for estimating PET were used in the studies that contributed to the data set.

5. Statistical Methods for Analyzing Controls of the Long-Term Mean Surface Water Balance

5.1. Identifying a Global Criterion to Analyze Controls of ET/P by Region

Climate type is a practical criterion to divide the world into regions with possibly different dominant factors controlling ET/P. Climatic conditions represented by geolocation, or directly by the Koeppen-Geiger climate type classification (Kottek et al., 2006) (Figure 5a) have been found to significantly influence ET/P (Williams et al., 2012; Xu et al., 2013). To confirm these previous results, we evaluate the hypothesis that ET/P varies with climate type using a Kruskal-Wallis test (Hollander et al., 2014). More formally, we test against the null hypothesis that the ET/P-data for each climate type come from the same distribution. In addition, we repeat the test with ω instead of ET/P to check if climate type adds information to ϕ for explaining the observed variability of ET/P.

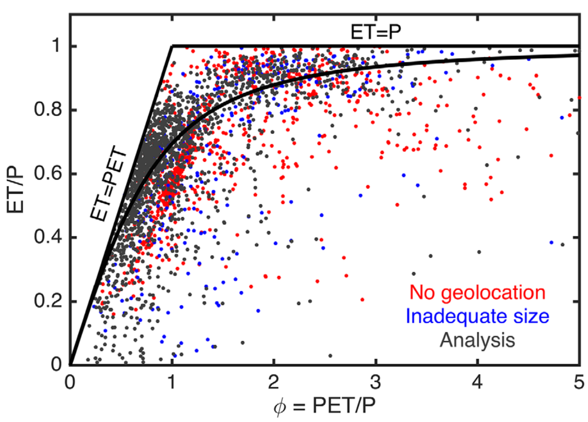

Figure 3. Variability of the catchment data (points) around the original Budyko curve (continuous line). Red points correspond to the data without geolocation information, blue points to those excluded from the analysis due to catchment size <12 km^2 or $>12{,}000$ km^2, and gray points to all catchments used in the analysis. The data set includes 36 additional points with values of $\phi > 5$ that are not shown.

5.2. Quantifying the Relative Importance of ϕ and Other Controls of ET/P by Region

Our objective is to assess within each (climate) region how important ϕ and other factors (represented by ω) are for explaining the partitioning of precipitation. To achieve this goal, we base our approach on the method described in Murray and Conner (2009), and use squared semipartial correlations to estimate the variance of ET/P that is exclusively explained by ϕ (equation (2)) and exclusively by ω (equation (3)).

$$E_\phi = \rho^2_{ET/P(\phi,\omega)} = \left[\rho_{ET/P,\phi} - \left(\rho_{ET/P,\omega}\right)\left(\rho_{\phi,\omega}\right)\right]^2 \Big/ \left(1-\rho^2_{\phi,\omega}\right) \tag{2}$$

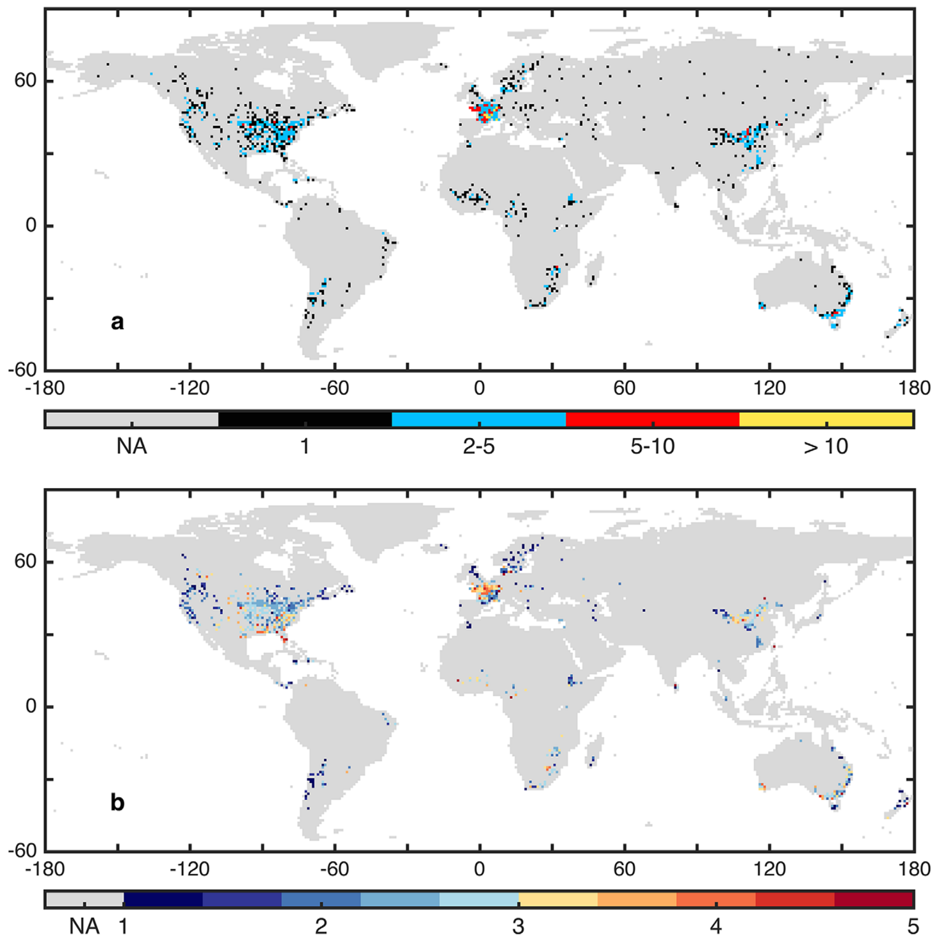

Figure 4. (a) Location of the catchments from the newly assembled data set. The color code indicates the number of catchments within each 1° grid cell. (b) Map of average ω values within each 1° grid cell used in the analysis.

$$E_\omega=\rho^2_{ET/P(\omega,\phi)}=\left[\rho_{ET/P,\omega}-\left(\rho_{ET/P,\phi}\right)\left(\rho_{\phi,\omega}\right)\right]^2\Big/\left(1-\rho^2_{\phi,\omega}\right) \tag{3}$$

Here $\rho_{X,Y}$ represents Spearman's nonparametric correlation between variables X and Y, whereas the semi-partial Spearman's correlation, $\rho_{X(Y,Z)}$, represents the correlation between X and Y after the influence of variable Z is removed from Y, but not from X. We use Spearman's correlation since the effects of ϕ and ω on ET/P are monotonic, but not linear within Budyko's framework. Consequently, the explained variance corresponds to that of the ranks of ET/P (Field et al., 2012).

The variance of ET/P that is redundantly explained by both ϕ and ω is given by

$$Rd=\rho^2_{ET/P,\phi}-\rho^2_{ET/P(\phi,\omega)}=\rho^2_{ET/P,\omega}-\rho^2_{ET/P(\omega,\phi)} \tag{4}$$

Distributing Rd to either ϕ or ω is not straightforward and beyond the scope of our study, nonetheless their explained variance (EV) ranges between E and $E+Rd$. Here we calculate the relative importance (RI) by normalizing the explained variance (EV) as follows:

$$RI_\phi=EV_\phi/\left(E_\phi+E_\omega+Rd\right) \tag{5}$$

$$RI_\omega=EV_\omega/\left(E_\phi+E_\omega+Rd\right) \tag{6}$$

The lower limit of RI corresponds to the exclusively explained variance ($EV=E$), whereas the upper limit to the sum of exclusive and redundantly explained variance ($EV=E+Rd$).

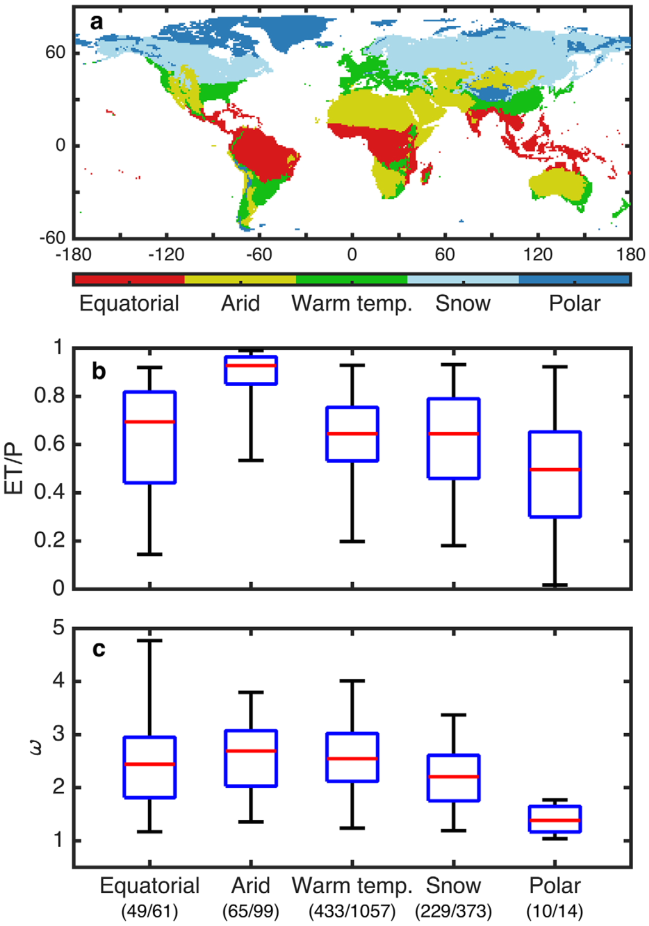

Figure 5. (a) Map of the 5 main Koeppen-Geiger climate types. Distribution of ET/P (b) and ω (c) for each climate type based on grid-cell data. The red line indicates the median, box edges the 25th and 75th percentiles, and whiskers the 5th and 95th percentiles. Data available as number of 1° grid cells/catchments is indicated below each climate type label.

5.3. Assessing the Significance of Proposed Controls of ET/P by Region

After quantifying the relative importance of ω for explaining ET/P, we determine which of the previously proposed controlling factors from Tables 1 and 2 are significantly related to this parameter. Since relations between ω and the indices characterizing the controls may be nonlinear, we use Spearman's rank correlation. However, by doing this we still assume that the relation between any given control and ω must be monotonic. To account for spatial correlation within our data, we test the significance of a proposed control through its partial Spearman correlation with ω, while accounting for latitude, longitude, and elevation as confounding factors (Xu et al., 2013).

A partial correlation describes the relationship between variables X and Y, after removing their relationship with Z (Field et al., 2012). First, the estimates $\hat{X}$ and $\hat{Y}$ are obtained, respectively, from the linear regression of X and Y with Z. Then the residuals are calculated as $X_{res}=X-\hat{X}$ and $Y_{res}=Y-\hat{Y}$. Finally the partial correlation corresponds to the Pearson correlation between X_{res} and Y_{res}. For the partial Spearman correlation, the regression is computed on the ranks instead of the actual values (Conover, 1999). The hypothesis test is analogous to that of the full correlation, but for a t-distribution with $n-2-k$ degrees of freedom; where k is the number of confounding variables + 1 (corresponding to the intercept of the regression). In our case, a multiple linear regression is necessary to compute the residuals because we have three confounding factors.

The large number of hypothesis tests ($N=$ number of proposed controls times number of climate types) increases the probability of false discoveries in the employed statistical testing procedure. We therefore follow the recommendation of Wilks (2016), and compute adjusted p-values using the Benjamini and Hochberg (1995) method. This method sorts all p-values in ascending order, i.e., $p_{(1)} \leq p_{(2)} \leq \cdots \leq p_{(N)}$, and then computes the adjusted p-value as:

$$p_{adj(i)}=p_{(i)} * \left(\frac{N}{i}\right) \tag{7}$$

A control is declared to be significant if the adjusted p-value of the correlation is equal or less than 0.01. For significant controls, the magnitude of its partial correlation with ω is an indication of its importance. However, we have to be aware of probable interactions between the suggested controls (Zhang et al., 2004), and coevolution of factors such as vegetation, climate, soil, and topography (Gentine et al., 2012; Troch et al., 2013, 2015; Yang et al., 2007). Therefore, we also compute the Spearman correlation matrix of the controls to support the discussion about relevant controls of ET/P encompassed in ω.

6. Results: Dominant Controls of the Long-Term Mean Surface Water Balance Around the World

6.1. Climate Type as a Global Criterion to Analyze Controls of ET/P by Region

The Kruskal-Wallis test confirmed that climate type has a significant influence on both ET/P and ω ($p<0.001$ in both cases), indicating a different distribution for at least one climate type (Figure 5). In general, ω is larger in Arid regions contributing to a higher value of ET/P (ET is favored over R), whereas the opposite occurs in regions with Snow or Polar climate types. Note that data availability is much larger for Warm temperate and Snow regions. The Polar climate type is omitted from all further analyses, as there is information for only 10 grid cells in the newly assembled collection. Nonetheless, the Kruskal-Wallis test still

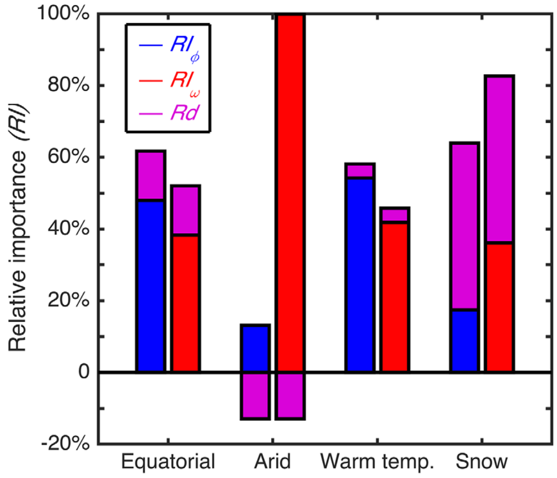

Figure 6. Relative importance of ϕ (RI_{ϕ}) and other controls (RI_{ω}) for ET/P. The lower limit of *RI* is related to the variance exclusively explained by the respective factors (*E*), whereas the upper limit corresponds to the sum of exclusive and redundantly explained variance (*E*+*Rd*). The opposite applies to Arid climates because ϕ and ω are negatively correlated. See section 5.2 for details.

confirms the significant influence of climate type even when omitting the Polar climate regions from the analysis for both ET/P and ω.

6.2. Relative Importance of ϕ and Other Controls of ET/P by Climate Type

Results from the semipartial correlation analysis help to disentangle the relative contributions of ϕ and other factors (ω) for explaining the partitioning of P into ET and R (Figure 6 and supporting information Table S1). The relative importance (*RI*) of ω is almost as high as that of ϕ in Equatorial and Warm temperate regions. In Snow regions, the net effect of controls contributing to ω appears to be more important than ϕ, although 44.3% of ET/P variance is redundantly explained by ϕ and ω. This redundancy suggests that ϕ may implicitly represent some additional process(es) controlling ET/P. Lastly, we show that controls different than ϕ are dominating the partitioning in Arid regions. On a side note for this climate type, we find that ET is largely driven by precipitation $\left(\rho^2_{ET,P}=0.83\right)$, which is consistent with the findings of Berghuijs et al. (2017).

These observational-based findings agree well with the analytical results from Gudmundsson et al. (2016, 2017). When $\phi > 2$, which generally corresponds to Arid regions, they show that changes in ω have a larger impact on ET/P than equal relative changes in ϕ. Whereas, for cases when $\phi \approx 1$ they conclude that changes in ET/P are equally likely dominated by changes in ϕ and ω. This case corresponds to the Equatorial, Warm temperate, and Snow regions, for all of which approximately 85% of the ϕ-data ranges between 0 and 2.

6.3. Assessment of Previously Proposed Controls of ET/P by Climate Type

Partial correlations between ω and indices previously proposed to represent controls of the partitioning of P into ET and R are shown in Figure 7. Interestingly, we find that for all regions, except those with Snow climate type, most of the previously proposed factors are not significantly correlated with ω. In the following, we present a detailed discussion of the results, which distinguishes between indices of climate and landscape controls, and also between the subcategories introduced in Tables 1 and 2. Cross correlations between these indices are presented in Figure 8 and taken into account for the discussion.

6.3.1. Climate Controls

Snow and Temperature. The correlation between the fraction of precipitation falling as snow (FSNOW) and ω in regions with Snow climate type, is the strongest of any climate control in any region. The negative correlation between FSNOW and ω indicates that runoff is favored in catchments with a larger snow fraction of precipitation. It has been suggested that this occurs due to the rapid melting of snow, at a time of the year when PET is low and the soil is saturated (Williams et al., 2012), however many other factors may also play a role (Berghuijs et al., 2014). We also find a significant effect of FSNOW in Equatorial regions. However this could be misleading, since the fraction of annual precipitation falling as snow, is less than 1% in all corresponding grid cells. The significance of mean annual temperature (MAT) is subject to its relation with FSNOW in regions with Snow climate. Nonetheless, MAT is also found as a significant control of ET/P in Warm temperate regions.

P–PET Accumulation. The phase shift between precipitation and potential evapotranspiration (PS P&PET) significantly favors lower ET/P in all regions, except for Equatorial climate type. This is likely related to runoff generated by excess water supply (P) when the atmospheric water demand is low (PET). PS P&PET has a high correlation with FSNOW, and thus may not add much additional information in regions with Snow climate. The maximum accumulation monthly surplus (MAMS) complements PS P&PET by including the magnitude of the difference between P and PET. The seasonal surplus index (SSI) is only significant in Snow climates, and its effect is likely confounded by other accumulation indices and FSNOW with which it correlates. Annual average soil moisture (SM) does not show a significant correlation with ω in any region.

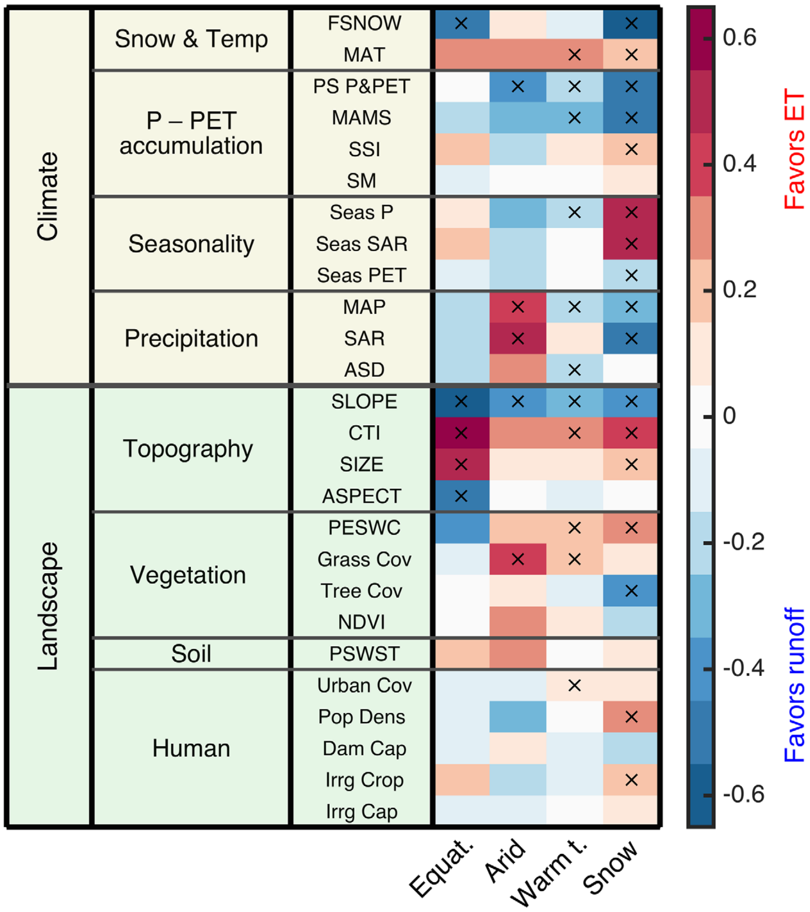

Figure 7. Partial Spearman correlations between ω and previously proposed controls of ET/P for each climate type. Marked boxes denote significant correlations at the 99% confidence level. For an increase in the control index, positive values (red) indicate that ET is favored over runoff, whereas for negative correlations runoff is favored over ET.

Seasonality. Indices that capture the seasonal cycle of relevant atmospheric drivers are mainly found to be significant at higher latitudes, which is likely related to the clearer contrast between seasons, namely summer and winter. In Snow regions, all indices show a similar level of correlation with ω and are cross correlated. Moreover, seasonality indices are strongly related to FSNOW and PS P&PET, and therefore likely represent similar processes. In Warm temperate regions, a higher concentration of precipitation in a shorter period of time (i.e., high Seas P) favors runoff over ET, likely due to saturation of the soil.

Precipitation. Mean annual precipitation (MAP) is most relevant in Arid climates, where higher values lead to higher ω and thus favor higher ET/P. In Snow and Warm temperate regions, MAP is found to be significant, although it is also correlated with MAMS. The storm arrival rate (SAR) is a highly significant control of ET/P in Arid regions—a higher frequency of wet days likely facilitates water consumption by the strong evaporative demand. For Snow regions SAR has significant negative correlation with ω, which may be linked to its strong correlation with FSNOW and PS P&PET. Higher average storm depth (ASD) favors runoff in Warm temperate regions, indicating a significant effect of high precipitation events on the long-term partition of P. This may be related to runoff produced by soil saturation or insufficient infiltration capacity during days with high precipitation depths.

6.3.2. Landscape Controls

Topography. Average grid-cell slope (SLOPE) has among all landscape controls the highest correlation with ω, and it is significant across all climate types. The negative correlations suggest that catchments with steeper slopes favor runoff, i.e., lower values of ET/P. Overall, the correlations for the compound topographic index (CTI), which includes slope and upstream drainage area, are not higher than those for SLOPE. The

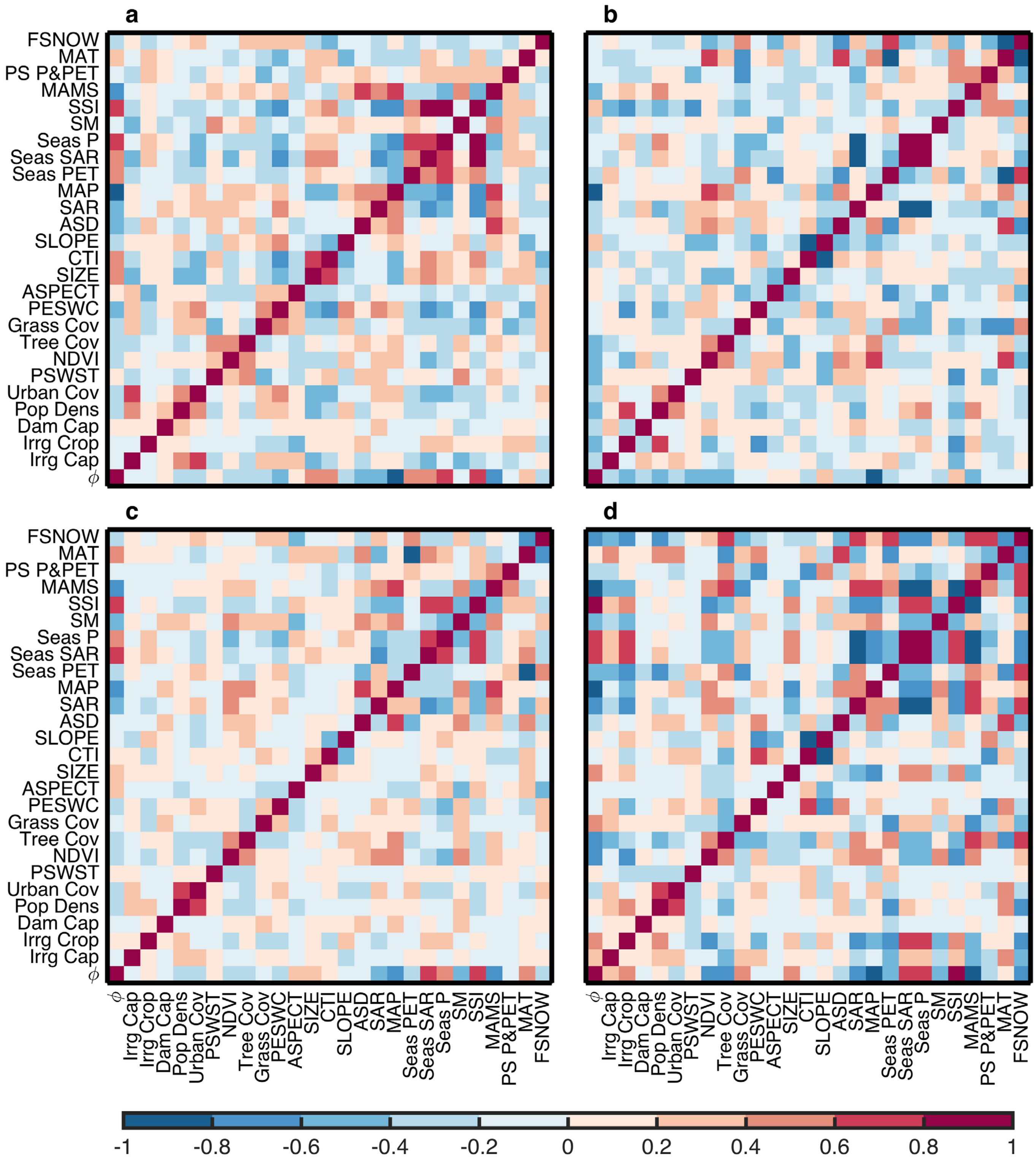

Figure 8. Spearman correlations between previously proposed controls of ET/P for (a) Equatorial, (b) Arid, (c) Warm temperate, and (d) Snow climate types.

positive correlation between catchment area (SIZE) and ω in Equatorial regions may result from a tendency for smaller catchments to have steeper slopes, whereas for Snow climates it seems to originate from smaller catchments having higher MAMS. The significant correlation with ASPECT indicates that Equatorial catchments with dominant northern (southern) facing slopes in the north (south) hemisphere favor runoff; note however that this correlation is no longer significant when replicating the analysis for all cases with modified data selection criteria (supporting information Figures S2–S4).

Vegetation. Higher values of Plant extractable soil water capacity (PESWC), which combines rooting depth and soil characteristics, significantly favor higher ET/P in Warm temperate and Snow regions. The area of grassland coverage also significantly favors ET over runoff, but in Warm temperate and Arid regions. Both of these results are likely related to more water being accessible to satisfy the atmospheric demand (PET). However, the correlations of these indices with ω are also likely amplified by the strong negative relation of PESWC with PS P&PET and SLOPE in Snow regions, as well as the correlation of grassland coverage with PS P&PET and SAR in Arid regions. Tree cover is highly correlated with FSNOW and SLOPE in Snow regions, which is likely the reason why it seems to favor runoff over ET. Finally, NDVI shows no significant correlation with ω for any climate type. Overall our results suggest that vegetation-related indices generally have a low contribution for explaining the spatial variability of ET/P, especially after accounting for the effect of relevant climate indices and catchment slope.

Soil. Soils with higher storage potential could have more water available for ET, and consequently favor higher values of ω and ET/P. However, the correlations are rather small and not significant in any climate type (except in Arid regions for the selected criteria of supporting information Figure S3).

Human. These indices exhibit overall a relatively small influence on ω, and hence on ET/P. The significant correlation of population density and irrigated cropland with ω in Snow regions is likely confounded by their strong negative correlation with the FSNOW index. Urban land cover shows a significant correlation with ω in Warm temperate regions, although the magnitude is low. It is also negatively correlated with SLOPE which might be a confounding factor.

7. Discussion

Although the presented results are generally robust against data selection criteria, based on catchment size and time period of the observations (see supporting information Figures S2–S4), it is important to recall caveats arising from the nature of this study. The quality of the data assembled from peer-reviewed publications is heterogeneous with respect to, e.g., spatial coverage, and methods for computing PET. Moreover, not all data correspond to the same period in time, although in most cases there is at least a 15 year overlap. We also note a spatial sampling bias, with higher concentration of data in the USA and Europe. Furthermore, the process of linking catchment-scale observations to gridded estimates of previously proposed factors influencing ET/P might impact the presented findings. The fact that the gridded data are evaluated at a spatial resolution of 1° implies that processes with smaller spatial scales cannot be resolved (Gudmundsson & Seneviratne, 2015). Finally, we recall that estimates of ET are generally obtained from the difference between precipitation and runoff, under the assumption that changes in long-term mean water storage are negligible.

Our findings emphasize the strong dependence of the spatial variability of ET/P on factors other than $\phi = \mathrm{PET/P}$. Overall, the net effect of these additional controls is of similar importance as ϕ, and much more important in Arid regions, with significant implications on the effects of environmental and climate change on the surface water balance over land. For example, the presented findings highlight the need to complement studies investigating climate change projections of ϕ (e.g., Fu & Feng, 2014; Sherwood & Fu, 2014) with possible changes in other controls to obtain more meaningful insights about future hydrological conditions. In relation to this, climate model projections show a small decrease in global ET/P over land by the end of the 21st century, in spite of a strong increase in ϕ (Roderick et al. 2015).

Among the controls of ET/P encompassed by ω, we find that climate-related controls and SLOPE dominate over other landscape characteristics. The snow fraction of precipitation (FSNOW) is of similar importance as ϕ in regions with Snow climate type, where it explains 67% of the variance in ET/P ranks. For other climate types, the following controls contribute in addition to ϕ and SLOPE the most to explaining ET/P: maximum accumulation monthly surplus (MAMS) in Warm temperate regions; storm arrival rate (SAR) in Arid regions; and slope direction (ASPECT) in Equatorial regions. Note, however, that the latter finding is not robust against catchment selection. The smaller number of significantly correlated controls in Equatorial and Arid climates is likely related to lower data availability, as well as higher observational uncertainties in these regions. Another notable feature are the underlying cross correlations between many of the factors proposed to influence ET/P. In recent years, numerous Budyko-based studies aiming to disentangle climate change and direct human influence (e.g., land use/cover) on the water balance have often fully attributed the changes in ω to the latter without testing this assumption comprehensively (e.g., Gao et al., 2016; Jaramillo & Destouni, 2015; Ning et al., 2016; Patterson et al., 2013; Wang & Hejazi, 2011; Zhang et al., 2017). Based on our findings we have to caution against this approach, since ω is highly correlated with climatic factors (e.g., FSNOW, MAMS, PS P&PET, SAR, and ASD) that are usually overlooked in these studies.

Interestingly our quantitative assessment suggests that vegetation-indices seem to play a minor role for explaining the spatial variability of ET/P, especially after accounting for the other relevant indices mentioned above. This might come as a surprise considering the extensive literature that has focused on vegetation as a factor that impacts the partitioning of precipitation into ET and runoff (e.g., Carmona et al., 2016; Dean et al., 2016; Donohue et al., 2007, 2010, 2012; Li et al., 2013; Oudin et al., 2008; Shao et al., 2012; Teuling et al., 2010; van der Velde et al., 2013; Williams et al., 2012; Xu et al., 2013; Yang et al., 2007, 2009; Zhang et al., 2001, 2004). Our results also point to an even smaller influence on ET/P from factors related to direct anthropogenic influence, such as irrigation, flow regulation and urbanization, which were found in other studies to be relevant for explaining temporal changes in ET/P (e.g., Jaramillo & Destouni, 2015; Wang & Hejazi, 2011). It is possible that these landscape factors might be more affected by some caveats of this study related, e.g., to the spatial resolution, inaccuracies when matching catchment-scale and gridded data, as well as spatial sampling biases (e.g., only few data from catchments in heavily irrigated regions like India and Spain). Nonetheless, the presented findings raise interesting questions regarding the true role of landscape characteristics, such as vegetation-indices, for explaining the spatial variability of long-term mean ET/P.

8. Conclusions

This study contributes to advance our understanding of factors that control the long-term mean partitioning of precipitation into evapotranspiration and runoff around the world. This is achieved by testing a comprehensive list of previously proposed controls of ET/P with observations from a new hydrometeorological data set assembled through a systematic literature search. Overall this assessment yielded robust quantitative results, despite the heterogeneity in both the observational methods and the data quality of the considered studies. Therefore, the results do also highlight the unexploited potential of systematic literature reviews for global hydrological and climatological research. Although the employed approach proved useful to mobilize an unprecedented number of catchment-scale in situ observations, it is important to note that a significant amount of studies had to be discarded as essential meta-data such as geolocation or quantitative information (e.g., long-term mean P, ET, PET) were not available in an explicit and easily accessible manner. Given the potential of meta-analysis for synthesizing case-study results, this calls for more complete documentation of relevant data in the scientific literature.

In conclusion, the presented results contribute to disentangle the role of factors controlling the long-term mean partitioning of precipitation into evapotranspiration and runoff worldwide, revealing a stronger role of factors different from mean atmospheric water supply (precipitation) and demand (potential evapotranspiration) than commonly assumed. In particular, slope and additional climate characteristics (e.g., snow, and the phasing of water supply and demand) are found to significantly impact the partitioning. Notably, we also find a smaller and often not significant influence of land cover and direct human interventions than frequently hypothesized in the literature. Finally, the newly assembled data set, together with the findings derived from testing process-based hypotheses, are expected to contribute to the evaluation and development of climate, land surface, and large-scale hydrological models with respect to factors controlling the long-term surface water balance over land.

Acknowledgments
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