

**The importance of climate and anthropogenic influence in precipitation partitioning
in the contiguous United States**

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Abstract

Understanding the process of precipitation partitioning into evapotranspiration and streamflow is fundamental for water resource planning. The Budyko framework has been widely used to evaluate the factors influencing this process. Still, its application has primarily focused on studying watersheds with minimal human influence and on a relatively small number of factors. Furthermore, there are discrepancies in the literature regarding the effects of climatic factors and land use changes on this process. To address these gaps, this study aims to quantify the influence of climate and anthropogenic activities on streamflow generation in the contiguous United States. To accomplish this, we calibrated an analytical form of the Budyko curve from 1990 to 2020 for 383 watersheds. We developed regional models of ω , a free parameter introduced to account for controls of precipitation partitioning not captured in the original Budyko equation, within different climate zones. We computed 49 climatic and landscape factors that were related to ω using correlation analysis and stepwise multiple linear regression. The findings of this study show that human activities explained a low variance of the spatial heterogeneity of ω compared with the watershed slope and the synchronization between precipitation and potential evapotranspiration, nevertheless, urban development emerged as a factor in temperate climates, whereas irrigated agriculture emerged in cold climates. In arid climates, mean annual precipitation explains less than 20% of the spatial variability in mean annual streamflow; furthermore, this climate is the most responsive to changes in ω . These results provide valuable insights into how land use and climate interact to impact streamflow generation differently in the contiguous United States contingent on the regional climate, explaining discrepancies in the literature.

Keywords: Budyko, Streamflow, Land use, Climate zones, Stepwise multiple linear regression

1 Introduction

Climatic and anthropogenic processes have significantly shaped the hydrological cycle and water availability over the last decades worldwide (Haddeland et al., 2014). Among them, climate change, land use changes, structural adaptation measures (e.g., levee systems and reservoirs), and deforestation have resulted in changes in streamflow at different spatial and temporal scales (Dey & Mishra, 2017). Land use changes profoundly impact regional water balances (Pielke et al., 2011), influencing interception, transpiration, evaporation, infiltration, and atmospheric blocking of precipitation, thus leading to changes in streamflow (Rogger et al., 2017; Tan et al., 2022). For instance, transforming vegetated areas into settlements may increase streamflow and reduce evapotranspiration (J. Du et al., 2012; Kundu et al., 2017; Wagner et al., 2013). Meanwhile, decreased areas under irrigated agriculture and decreased areas of forest cover have been associated with lower evapotranspiration and increased streamflow (Haddeland et al., 2006; Wagner et al., 2016). Augmenting irrigation results in a decline in streamflow through water withdrawals and an increase in water availability for evapotranspiration (Rost et al., 2008). Deforestation reduces evapotranspiration, leading to an increase in soil moisture and a decrease in soil storage capacity (Brown et al., 2005).

Several areas of the contiguous United States (CONUS) have undergone substantial changes in land use due to many external factors such as land clearing, expansion of croplands, and urban growth (X. Li et al., 2023; Sohl et al., 2016). For example, the Corn Belt region has shifted from perennial grassland to annual row crops (Auch et al., 2018; Schilling et al., 2008). Forest extent has declined because of harvest, and shrubland and grassland have grown at the expense of this forest loss (Homer et al., 2020). Urban areas have shown a persistent increase, faster in southern states than in northern states (Homer et al., 2020). Future projections suggest rapid urban

expansion, some gain in forest cover, loss in pastures, and a possible increase in cropland, although these scenarios heavily depend on the underlying drivers of change (e.g., policy incentives, crop prices) (Lawler et al., 2014).

Various studies have employed hydrological models to evaluate and project the impacts of land use on the hydrological cycle of various regions in the CONUS (e.g., Caldwell et al., 2012; Giri et al., 2019; Mishra et al., 2010; Parajuli et al., 2016). These studies have examined the impacts of diverse land uses on streamflow, encompassing shifts in cropping systems (Ahiablame et al., 2017; Frans et al., 2013; Schilling et al., 2008), irrigated agriculture (Ozdogan et al., 2010), and urbanization (C. Li et al., 2020). However, there is no consensus on the impact of land use changes on streamflow. For instance, Gupta et al. (2015) found a negligible influence of land use on increased streamflow in the midwestern USA. Meanwhile, Schilling (2016) and Schilling et al. (2008) have refuted this conclusion, asserting that the impacts of land use changes on streamflow in this region should not be neglected. These conflicting results highlight the research gaps in understanding the interactions between climate, hydrological processes, and land uses.

The Budyko framework (Budyko, 1974) is a simple yet effective tool for evaluating how climate, surface characteristics, and land use interact and influence the water-energy balance. Under long-term steady-state conditions and negligible changes in water storage, the Budyko framework assumes that the water balance is primarily governed by the water supply (i.e., precipitation) and the water demand (i.e., potential evapotranspiration) (H. Li et al., 2020). However, deviations of measured data from the original Budyko curve have led to adopting parameterized versions, often using a single shape parameter (e.g., Choudhury, 1999; Fu, 1981; Pike, 1964; Turc, 1954; H. Yang et al., 2008). The shape parameter is named the catchment characteristic or landscape parameter,

and it captures the combined influence of climate factors beyond supply and demand, like geology, vegetation, topography, and human activities, including land use, on precipitation partitioning.

Several studies have explored the relationship between the single shape parameter ω (Fu 1981) and diverse physical factors such as slope, elevation, vegetation, soil storage, etc. (e.g., Bai et al., 2020; D. Li et al., 2013; Liu & You, 2021; Xu et al., 2013). In the CONUS, Abatzoglou and Ficklin (2017) developed a generalized additive model of ω using topographic and climatic factors. Their model was built with 211 gages with minimal human influence, explaining 81.2% of the variability. However, when the model's performance was evaluated using 164 watersheds from the Model Parameter Estimation Project (MOPEX) with less stringent requirements in terms of human influence, the explained variability decreased to 65%. A previous study by Wang and Hejazi (2011) already pointed out that MOPEX watersheds are not free of human interferences and hypothesized possible relationships between streamflow change and human activities, such as irrigation or cropland area, but without a direct estimation of the effect or countereffects of these human activities on streamflow. A subsequent study by Z. Li and Quiring (2021b), relates the calibrated ω for 126 reference and 765 non-reference watersheds with physiographic and anthropogenic factors from the USGS database GAGES-II: Geospatial Attributes of Gages for Evaluating Streamflow (Falcone, 2011; Falcone et al., 2010). The authors concluded that forest coverage is important in representing spatial variability of ω in watersheds with limited human impact or reference watersheds. Meanwhile, urbanization is relevant in explaining spatial variability of ω in non-reference watersheds or watersheds with higher human imprints. While this study is a first attempt to quantify the contribution of different land uses and human activities in explaining the spatial variability of ω , the model's performance exhibited regional differences. These differences can be attributed to the limitations of a model for the entire CONUS to account

for regional variations in significant independent variables. A recent global-scale study by Liu and You (2021) showed that the factors explaining the spatial variability of ω vary by region, particularly with climate regions, highlighting the necessity of developing regional models of ω . However, this global scale study used non-human disturbed basins and natural catchment attributes.

Although these prior studies have provided valuable insights, to the best of our knowledge, none have examined how climatic and landscape factors (i.e., topography, vegetation, geology, and anthropogenic activities) interact and influence ω differently in human-impacted and non-human-impacted watersheds across various climatic regions within the CONUS. Additionally, previous studies have been limited in examining only a subset of these possible factors in the CONUS, mainly natural physiographic variables, despite the broad range of factors explored in the literature.

Our study investigates the influence of anthropogenic activities and other catchment characteristics on the long-term water balance using the Budyko Framework for different climate zones in the CONUS, employing an extensive list of 49 factors. Specifically, this study focuses on how land use and its variability influence water-energy partitioning. We also identify which climates are more responsive to alterations in catchment characteristics, including land use changes. To accomplish this, we examine which variables, precipitation, potential evapotranspiration, or landscape factors account for the spatial distribution of mean annual streamflow in the CONUS.

The specific questions of this study are:

1. To what extent do climate variables and land uses explain the spatial heterogeneity of ω within climate regions?

2. What is the spatial variability in streamflow explained by climate and catchment characteristics in different climate regions?

To answer these questions, we classified watersheds in the CONUS by land use type and grouped them by climate region. Then, we calibrated ω from 1990 to 2020 using long-term hydroclimatic data. We calculated an extensive list of climatic, topographic, anthropogenic, vegetation, and geologic factors to select potential controls of ω . After, we developed stepwise multiple linear regression models to explore how a subset of these controls explains the spatial variability of ω within different climate regions. Finally, we computed the spatial variability on mean annual streamflow explained by precipitation, potential evapotranspiration, and ω also using linear regression models.

2 Materials and Methods

2.1 Hydro-climatic data and watershed classification

Streamflow gages from the GAGES-II database were selected for this study (Falcone, 2011; Falcone et al., 2010). The GAGES-II database provided geospatial data, environmental characteristics, and anthropogenic influences for 9067 basins in 9 ecoregions of the CONUS. Daily streamflow data from 1990 to 2020 were submitted to a completeness requirement to ensure data gaps do not bias results. Streamflow gages must have complete data (a daily value for every day of the year) for at least eight out of every ten years for each decade (e.g., 1990-1999) and a maximum of 10 days missing in the other two years (Dudley et al., 2020). A total of 3165 gages out of the 9067 met this criterion. We also discarded basins smaller than 300 km², reducing the streamflow gages for further study to 2193. We selected this threshold to strike a balance between

having sufficient watersheds in our sample and considering the spatial resolution of the climate raster data used.

The 2193 basins were classified as either reference or non-reference watersheds according to their anthropogenic alteration. Reference basins represent near-to-natural flow conditions, while non-reference basins are affected by human processes (e.g., urbanization). Non-reference basins were further subdivided into urban, agricultural, or regulated, using the thresholds that Dudley et al. (2020) proposed (Table 1). A basin was classified as “Other” if it failed to meet any of the criteria. Dudley et al. (2020) defined the high and low thresholds as the highest quartile and lowest half values of the human activities (e.g., urban area, cultivated land) among the gages, respectively. The 2019 National Land Cover Database (NLCD) (Dewitz & U.S. Geological Survey, 2021) is used to estimate the percentage of the basin used for cultivated crops and developed land. The normalized dam storage is calculated as the normalized dam storage of the reservoirs in the watershed multiplied by the drainage area and divided by the mean annual streamflow from 1990 to 2020.

Reference basins are minimally affected by direct human activities and belong to the USGS Hydro-Climatic Data Network 2009 (HCDN-2009) (Lins, 2012). There are 261 watersheds that belong to the HCDN-2009, but only 158 of these watersheds met the low land-use thresholds in the 2019 NLCD. A total of 86 watersheds exceeded the limits of cultivated land and 40 the threshold of urban land. Also, 23 watersheds have more than 60 days of normalized storage. This classification led to 158 reference gages, 68 urban gages, 172 agricultural gages, 209 regulated gages, and 1586 gages in the “Other” group (Table 1). Only reference, urban, and agricultural gages (a total of 398) are used for subsequent analysis (Figure 1a), as regulated gages commonly violate the negligible change in storage assumption.

Both reference and non-reference basins were grouped in climate zones using the updated Köppen-Geiger climate classification at 1 km resolution by Beck et al. (2018). This updated map exhibits greater accuracy compared to previous versions due to their generation using topographically corrected climatic maps. Then, we grouped some of the climate zones using the criterion proposed by Liu and You (2021) (Table 2) to prevent groups with low numbers of watersheds while preserving the primary climate characteristics related to the temperature and precipitation of each Köppen-Geiger climate zone (Table S1). We selected the climate that covers the largest fraction of the watershed when the watershed area falls in more than one climate zone. This classification resulted in 5 climate groups (Table 2). A total of four watersheds that belonged to the Dwb climate (Cold, Dry winter, Warm summer) were excluded from the analysis due to insufficient sample size. The Mid-Atlantic and New England regions belong to Cold2, the South to Temperate2, the Great Plains and Midwest to Cold2 and Arid, the West Coast to Temperate1, and the Rocky Mountains to Cold1 (Figure 1b).

Daily precipitation and reference evapotranspiration were extracted from gridMET (Abatzoglou, 2013) from 1990 to 2020 and averaged over each basin. The gridMET is a high-spatial-resolution (~4 km) gridded surface meteorological dataset, and it has been previously used in the context of the Budyko Framework in the CONUS (Abatzoglou & Ficklin, 2017; Guillén et al., 2021). There are several approaches to estimating the potential evapotranspiration, such as pan evaporation (Greve et al., 2015), the Penman-Monteith method based on a reference crop surface (Greve et al., 2020), or the Hargreaves-Samani method based on temperature (Istanbulluoglu et al., 2012). The reference evapotranspiration is the evapotranspiration for a short well-watered grass with a static albedo of 0.23 (Allen et al. 1998). This method follows the standardized ASCE approach and was also used by Abatzoglou and Ficklin (2017).

Table 1 Low and high thresholds for watershed classification into reference and non-reference (agricultural, regulated, or urban)

Classification by land use and regulation	HCDN-2009	High land-use threshold	Low land-use threshold	# watersheds
Reference	Yes	none	≤ 60 days normalized dam storage; $\leq 6\%$ developed land; $\leq 2\%$ cultivated crops	158
Agricultural	No	$> 20\%$ cultivated crops	≤ 60 days normalized dam storage; $\leq 6\%$ developed land	172
Regulated	No	> 180 days normalized dam storage	$\leq 2\%$ cultivated crops; $\leq 6\%$ developed land	209
Urban	No	$> 10\%$ developed land	$\leq 2\%$ cultivated crops; ≤ 60 days normalized dam storage	68

Table 2 Defining criteria of the Köppen-Geiger climate zones based on Beck et al. (2018) and Liu and You (2021)

Classification by climate	Code	Abbreviation	Precipitation type	Description	Definition	# watersheds
Cold	Dsc, Dsb	Cold1	Dry summer		$P_{sdry} < 40$ & $P_{sdry} < P_{wwet}/3$	23
	Dfa, Dfb, Dfc	Cold2	Without dry season	Not Arid & $T_{hot} > 10$ & $T_{cold} \leq 0$	Not ($P_{sdry} < 40$ & $P_{sdry} < P_{wwet}/3$) or Not ($P_{wdry} < P_{swet}/10$)	220
Temperate	Csa, Csb	Temperate1	Dry summer	Not Arid & $T_{hot} > 10$	$P_{sdry} < 40$ & $P_{sdry} < P_{wwet}/3$	21
	Cfa, Cfb	Temperate2	Without dry season	& 0 < $T_{cold} < 18$	Not ($P_{sdry} < 40$ & $P_{sdry} < P_{wwet}/3$)	108

or Not ($P_{\text{wdry}} < P_{\text{swet}}/10$)					
Arid	BSk, BSH	Arid	Steppe	$\text{MAP} < 10 \times P_{\text{threshold}}$	$\text{MAP} \geq 5 \times P_{\text{threshold}}$

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Note. MAP indicates the mean annual precipitation; T_{cold} and T_{hot} represent the average air temperature during the coldest and warmest months, respectively; P_{sdry} and P_{wdry} denote the precipitation in the driest months of summer and winter, respectively; P_{swet} and P_{wwet} represent the precipitation in the wettest months of summer and winter, respectively; and $P_{\text{threshold}}$ means the precipitation threshold. Units: MAP in mm y^{-1} ; T_{cold} and T_{hot} in $^{\circ}\text{C}$ and P_{swet} , P_{wdry} , and $P_{\text{threshold}}$ in mm.

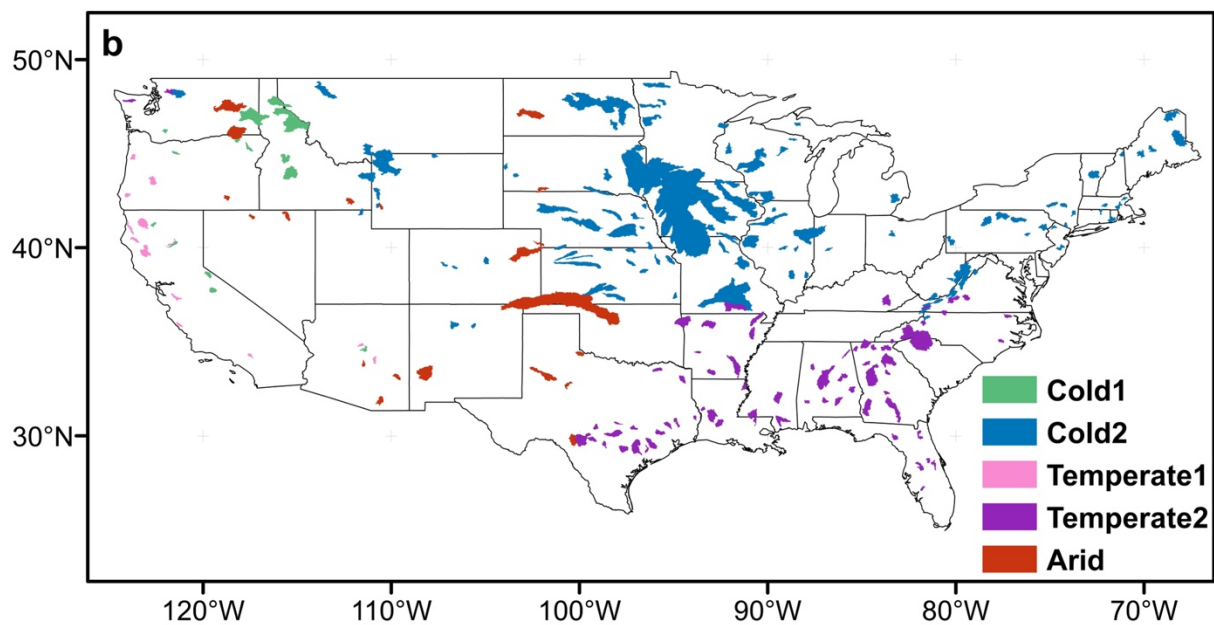
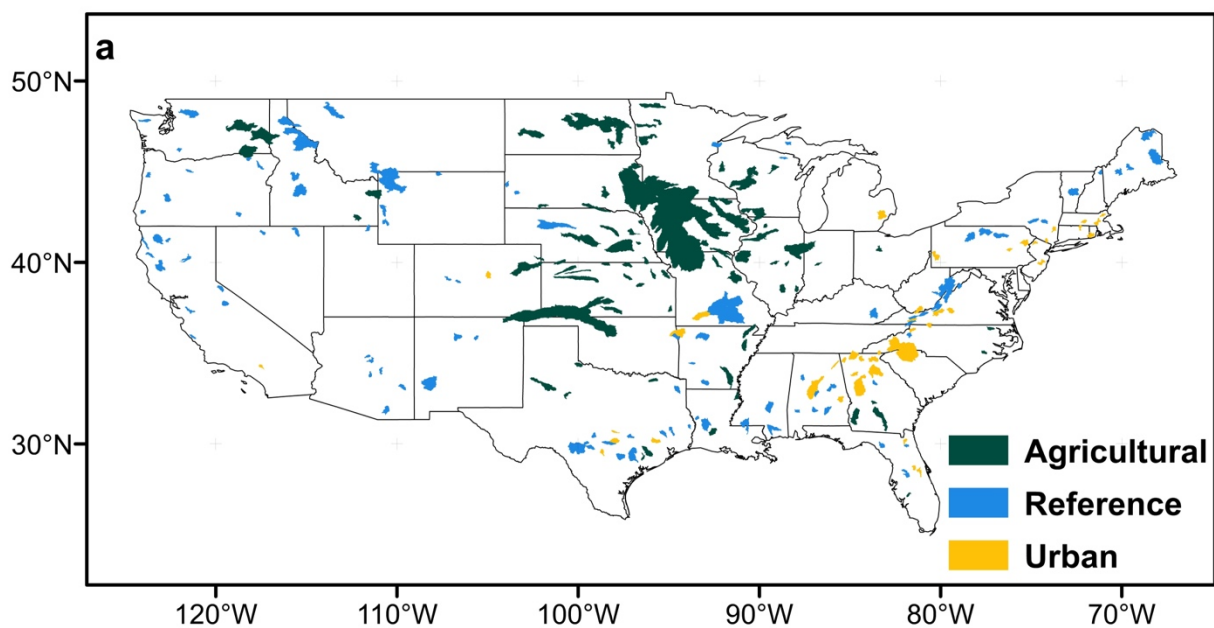


Figure 1 (a) Spatial distribution in the CONUS of the reference, agricultural, and urban watersheds and (b) grouped by climate

2.2. Water-energy balance

This study used the analytical form of the Budyko hypothesis proposed by Fu (1981), extensively implemented to study water-energy balances at different spatial and temporal scales (e.g., L. Cheng et al., 2011; C. Du et al., 2016; Greve et al., 2015; Koppa & Gebremichael, 2017; S. Li et al., 2022; Lv et al., 2019; Qiu et al., 2019; Sinha et al., 2019; L. Zhang et al., 2004; Zhao et al., 2020). The Fu equation estimates the watershed's long-term evapotranspiration (ET) as a function of the ratio between the available water (precipitation, P) and energy (potential evapotranspiration, PET), also called aridity index (ϕ), and the catchment characteristic parameter (ω). Fu's equation is expressed as follows:

$$\frac{ET}{P} = 1 + \frac{PET}{P} - \left[1 + \left(\frac{PET}{P} \right)^\omega \right]^{\frac{1}{\omega}} \quad (1)$$

where ω can be calibrated with historical P and streamflow (Q). When ω equals 2.6, Fu's curve corresponds to the traditional Budyko curve. High values of ω indicate watersheds where most of the P is used for ET. In contrast, low values of ω represent watersheds where a significant fraction of P becomes Q. For $\omega < 2$, watersheds have a higher sensitivity to land use factors relative to climate factors, whereas for $\omega > 2$, the climate factors tend to have greater importance (Zhou et al., 2015).

We calibrated ω for each watershed by minimizing the difference between the long-term mean ET ($ET = P - Q$) from 1990 to 2020 and the estimated ET by substituting the long-term mean P and PET into Fu's equation. We deemed a 31-year time frame sufficient to guarantee insignificant changes in storage. According to Z. Li and Quiring's (2021a) study, 84.4% of the 954 human-impacted watersheds they used from the GAGES-II database had a closed water balance for an 11-year time period. However, it is important to note that some watersheds, especially in arid catchments in the

western U.S., might have experienced storage changes due to groundwater withdrawals. Still, our sample size in this region is relatively small. The ω values were sampled from a uniform distribution from 1.25 to 9 with 0.01 increments, following the approach by Abatzoglou and Ficklin (2017). To ensure plausible water balances, we eliminated watersheds where $Q > P$ or $ET(P - Q) > PET$ (Peel et al., 2010). We also excluded watersheds with a calibrated ω equal to 1.25, as it represents the minimum value for bare soil (Donohue et al., 2012). Furthermore, we tested the hypothesis that ET/P and ω varies across different climate regions and land uses using the Kruskal-Wallis's test.

2.3. Selecting potential controls of ω

The literature provides an extensive list of controls that may govern ω , which can generally be classified into two groups: climate-based and landscape controls (Padrón et al., 2017; Shao et al., 2012; Vora & Singh, 2021). However, no primary control of ω has been defined to date because ω has no prior physical meaning (Greve et al., 2015). The selection of factors was based on a systematic review conducted by Padrón et al. (2017) that investigated ω 's controls at regional and global scales up until 2016. Additionally, we included the soil factors added to this review by Vora and Singh (2021) and other topographic and anthropogenic factors that Z. Li and Quiring (2021b) considered in their study conducted in the CONUS (Text S1). We computed 49 possible controls of ω classified into five categories, climatic (14), topographic (11), vegetation-related (5), anthropogenic (12), and geologic (7) (Table S2 and Table S3).

Given the large number of controls considered, we expect possible cross-correlations that could weaken the inference in determining the effect of each control. Therefore, we need first to select a subset of potential controls of ω (Text S2). To do this, we evaluated the Spearman correlations

between ω and each control. We selected factors with the highest significant correlation with ω and highly correlated with the other factors in the same category (Table S4 and Figure S1). In this way, we eliminate internally correlated factors while assuming that the selected factors are sufficient to represent the excluded factors. Previous studies have used a similar approach (e.g., Vora & Singh, 2021).

We selected ten variables to investigate their potential relationship with ω . These variables include relative cumulative moisture surplus (rCMS), fraction of precipitation falling as snow (SF), slope (Slope), forest cover (TreeCover), urban land (Settlements), cultivated land (Cultivated), irrigated agriculture (IrrAgri), percentage of urban land adjacent to a 100-meter width at each side of the main river (MAIN100DEV), number of dams in the watershed (NDams), and ratio of available water capacity in the top 1.5 meters of soil to precipitation (AWC0150:P).

These ten variables became the independent variables against which omega was regressed in the stepwise multiple linear regression (SMLR) (Chu et al., 2019). All the retained variables in the SMLR are statistically significant at $p\text{-value} < 0.05$ and have a Variance Inflation Factor < 5 and tolerance > 0.02 . We normalized the dependent variable by applying a log transformation. Similarly, we applied either log or square root transformations for some of the independent variables that did not exhibit a linear relationship with ω . Subsequently, we standardized the independent variables by subtracting their mean and dividing them by their standard deviation. The standardization is done to assess variable importance. Finally, we validate the variance explained by the factors in the SMLR models by constructing 10,000 models through bootstrap sampling with replacement (Text S3).

2.4.Spatial variability of streamflow in different climate regions

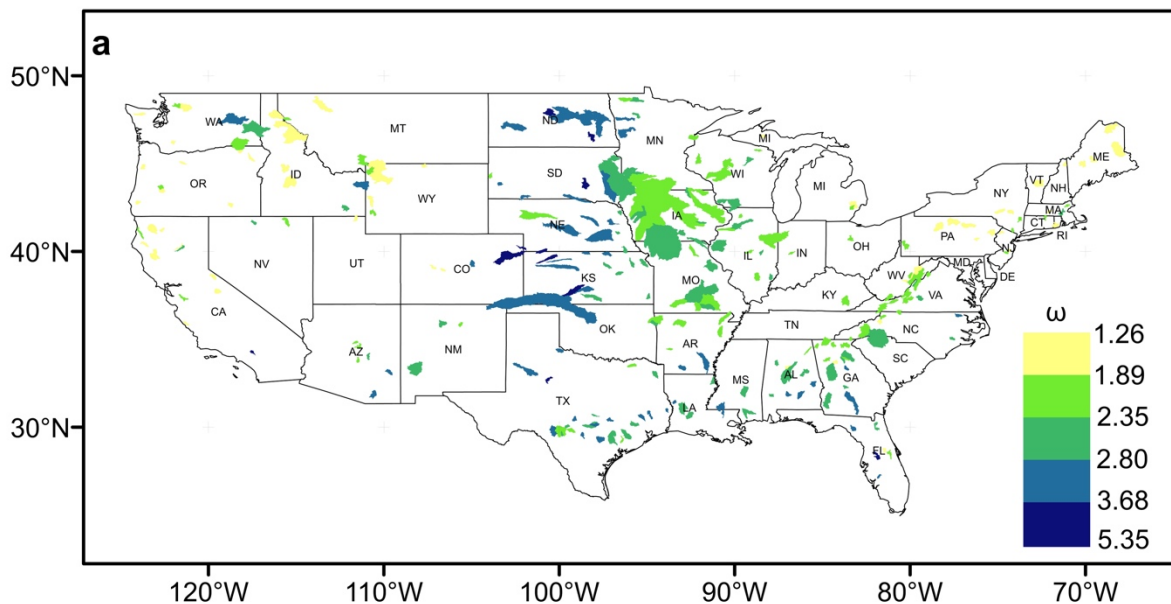
We assessed the spatial variability of mean annual Q explained by climate (i.e., P or PET) and catchment characteristics (i.e., ω) using SMLR. We created a SMLR for each climate region, using mean annual Q from 1990-2020 as the dependent variable and mean annual P, mean annual PET, and ω as predictors. To satisfy the requirement of constant variance in SMLR and to address an observed curvilinear relationship in the residuals versus fitted plot, we used quadratic terms for the variables P and PET instead of linear terms. All the retained variables in the SMLR are statistically significant at $p\text{-value} < 0.05$ and have a Variance Inflation Factor < 5 and tolerance > 0.02 . We also standardized the independent variables by subtracting their mean and dividing them by their standard deviation.

3 Results

3.1 Values of ω by climate region and land use

The total number of watersheds was reduced from 394 to 383, because for 4 watersheds $ET > PET$, and for 7 watersheds, ω equals 1.25. The climate zone has a significant influence on both ET/P (chi-squared or test statistic H of the Kruskal-Wallis's test = 70.29 and $p\text{-value} < 0.005$) and ω (H = 71.52 and $p\text{-value} < 0.005$). Also, the land use has a significant influence on both ET/P (H = 93.12 and $p\text{-value} < 0.005$) and ω (H = 71.15 and $p\text{-value} < 0.005$). Our values of ω across CONUS range between 1.26 and 5.35, with overall, $\omega > 3$ in the Great Plains and $\omega < 2$ in the Northeast and along the West Coast. The highest ω corresponds to arid basins with a mean value of 2.96, primarily located in the Great Plains and Midwest, and the lowest ω to basins in the dry summer cold climate (Cold1) with a mean value of 1.70, mainly found along the Rocky Mountains in Idaho (ID), Montana (MT) and Wyoming (WY) (Figure 2a). Forty-eight watersheds have values of ω higher

than 3 and are primarily located in the Great Plains (Figure 2a), belong to cold climate without dry
 season (Cold2) (Figure 3a), and are agricultural (Figure 3b). Despite being in a humid climate,
 these watersheds are in the water-limited region ($\phi > 1$) (Figure 2b); therefore, high values of ω are
 not unexpected. Only 25% of the humid climate watersheds (Cold2) are in the energy-limited
 region ($\phi < 1$) (Figure 3a) and are in the Mid-Atlantic and New England. In Temperate2, exposed
 to higher temperatures than Cold2, approximately 50% of watersheds are in the water-limited
 region, mainly in Florida (FL) and Texas (TX). The other 50% of watersheds in the energy-limited
 region are in the Appalachian Mountains and Mississippi (MS). We found similar variation when
 looking at the Temperate1 climate. Watersheds belonging to this group in the northwest (Oregon
 (OR) and Northern California (CA)) are in the energy-limited region. Meanwhile, watersheds in
 the southwest (Arizona (AZ) and Southern California (CA)) are in the water-limited region.
 Overall, temperate climates have slightly higher ω than cold climates (Figure 4a), and agricultural
 watersheds have higher ω , followed by urban and reference watersheds (Figure 4b).



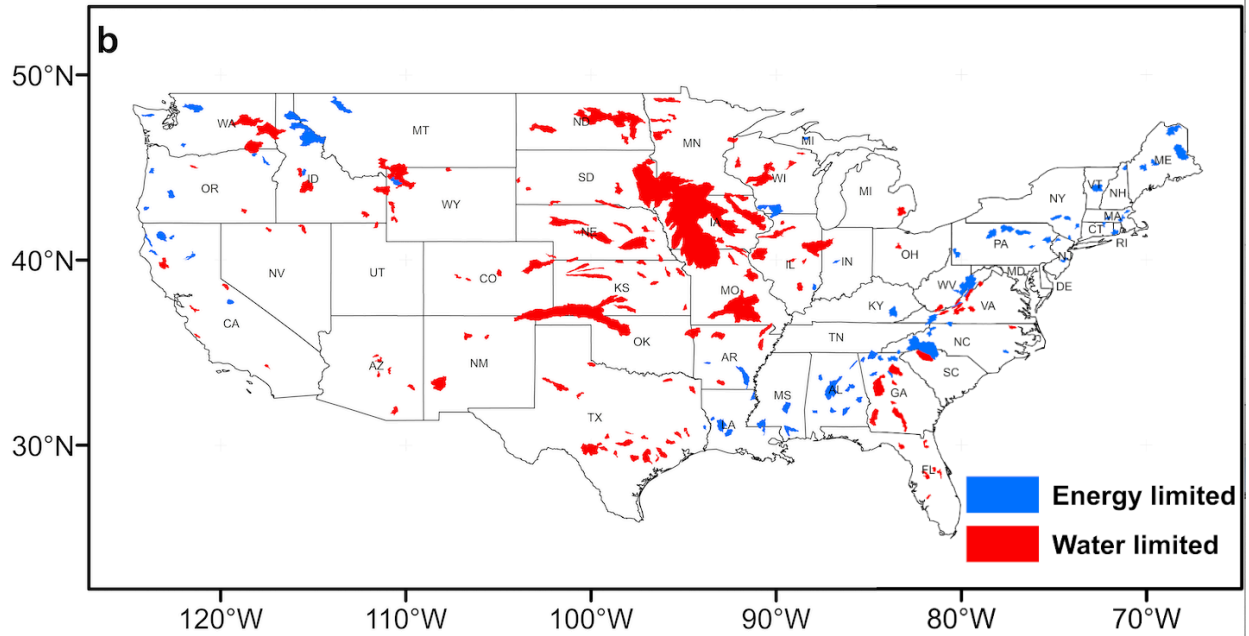


Figure 2 (a) Calibrated ω for the 1990–2020 period for the 383 watersheds; (b) Watersheds classified as energy limited (aridity index (ϕ) <1) or water limited (ϕ >1)

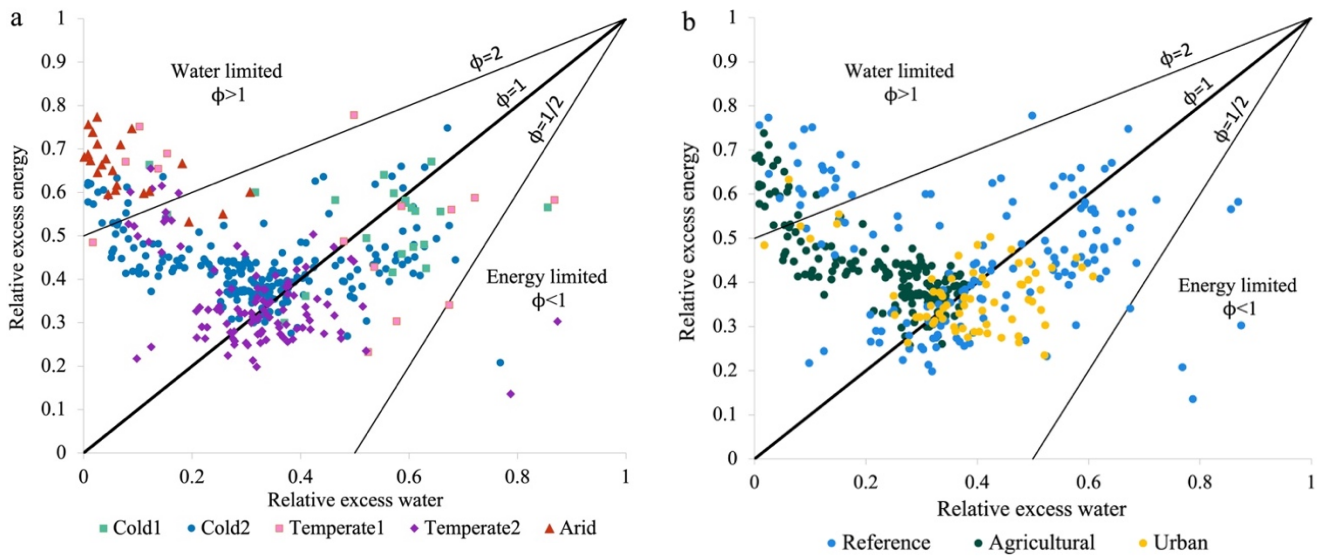


Figure 3 Diagram of relative excess energy (PET/ET) and relative excess water ($1 - P/PET$) with lines of constant aridity (ϕ). The dot colors are the classification of watersheds based on (a) climate and (b) land use

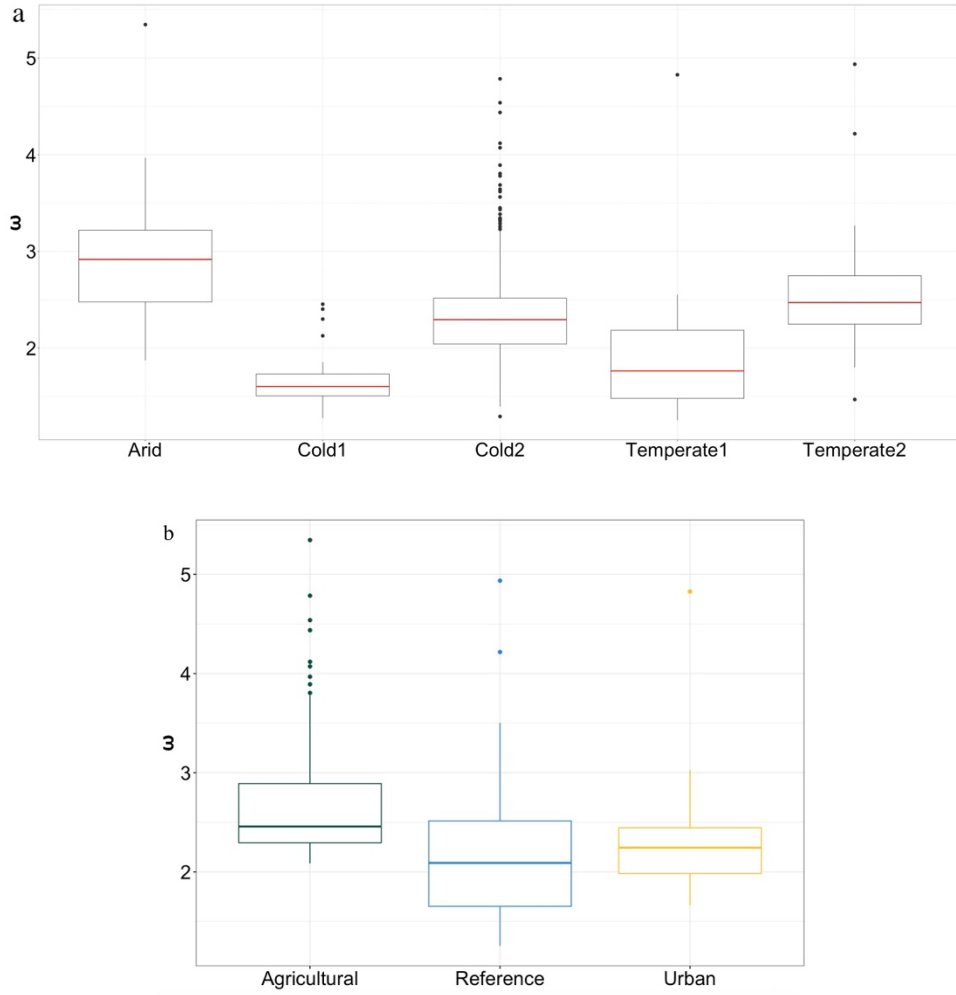


Figure 4 Boxplots of ω for (a) each climate region and (b) land use in the watershed. The middle line indicates the median, the box edges the 25th and 75th percentiles, and the dots are the outliers outside the whiskers at the 5th and 95th percentiles

3.2 Climate and landscape controls explaining spatial heterogeneity of ω by climate region

Different independent variables are identified as explanatory factors of the spatial variability in ω across the various climate zones (Table 3). In the Cold1 climate, the slope is the only significant factor with an adjusted R^2 of 0.43. Watersheds in the Cold1 climate, which exhibit the lowest ω ,

are predominantly located on the sides of the Rocky Mountains in Idaho, and have the steepest slopes among all watersheds, ranging between 18° and 28° . Conversely, watersheds in the same climate group, located along the west coast in California and Oregon, display higher ω values and are marked by less steep slopes.

Within the Cold2 climate, we have identified four factors that collectively account for 76% of the spatial variability in ω . These factors include two climatic controls, one human-related control, and one soil-related control. Among these, the most influential is the relative cumulative moisture surplus (rCMS), which represents the synchronization between P and PET. This factor explains 65% of the variability alone. Geographically, P and PET display lower synchronization (higher rCMS) in the Northwest and Northeast leading to increased Q, and higher synchronization (lower rCMS) in the Midwest (Figure 5). The second most significant factor, though considerably less impactful than rCMS, is irrigated agriculture (IrrAgri), explaining 7% of the variability. Noteworthy agricultural watersheds with substantial irrigated land, such as Nebraska and Kansas (Dieter et al., 2018), exhibit a mean ω above 3. Conversely, watersheds in Iowa, North Dakota, and South Dakota, characterized by extensive cultivated land but minimal irrigated land, display an average ω below 3. Additionally, the available water for plants (AWC0150:P) and the snow fraction (SF) explained a residual variance. AWC0150:P is higher in the Midwest compared to the Northwest and Northeast regions (Figure 5), favoring higher ET due to increased water retention in the soil. In the northern part of the Midwest (North Dakota, South Dakota, and Minnesota) and Northwest, SF is higher favoring Q (Figure 5).

In the Temperate1 climate, rCMS explains around 40% of the ω 's spatial variability. The values of rCMS show a decreasing trend as we move from Oregon, where it reaches a maximum, along the west coast, reaching its lowest value in Arizona. Watersheds in Oregon exhibit a higher phase

shift P and PET, whereas in California and Arizona, P and PET are more seasonally synchronized, or PET sometimes exceeds P. The urban land in the riparian zone (MAIN100DEV), explains around 20% of the variability. This finding can be attributed to the distinctive characteristics of the urban watershed within this group, which stands out due to its high percentage of MAIN100DEV land and the highest value of ω .

Within the Temperate2 climate, slope is the most important factor, explaining 29% of the ω 's spatial variability. Watersheds along the Appalachian Mountains exhibit the highest slopes within the group, ranging from 5° to 20° (Figure 6), with an average ω below 2.3. The level of urbanization (Settlements) served as a second factor, explaining 11% of the ω 's spatial heterogeneity. Highly urbanized watersheds (>40% of the watershed's area) are concentrated in South Carolina, Georgia, and Alabama and have an average ω of 2.1. Urbanization leads to increased streamflow, potentially due to reduced infiltration and soil moisture storage (O'Driscoll et al., 2010). SF accounts for a negligible variance, contributing only 3%. The watersheds in the Appalachian Mountains and Ouachita-Ozark Mountains in Arkansas have higher average SF values compared to those in the Coastal Plains (Figure 6).

In arid regions, rCMS explains 63% of the total ω 's spatial variability, while the slope accounts for 13% of the total variability, which amounts to 76%. Arid watersheds in the southwest regions of Arizona, New Mexico, and Nevada, as well as the Northwest in Oregon, exhibit higher slopes and rCMS values, resulting in lower ω values compared to arid watersheds in the Great Plains.

The findings of the SMLR models constructed using bootstrapping sampling (Text S3) validate the variance explained by the controls (Table 3). We observed nearly identical average variances explained by each control when utilizing 10,000 SMLR models constructed via bootstrapping,

384 compared to using the original dataset. Nonetheless, discrepancies increase as the variance
385 explained by the control decreases.

386 **Table 3** SMLR results for each climate region using ten controls of ω . The Cumulative Adj. R^2
387 represents the incremental Adj. R^2 added to the model with the inclusion of each variable and AIC
388 is the Akaike Information Criterion of the model

Climate	Variable	Coefficient	Std. Error	t-value	Pr ($> t $)	p-value model	Cum. Adj. R^2	Adj. R^2	AIC
Cold1	Slope	-0.12	0.03	-3.99	7.82e-04	7.82e-04	0.43	0.43	-81.53
	rCMS	-0.12	0.01	-9.96	$< 2.2e-16$		0.65		
Cold2	IrrAgri	0.03	0.01	3.09	0.002	$< 2.2e-16$	0.72	0.76	-314
	AWC0150:P	0.08	0.02	5.40	1.77e-07		0.73		
	SF	-0.05	0.01	-4.85	2.37e-06		0.76		
Temperate1	rCMS	-0.23	0.05	-4.30	1.03e-03	6.63e-05	0.40	0.61	0.21
	MAIN100DEV	0.25	0.04	5.91	7.11e-05		0.61		
Temperate2	Slope	-0.07	0.02	-4.29	4.05e-05		0.29		
	Settlements	-0.06	0.01	-4.94	3.09e-06	2.33e-13	0.40	0.43	-132.35
	SF	-0.04	0.02	-2.32	0.022		0.43		
Arid	rCMS	-0.14	0.03	-4.66	1.69e-04	1.05e-06	0.63	0.76	15.06
	Slope	-0.11	0.03	-3.99	7.80e-04		0.76		

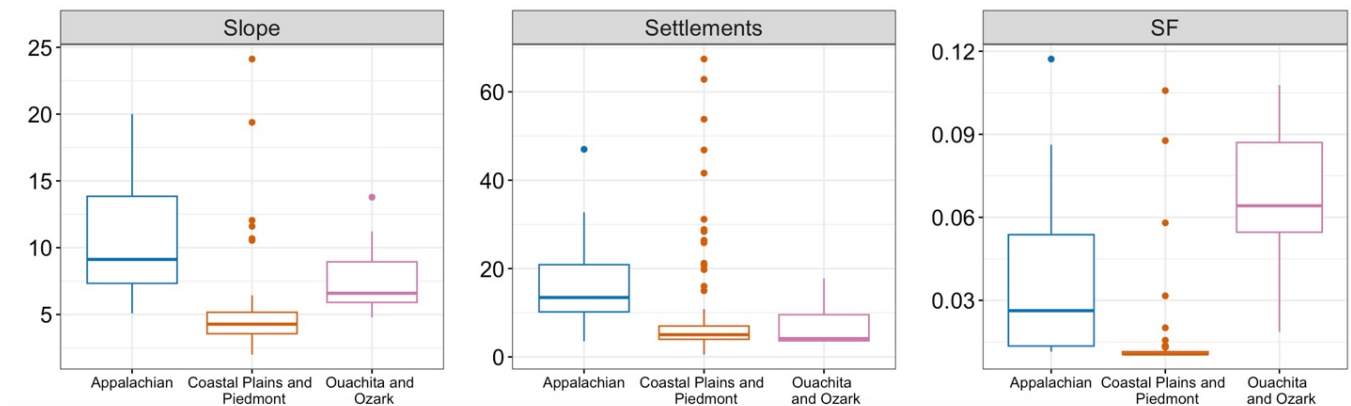


Figure 5 Boxplot of climatic variables explaining spatial heterogeneity of ω for Cold2 climate across the three geographical regions

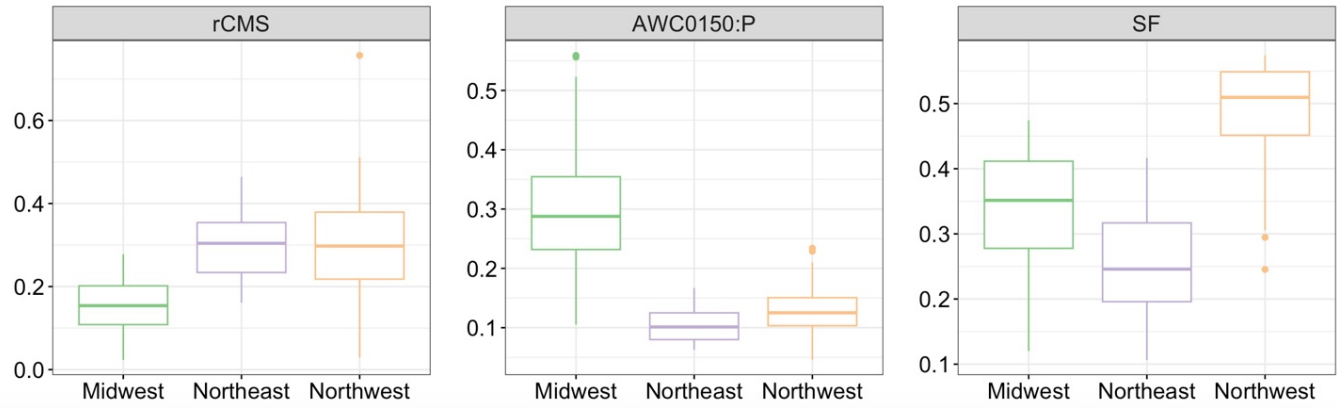


Figure 6 Boxplot of variables explaining spatial heterogeneity of ω for Temperate2 climate across different geographical regions

3.3 Spatial variability of streamflow explained by climate and catchment characteristics across different climate regions

The spatial variability of streamflow, attributed to climate and catchment characteristics, differs across various climate regions (Table 4). Precipitation accounts for more than 80% of the spatial variance in mean annual Q in all the climates, except in arid climates, where it only explains about 16%. The catchment characteristics (ω) exhibit the most substantial influence on the spatial variance of mean annual Q in arid climates, explaining up to 48% of the variability, which is considerably higher than the other climates. In the Cold2 climate, catchment characteristics explain

10% of the spatial variance on mean annual Q, while in the remaining climates, the percentage of spatial variance explained by ω is below 10%.

Table 4 SMLR results for each climate region using Q as dependent variable and P, PET, and ω as independent variables. Var is the variable P, PET or ω . The Cumulative Adj. R^2 represents the incremental Adj. R^2 added to the model with the inclusion of each variable and AIC is the Akaike Information Criterion of the model.

Climate	Var.	Coefficient	Std. Error	t-value	Pr (> t)	p-value model	Cumulative Adj. R^2	Adj. R^2 model	AIC
Cold1	P	0.87	0.03	26.31	3.2e-15	< 2e-16	0.91	0.99	-31.46
	ω	-0.26	0.02	-10.62	6.4e-09		0.98		
	PET	-0.06	0.02	-2.62	0.018		0.99		
Cold2	P	0.69	0.03	27.47	< 2e-16	< 2e-16	0.81	0.93	59.93
	ω	-0.28	0.03	-10.73	< 2e-16		0.91		
	PET	-0.11	0.02	-5.36	2.1e-07		0.93		
Temperate1	P	0.77	0.06	11.98	1.2e-07	8.5e-10	0.93	0.98	-8.53
	ω	-0.14	0.05	-3.13	0.009		0.97		
	PET	-0.18	0.07	-2.67	0.02		0.98		
Temperate2	P	0.87	0.03	26.72	< 2e-16	< 2e-16	0.94	0.99	-181.9
	ω	-0.13	0.01	-21.58	< 2e-16		0.98		
	PET	-0.11	0.01	-8.64	8.1e-14		0.99		
Arid	ω	-0.29	0.08	-3.42	0.003	2.0e-05	0.48	0.79	36.77
	P	0.47	0.11	4.26	0.0004		0.64		
	PET	-0.36	0.10	-3.55	0.002		0.79		

4 Discussion

4.1. To what extent do climate variables and land uses explain the spatial heterogeneity of ω within climate regions?

Our analysis reveals that climatic variables, specifically the phase shift between P and PET, are more relevant in humid climates in the Northeast and Midwest (Cold2 climate) and arid climates

in the Southwest and Great Plains relative to other areas. In contrast, in other climates, topographic variables, such as slope, appear to be more important, notably in the Southeast (Temperate2 climate) and Northwest (Cold1 climate) (Table 3). This finding aligns with our expectations, as we observed variations in the Spearman correlations between ω and these factors across different climates (Table S4). Our Spearman correlations between ω and the climatic factors for the Cold2 climate (i.e., 0.72 for AWC0150:P and -0.77 rCMS, Table S4), which represents the largest group, align in magnitude with those reported by Abatzoglou and Ficklin (2017) for the entire CONUS. However, these correlations significantly diminish in other climates. Hence, using the same factors to predict ω in the entire CONUS overlooks distinctions in the roles of climatic and landscape factors to explain regional differences in water balances. Abatzoglou and Ficklin (2017)'s model for the entire CONUS attributed a nominal influence of slope on ω . However, our findings demonstrate its relevance, particularly in Cold1 and Temperate2 climates, where the Rocky Mountains and Appalachian Mountains are located. Meanwhile, Guillén et al. (2021) determined that elevation as the primary landscape factor in their localized study of watersheds in the Appalachian Mountains due to the direct positive relationship between altitude and precipitation. These differences demonstrate the scale-dependent nature of the factors governing precipitation partitioning. Consequently, factors like elevation or snow might have minimal influence on broader regional climate patterns but still affect precipitation partitioning at smaller, localized scales.

A novelty of this study is our emphasis on anthropogenic activities, which extends previous research using the Budyko framework focused on studying non-human modified basins. In the CONUS, Wang and Hejazi (2011) hypothesized about the potential influence of human activities (e.g., dam storage, population density, cropland area) on streamflow changes. Meanwhile, Z. Li

and Quiring (2021b) observed that factors explaining spatial differences in ω differ between human-impacted and non-human-impacted watersheds. Z. Li and Quiring (2021b) found that dam storage and urbanization better represent the spatial heterogeneity of ω in human-impacted watersheds. In this study, the number of dams does not appear to be a significant factor in any of the SMLRs, which may be attributed to the exclusion of regulated watersheds from the analysis. We found that in the climates with the largest sample of watersheds (Cold2 and Temperate2 climates), different anthropogenic activities account for spatial differences in the long-term water balances, as agricultural watersheds concentrate in the Cold2 climate and urban watersheds in the Temperate2 climate. This highlights the importance of climate regions in shaping the effects of land use change on streamflow generation and emphasizes the need to build regional models of ω . Over the period from 1990 to 2020, irrigated agriculture in the Midwest and Central Plains has intensified ET, while urban areas in the Southeast have increased Q.

Water balances in humid watersheds of the Northeast and Midwest and arid watersheds of the Southwest and Great Plains are driven by the synchronization between P and PET (Table 3). Consequently, any shift in the seasonal dynamics of P and PET can greatly impact droughts and freshwater availability in these regions. Agricultural watersheds in the Midwest have benefited from a strong synchronization between P and PET complemented by their capacity to retain soil moisture (Figure 5). However, the region may encounter challenges in the future due to rising warm-season temperatures and the increasing occurrence of more variable and extreme precipitation events (Angel et al., 2018). These shifts in P and PET patterns could lead to excess soil moisture in the spring caused by increased precipitation, followed by insufficient levels during the summer growing season due to elevated temperatures (Wehner et al., 2017). Increased humidity in the spring, resulting in increased rainfall, is also associated with a higher frequency of

flooding events (Angel et al., 2018), posing risks to both the population and agriculture fields (Wing et al., 2018). Concurrently, rising temperatures will lead to an increased vapor pressure deficit, compelling farmers to extend their irrigation areas, which currently rely on rain, to maintain crop productivity since precipitation is not expected to increase at the same rate (DeLucia et al., 2019; Overpeck & Udall, 2020). Szilagyi (2018) found that, in the most extensively irrigated fields in Nebraska, ET rates have increased by 7mm decade⁻¹ from 1979 to 2015 along with a reduction of P. This phenomenon occurred because irrigation resulted in a more stable air stratification over the cooler irrigated crop surfaces, ultimately causing the excess moisture to be dropped somewhere downwind. This study shows that irrigated agriculture explains 7% of the spatial variability in ω in the Midwest (Table 3), with a correlation coefficient of 0.6 (p-value<0.05) (Table S4). Therefore, the anticipated increase in irrigation will further intensify ET under high-temperature days when evaporative demand is the greatest, consequently exacerbating the long-term aridification of these watersheds.

Spatial differences in water balances across the Southeast can be attributed to the watershed's slope and level of urbanization. The Southeast is experiencing significant urbanization, with some of the fastest-growing cities in the USA, particularly in swiftly developing urban centers in Florida, North Carolina, and South Carolina. This region has also experienced an increase in the frequency and intensity of precipitation events, and this trend is projected to persist in the future (Easterling et al., 2017). Urbanization in the Southeast has been linked to processes that amplify intense rainfall events, such as urban heat island dynamics or elevated aerosol production, and it has also led to higher runoff ratios and peak flows (Ashley et al., 2012; O'Driscoll et al., 2010). For instance, Diem et al. (2018) showed a 26% increase in annual streamflow and a rise in runoff ratio from 0.35 to 0.45 due to urbanization in some watersheds in the Atlanta Metropolitan area from 1986

to 2015. C. Li et al. (2020) reported that the southeastern US exhibits a more pronounced hydrological response to urbanization compared to other regions in the CONUS, resulting in a higher water yield due to the expansion of impervious areas and loss in vegetated areas. In this study, we found that in the Southeast, the urban area within the watershed accounts for 11% of the spatial variability in ω between 1990 and 2020 (Table 3), with a correlation coefficient of -0.22 (p-value<0.05) (Table S4).

In the other climate groups, the sample size constrains the range of variability of the controls, thereby limiting the interpretation of the SMLRs. We selected a subset of factors to regress against ω ; however, due to the unknown nature of ω and the broad range of factors that may influence it, we acknowledge that this selection can be somewhat subjective. However, it is important to note that the parameter ω is highly correlated with the selected controls, which are also highly cross-correlated with the other controls in the same category (Figure S1), meaning that they represent similar hydrological processes. Also, the significant relationship between the selected controls and ω indicates that modification of these controls can affect precipitation partitioning. In this analysis, we used ω as a proxy of ET/P to regress against the controls; by doing so, we introduced some uncertainties, especially when a catchment reaches the water and energy limits (Reaver et al., 2022). Nevertheless, employing ω as the dependent variable instead of ET/P enables the identification of controls beyond those exerted by ϕ . While we relied on past studies to assess the closed water balances (i.e., Z. Li & Quiring, 2021a), we recognize a limitation that certain human-affected basins might have undergone alterations in water storage due to groundwater withdrawals. The groundwater depletion is more notable in semiarid to arid watersheds in the western US (Konikow, 2013), but our sample size in this region is relatively small.

4.2. What is the spatial variability in streamflow explained by climate and catchment characteristics in different climate regions?

Our results indicate that arid climates are especially sensitive to changes in the catchment characteristics represented by ω . Specifically, ω explains around half of the spatial variability in the mean annual Q of arid catchments, meanwhile, mean annual P explains less than one-fourth (Table 4). In arid regions, alterations to forest cover or other land-use/land-cover types can result in more significant streamflow changes. Also, past research has found that streamflow is more responsive to land use and vegetation changes in arid regions (Wang & Hejazi, 2011; S. Zhang et al., 2016; Zhou et al., 2015; Bhaskar et al., 2020). For example, vegetation shows higher sensitivity to precipitation in dry regions, leading to an increase in vegetation cover, soil moisture, and changes in water availability (Y. Zhang et al., 2022). It is also important to note that ω encompasses other factors beyond anthropogenic activities, such as changes in topography, soil characteristics, precipitation patterns, and temperature. These factors also influence ω but typically involve longer-term processes (i.e., erosion, climate change) and are considered relatively more stable over time than rapidly changing human-induced activities (i.e., land use changes). To better assess the sensitivity of arid regions to land use changes, future research should investigate a larger number of watersheds affected by diverse land use/land cover alterations (e.g., urban expansion, deforestation). The sample we studied within this region is relatively small, with half of the watersheds categorized as reference or free from human intervention. Cold and Temperate climates, on the other hand, are primarily driven by the mean annual P, although cold climates show slightly higher sensitivity to changes in ω than temperate climates. This finding helps reconcile contradictions in the literature by demonstrating that some climates are more sensitive to changes in catchment characteristics, including land use and land cover changes, than others.

Climate has a significant influence on ω and ET/P ratio in the CONUS, as observed in other intra-regional (Guillén et al., 2021) and global studies (Liu & You, 2021; Padrón et al., 2017). Arid regions exhibit the highest ω values, followed by temperate and cold regions. These findings highlight how climate groups can account for a portion of the spatial variability in ω across the CONUS, although there are broad ranges of ω within groups (Figure 4a). Land use also exerts a significant influence on ω and ET/P ratio in the CONUS. Agricultural watersheds display the highest ω values, while reference watersheds display higher dispersion (Figure 4b). Most of the watersheds (72%) in humid climates (Cold1 and Cold2) and half in temperate climates (Temperate1 and Temperate2) are water-limited and not energy-limited, contradicting commonly held assumptions (Figure 3a). We found that humid watersheds falling within the water-limited spectrum are mainly agricultural and concentrated in the Midwest, whereas water-limited watersheds in the temperate climate are primarily urban and spread across the South. We showed that there are complex interactions between climate factors and agricultural-urban factors that make the effect of land use different across climates. By building regional models of ω , we gained insight into how land use contributes to disparities in water balances within distinct climate regions. Our findings provide valuable insights into the critical factors to consider in the management of regional water resources and inform about the hydrological sensitivities to future climate and land use changes.

CRedit author statement

Sara Alonso Vicario: Conceptualization, Methodology, Software, Formal analysis, Investigation, Data Curation, Visualization, Writing - Original Draft, Writing - Review & Editing. **George M. Hornberger:** Conceptualization, Methodology, Writing - Review & Editing, Supervision. **Maurizio Mazzoleni:** Conceptualization, Methodology, Writing - Review &

554 Editing, Supervision. **Margaret Garcia:** Conceptualization, Methodology, Writing - Review &
555 Editing, Project administration, Resources, Funding acquisition, Supervision.

556 **Competing interests**

557 The authors declare that they have no conflict of interest.

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561 **Data Availability Statement**

562 All data used in the study are freely available for academic research in the public domain. The
563 GAGES-II data set is available from
564 https://water.usgs.gov/GIS/metadata/usgswrd/XML/gagesII_Sept2011.xml. The streamflow data
565 is available from <https://waterdata.usgs.gov/nwis>. The gridMET data set is available from
566 <https://www.climatologylab.org/gridmet.html>. References to other data can be found in the sources
567 cited in Table S2 and Table S3 of the Supplementary material. A list of the gauging stations and
568 the controls used in the SMLR models can be found in Table S5 of the Supplementary material.
569 The values for the remaining controls are available upon request to the corresponding author.

570

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