# On the similarity of hillslope hydrologic function: a clustering approach based on groundwater changes

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## Abstract

Hillslope similarity is an active topic in hydrology because of its importance to improve our understanding of hydrologic processes and enable comparisons and paired studies. In this study, we propose a holistic bottom-up hillslope clustering based on a region's integrative hydrodynamic response quantified by the seasonal changes in groundwater levels ΔP. The main advantage of the ΔP clustering is its ability to capture recharge and discharge processes. We test the performance of the ΔP clustering by comparing it to seven other common hillslope clustering approaches. These include clustering approaches based on the aridity index, topographic wetness index, elevation, land cover, and machine-learning that jointly integrate multiple data. We assess the ability of these clustering approaches to identify and categorize hillslopes with similar static characteristics, hydroclimate, land surface processes, and subsurface dynamics in a mountainous watershed, the East River, located in the headwaters of the Upper Colorado River Basin. The ΔP clustering performs very well in identifying hillslopes with 6 out of the 9 characteristics studied. The variability among clusters as quantified by the coefficient of variation (0.2) is less in the ΔP and the machine learning approaches than in the others (>0.3 for TWI, elevation, and land cover). We further demonstrate the robustness of the ΔP clustering by testing its ability to predict hillslope responses to wet and dry hydrologic conditions, of which it performs well when based on average conditions.

**Keywords:** Hillslope, similarity, seasonal groundwater variations, integrated hydrologic modeling, hillslope clustering, hydrologic function

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# 1. Introduction

The ability to delineate areas into spatially defined regions for their use in characterizing hydrologic flow and transport behavior is important for several reasons, including the assessment, monitoring, and modeling of water quantity and quality. Hillslopes are the scale at which hydrologic flow and transport processes can be tractably and frequently measured. It is also the scale at which flow and travel time are quantified, and the instrumentation, conceptualization, and modeling of hydrologic processes occur (Fan et al., 2019, Wainwright et al., 2022). While advancements have been made in the general understanding of hillslope dynamics over the last several decades, there is yet to be a globally agreed-upon classification and/or clustering for this important scale of interest in hydrology (McDonnell & Woods, 2004). Hydrologic signatures within hillslopes are the results of several simultaneous and nonlinear above- and below-ground processes. The uniqueness of a given location's characteristics (for example, the topography, geology, vegetation, etc.) limits our ability to draw general hypotheses and to develop a similarity framework (Beven, 2000). Nevertheless, a classification is needed to provide guidance on catchments and hillslopes comparisons (McDonnell & Woods, 2004), paired studies (Andréassian et al., 2012; Bosch & Hewlett, 1982; Brown et al., 2005), and improve our understanding of the changes in hydrologic processes across the world. Further, hillslope similarity is potentially an important step toward developing reduced-order models and machine learning algorithms, where identifying regions based on their similarities can substantially reduce computational costs (Chaney et al., 2018). The scaling of hillslope to catchment classifications can also be useful in the prediction of hydrologic behavior in ungauged basins (Sivapalan et al., 2003), an exceedingly important challenge.

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Hillslope similarity clustering approaches include the Topographic Wetness Index TWI (Beven & Kirby, 1979), which was proposed to quantify the topographic control on hydrology as topography plays a key role in the movement of water. Many other variants of this index have been later proposed to improve the definition of topographic similarity (Grabs et al., 2009; Hjerdt et al., 2004; Loritz et al., 2019). Other clustering approaches are based on hydroclimate (Carrillo et al., 2011), soil type and texture (Bormann, 2010), and land cover type (e.g., forest, urban, etc. (Wagener et al., 2007)). These indices assume that hillslopes with similar topography and land cover will have similar hydrologic responses. However, given that hydrologic processes are governed by many characteristics of the hillslope, clustering approaches relying on multiple landscape characteristics have also been proposed (Aryal et al., 2002; Sawicz et al., 2011). These top-down clustering approaches assume that areas with similar physical characteristics will lead to similar hydrologic processes (Oudin et al., 2010). Other clustering approaches use a bottom-up approach, where similarity is based on the hydrologic process. This clustering allows the estimation of the "hidden" hillslope characteristics such as soil texture, and geology that may drive similar hydrologic responses (Carrillo et al., 2011). Among the process-based clustering approaches existing in the literature we can cite: the Péclet number characterizing the diffusive and advective transfer of water at hillslope scale (Berne et al., 2005; S. W. Lyon & Troch, 2007; Steve W. Lyon & Troch, 2010) and the catchment seasonal water balance (Berghuijs et al., 2014). Other authors have derived hillslope similarities from subsurface flow dynamics (Harman & Sivapalan, 2009).

One challenge in developing a similarity framework is the inherent heterogeneity of a given hillslope. For example, Snow Water Equivalent (SWE), infiltration (I) and actual evapotranspiration (ET) distributions can range over an order of magnitude within a single

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**Deleted:** can vary up to 300 mm; similarly, infiltration (I) and actual evapotranspiration (ET) rates hillslope (Wainwright et al., 2022). Defining a single integrative measure that can capture this spatio-temporal variability is difficult. However, groundwater fluctuations are often tightly linked to seasonal changes in climate and have been shown to play an important role in surficial processes such as ET (Maina et al., 2022; Maina & Siirila-Woodburn, 2020; Maxwell & Condon, 2016). Thus, groundwater measures may serve as a good proxy for the aggregated hydrologic response. Groundwater dynamics could help overcome the issue of uniqueness of place because even if there are strong differences in the characteristics of the hillslope, the integrated response may be similar as some of the processes might not be important. Finally, the implications of groundwater changes are also important. For example, many regions are characterized by groundwater-dependent ecosystems or are hypothesized to have water table fluctuations affecting bedrock weathering rates and therefore the concentration and fluxes of metals and nutrients exports (e.g., Winnick et al., 2017).

In this study, we define a holistic bottom-up hillslope clustering using the integrative hydrologic response quantified by the seasonal changes in groundwater levels. A caveat to this clustering is that groundwater dynamics are difficult to quantify, and their measurements are frequently scarce. Hence, there are very few studies that use this variable to develop a hillslope similarity classification (Aryal et al., 2002; S. W. Lyon & Troch, 2007). However, today, thanks to advances in integrated hydrologic modeling (Brunner & Simmons, 2012; Maxwell & Miller, 2005), accurate quantification of the groundwater dynamics at high resolution in both time and space, as well as their interaction with the key land surface processes and features, is now feasible. These models (e.g., HydroGeoSphere (Brunner and Simmons, 2012), ParFlow (Maxwell & Miller, 2005), Advanced Terrestrial Simulator, (Coon et al., 2016)) that can be constrained with ground observations and measurements at ultra-high resolutions through aerial or remote sensing (i.e.,

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drones, planes, or satellites) account for the two-way interactions between groundwater and land surface processes. Spatially resolved hydrologic flow models also enable us to jointly quantify other hydrologic variables useful to identify hillslope with similar hydrologic responses, namely trends in ET, SWE, and I. Nevertheless, we acknowledge that groundwater dynamics in some regions such as arid areas could be disconnected to land surface processes and less dependent to many key physical features of the hillslope, which may impede the ability of the proposed clustering in these regions.

We test the proposed hillslope clustering on the site of the Department of Energy's (DOE) Watershed Function Scientific Focus Area (SFA) located in the headwaters of the Upper Colorado River Basin. The East River watershed is not only representative of many headwater catchments in the western United States in terms of its spatial heterogeneity of above and below-ground characteristics but also serves as an important proxy of water quantity and quality trends which ultimately impact a large population of water supply in the western United States for municipal, agriculture, and industrial use (Hubbard et al., 2018). We test the robustness of the proposed hillslope clustering by comparing it to seven other common hillslope clustering approaches based on the aridity index (AI), TWI, elevation, land cover and more sophisticated machine-learning approaches that jointly integrate multiple input data layers such as elevation, land cover, and geology, and model outputs including ET, and SWE. We assess the ability of these clustering approaches to identify and categorize hillslopes with similar physical characteristics (land cover and elevation), hydroclimate (precipitation and temperature), land surface processes (ET and SWE), subsurface dynamics (soil saturation, water table depth WTD, and seasonal changes in groundwater). We aim to provide answers to the following questions:

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- What are the best clustering approaches for identifying hillslopes with similar hydrologic processes?
- Is a similarity index based on the seasonal groundwater variations sufficient to capture all the complex processes taking place at a hillslope scale?

# 2. Methodology

## 2.1. Modeling framework

### 2.1.1. Selected integrated hydrologic model: ParFlow-CLM

We use the integrated hydrologic model, ParFlow, which has the advantages of simulating the water and energy balance from the bedrock to the lower atmosphere and therefore connect groundwater dynamics with land surface processes. ParFlow solves the subsurface flow using the three-dimensional mixed form of the Richards equation (Richards, 1931) given by the following equation:

$$S_S S_W(\psi_P)\frac{\partial \psi_P}{\partial t} + \phi \frac{\partial S_W(\psi_P)}{\partial t} = \nabla.[K(x)k_r(\psi_P)\nabla(\psi_P - z)] + q_s \quad (1)$$

Where is $S_S$ the specific storage [$L^{-1}$], $S_W(\psi_P)$ is the degree of saturation [-] associated with the subsurface pressure head $\psi_P$ [L], $t$ is the time [T], $\phi$ is the porosity [-], $k_r$ is the relative permeability [-], z is the depth [L], $q_s$ is the source/sink term [$T^{-1}$] and $K(x)$ is the saturated hydraulic conductivity [L $T^{-1}$] which is assumed to be a diagonal tensor with entries given as: $k_x(x)$, $k_y(x)$ and $k_z(x)$. We assumed in this work that the domain is isotropic, and that the tensor is equal to 1 for all the three directions at each cell of the discretized model. In the unsaturated zone, both $S_W$ and $k_r$ depend on the $\psi$. The relationships between $S_W$ and $k_r$ and $\psi$ are described by the van Genuchten model (van Genuchten, 1980).

Overland flow (equation 2) is solved by the kinematic wave equation in two dimensions.

$$-k(x)k_r(\psi_0)\nabla(\psi_0 - z) = \frac{\partial\|\psi_0, 0\|}{\partial t} - \nabla.v\|\psi_0, 0\| - q_r(x) \quad (2)$$

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Where $\psi_0$ is the ponding depth, $\|\psi_0, 0\|$ indicates the greater term between $\psi_0$ and 0, $v$ is the depth averaged velocity vector of surface runoff [L T$^{-1}$], $q_r$ is a source/sink term representing rainfall and evaporative fluxes [L T$^{-1}$]. Surface water velocity at the surface in *x* and *y* directions, $(v_x)$ and $(v_y)$ respectively, is computed using the following set of equations:

$$v_x = \frac{\sqrt{S_{f,x}}}{m}\psi_0^{\frac{2}{3}} \text{ and } \; v_y = \frac{\sqrt{S_{f,y}}}{m}\psi_0^{\frac{2}{3}} \qquad (3)$$

Where $S_{f,x}$ and $S_{f,y}$ friction slopes along *x* and *y* respectively and $m$ is the manning's coefficient. ParFlow employs a cell-centered finite difference scheme along with an implicit backward Euler scheme and the Newton Krylow linearization method to solve these nonlinear equations. The computational grid follows the terrain to mimic the slope of the domain (Maxwell, 2013).

ParFlow is coupled to the Community Land Model (CLM, (Dai et al., 2003)) which allows for the simulation of important land surface processes such as ET and SWE and the quantification of water leaving or entering the surface and subsurface ($q_s$ and $q_r$ respectively in the Richards and kinematic wave equations). CLM models the thermal processes by closing the energy balance at the land surface given by:

$$R_n(\theta) = LE(\theta) + H(\theta) + G(\theta) \qquad (4)$$

Where $R_n$ is the net radiation at the land surface [E/LT] a balance between the shortwave and longwave radiation, $LE$ is the latent heat flux [E/LT] which captures the energy required to change the phase of water to or from vapor, *H* is the sensible heat flux [E/LT] and *G* is the ground heat flux [E/LT]. All terms are a function of $\theta$, the water content, which is computed by ParFlow.

Computing the different components of the energy balance requires meteorological forcing, vegetative parameters, and soil moisture. The latter is computed by ParFlow using equations 1 and 2. Meteorological forcing includes precipitation, temperature, east to west and north to south wind speed, longwave and shortwave solar radiation, air pressure, and relative humidity. Vegetative parameters include maximum and minimum leaf area index, stem area index, aerodynamic roughness height, optical properties, stomatal physiology, roughness length, and displacement height. More details about the coupling between ParFlow and CLM as well as the equations governing the snow dynamics and *ET* can be found in the following papers: Jefferson et al., (2015); Maxwell & Miller, (2005); Ryken et al., (2020). ParFlow-CLM has been used in many studies to understand the interactions between groundwater dynamics and lower atmosphere (Maina et al., 2022; Maina and Siirila-Woodburn, 2020) at different scales from watershed (Foster and Maxwell, 2019; Maina et al., 2020) to continental scale (Maxwell and Condon, 2016).

### 2.1.2. East River watershed model set-up

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The East River watershed (Figure 1), located in the Upper Colorado Basin, is one of the two major tributaries that form the Gunnison River, which in turn accounts for just under half of the Colorado River's discharge at the Colorado-Utah border. The total area of this watershed is approximately 255 km$^2$ and the elevation varies from approximately 2700 to 3900 m. The watershed is characterized by strong heterogeneities in vegetation, geomorphology, and bedrock composition (Hubbard et al., 2018). The vegetation includes grasses, conifers, mixed conifers, aspens, and meadows and lies on a complex geologic terrain, which is comprised of a diverse collection of Paleozoic and Mesozoic sedimentary and unconsolidated rocks. The watershed is also characterized by a strong hydroclimate gradient. The average precipitation is 1200 mm/year while the average temperature is around 0°C. Because of its very low cold winter with temperature below 0°C, most of the winter precipitation is in the form of snow.

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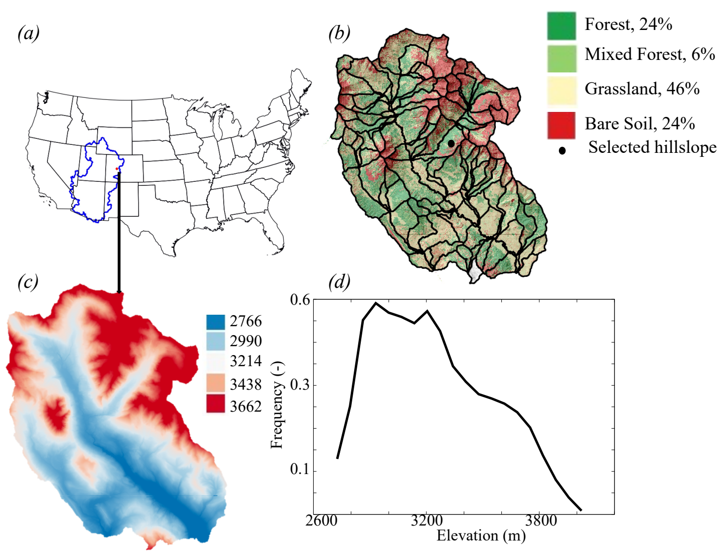


Figure 1: (a) location of the East River watershed, (b) land cover (NEON dataset, 2020), (c) LiDAR Digital elevation, and (d) elevation distribution within the East River.

ParFlow-CLM used here is based on a previous version of the East River watershed model, as described by Foster and Maxwell (2019). 5 layers constitute the model in the vertical direction with varying thickness from 0.1 m at the land surface to 21 m at the bottom of the domain. The land use and land cover are derived from the high-resolution airborne remote sensing NEON campaign (Chadwick, et al., 2020; Falco, et al., 2019; Goutlten, et al., 2020). From the hyperspectral spectrometer and LiDAR readings, 4 major types of land cover are grouped as follows: forests (i.e., conifers and aspens), mixed forests, grasses, and bare soil. Parameterization of these different land cover types is derived from the IGBP database (IGBP, 2018).

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The subsurface of the study area is heterogeneous in both vertical and horizontal directions. The subsurface of the top 1 m corresponds to three soil layers as defined by the SSURGO database and then corrected based on the land cover and geologic maps to include the outcropping of the bedrock. Two main types of soil are distinguished within the area: sandy loam and clay loam. The geology of the subsurface between 1 m and 8 m below the ground was defined with USGS maps, which were further improved by local knowledge by Pribulick et al., (2016). This subsurface region is highly heterogeneous with different formations such as crystalline, sedimentary rocks, unconsolidated rocks, alluvial deposits, and debris flow. The bottom layer of the domain (extending from 8 m below the ground surface to the bottom of the model) is assumed homogeneous and represents the fractured bedrock.

We simulated the water year (WY) 2015, a relatively average WY in the region based on average precipitation and temperature patterns. The meteorological forcing of the model has a resolution of an hour and is derived from two gridded datasets: PRISM and NLDAS. The PRISM dataset (Daly et al., 2008) is used for precipitation and temperature because of its accuracy and high spatial resolution (800m). However, the daily resolution of PRISM impedes its ability to be used to reproduce diurnal cycles, an important factor when studying land surface processes requiring hourly forcing. The phase 2 of the North America Land Data Assimilation System NLDAS-2 forcing (Cosgrove et al., 2003) on the contrary provides hourly changes in precipitation and temperature yet are only available at coarser, 1/8 degree, resolutions. As such, we employ a mass-conservative temporal interpolation, which disaggregates the total daily PRISM precipitation into an hourly time series based on the signal of the NLDAS-2 precipitation and temperature trends. For the other forcing variables (i.e., shortwave and longwave radiation, wind speed, atmospheric pressure, and specific humidity), we use NLDAS-2 forcing, (Cosgrove et al., 2003). Simulated river stages and SWE were compared to observations in previous studies (Maina et al., 2022; Foster and Maxwell, 2019). Groundwater measurements are scarce in the watershed and the

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majority of the measurements are performed near a station measuring changes in river stages. Therefore, river stages and groundwater measurements at this point provide similar information.

## 2.2. Hillslopes delineation

As shown in Figure 1b, 127 hillslopes are delineated in the East River watershed based on the elevation following (Noël et al., 2014) and using Topotoolbox developed by (Schwanghart & Scherler, 2014). A threshold of flow accumulation was set to match the stream observations at major tributaries of the East River (Carroll et al., 2018). Because the hillslope delineation could be sensitive to the threshold of the drainage area, we tested different threshold values to find that the selected threshold value (810,000 $m^2$) represents the scale of hillslope at which the within-hillslope variability of key properties (such as elevation and aspect) is minimized and hillslope-averaged properties can account for the majority of watershed-scale variability (Wainwright et al., 2022).

## 2.3. Hillslopes clustering approaches

We use eight hillslope clustering approaches:

1. The $\Delta P_1$ clustering, proposed in this study, identifies hillslopes with similar groundwater dynamics. Figure 2 shows the temporal variations of the simulated SWE and WTD at a selected hillslope (see its location in Figure 1). All hydrologic variables have been computed at a hillslope scale by computing the arithmetic average of all cells in each hillslope. In this mountainous watershed, where the largest changes in WTD are mostly a result of snowmelt, WTD decreases from the beginning of the WY (i.e., October) to the beginning of snowmelt (i.e., starting from April). As the snow starts to melt and precipitation starts to fall as rain instead of snow, WTD starts to rise. The shallowest WTD is June and July when the snow has completely melted and has had time to percolate

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The dynamics show two periods characterize the dynamics of the hillslope: from the initial conditions to the baseflow conditions when the hillslope is losing water, then from baseflow conditions to the peak of WTD when the hillslope is gaining water. To characterize these groundwater dynamics, we define two variables:

- $\Delta P_1$ represents the change in WTD between the beginning of the water year and the deepest WTD during the baseflow conditions. This variable quantifies the amount of water released by the hillslope during the dry period at the beginning of the water year. It thus contains information about the amount of water that the hillslope typically releases/loses, mainly by ET and discharge, given its physical characteristics and climate dynamics.
- $\Delta P_2$ represents the changes in WTD between the peak flow (i.e., the period with the shallowest WTD) and the baseflow conditions. ΔP2 quantifies the amount of water gained in the hillslope by recharge, and thus contains information about the recharge ability of the hillslope given its physical characteristics and climate dynamics.

These two key variables allow us to quantify water release ($\Delta P_1$) and recharge ($\Delta P_2$) within a hillslope, two key dynamics of the watershed hydrologic function (Sivapalan, 2006; Wagener et al., 2007, Wainwright et al., 2022). We note that these dynamics are also illustrated by the changes in measured groundwater levels as depicted in Appendix A.

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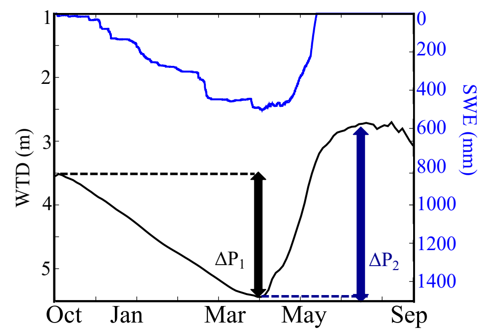


Figure 2: Temporal variations of water table depth (WTD) and SWE at an example hillslope. The location of the hillslope is shown in Figure 1.

2. Elevation: in mountainous watersheds, because the differences in hydroclimate are primarily driven by elevation, hillslopes with similar elevations could potentially have similar land surface processes signatures.
3. Land cover: hillslopes can also be clustered by their dominant land cover. Land cover shapes land surface processes, which in turn affect subsurface dynamics and the water balance at the hillslope scale.
4. TWI: The Topographic Wetness index commonly used to cluster hillslopes is given by: $ln\left(\frac{\alpha}{tan(\beta)}\right)$. Where $\alpha$ is the upslope draining area and $\beta$ the local angle.
5. AI: the AI (ETP/Precipitation, where ETP is the potential evapotranspiration) represents the ratio of the average demand for moisture to the average supply of moisture. We derive the spatial distribution of the AI in the East River from the Global Aridity Index dataset (CGIAR-CSI, 2019).
6. Clustering: we define the hillslope similarity using the clustering of ParFlow-CLM input and output data layers. Clustering was performed in three different ways, using the

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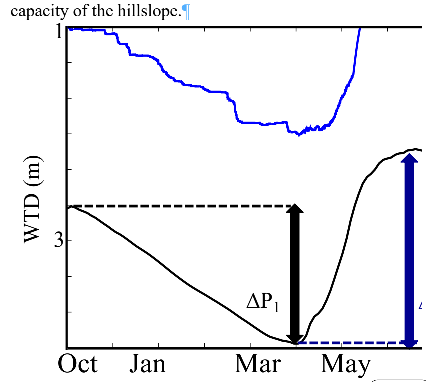
ΔP2 quantifies the changes in groundwater levels between the peak flow (i.e. the period with the shallowest water table depth) and the baseflow conditions and hence contains information about the storage and the recharge capacity of the hillslope.¶

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following data: (1) model input (elevation, percentage of the main land cover type, TWI, and AI), referred to hereafter as the "clustering input" (C.I.) method, (2) model output (ET, SWE, WTD, and $\Delta P_1$), referred to hereafter as the "clustering output" (C.O.) method, and (3) both model input and output data layers, referred to hereafter as the "clustering input-output" (C.I.O.) method. We use hierarchical clustering, which is a decision-tree-based method that divides data points based on a series of binary splits (Devadoss et al., 2020; Kassambara, 2017; Wainwright et al., 2022). We define the linkage (or the distance) between any two clusters based on the Euclidian distance and the Ward method that computes the variance within each cluster, measuring the distance between each observation and the cluster's mean, and then taking the sum of the distances' squares.

## 2.4. Hillslope clustering comparisons

To test the ability of the eight selected clustering approaches to identify and categorize hillslopes with similar static characteristics and dynamics, we assess each clustering's ability to describe several characteristics of the hillslope: elevation, land cover, hydroclimate (i.e., precipitation), land surface processes (SWE and ET), and subsurface dynamics (WTD values and variations). For each clustering, we define three zones. For each variable, zone, and clustering, we compute the mean ($\mu$) of the hillslope values and the corresponding coefficient of variation (CV). We also calculate the mean of the CV of the different zones for each variable and clustering.

# 3. Results

## 3.1. Hillslope characteristics

Figure 3 shows the spatial distribution of hillslope temperature, precipitation, SWE, ET, WTD, and $\Delta P_1$.

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**Moved (insertion) [2]**

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**Deleted:** These include a spectrum of datasets varying from those which are widely available (e.g. LULC and elevation) to those which are time-variant (e.g. hydroclimatic data such as temperature and precipitation), and modeled descriptions (e.g. water and energy fluxes).

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**Deleted:** This allows us to determine the classification scheme that categorizes zones with the least variability, an important metric that provides a degree of performance for the method's ability to delineate zones.

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**Moved up [1]:** As shown in Figure 1b, 127 hillslopes are delineated in the East River watershed based on the elevation following (Noël et al., 2014) and using Topotoolbox developed by (Schwanghart & Scherler, 2014). A threshold of flow accumulation was set to match the stream observations at major tributaries of the East River (Carroll et al., 2018). Because the hillslope delineation could be sensitive to the threshold of the drainage area, we tested different threshold values to find that the selected threshold value represents the scale of hillslope at which the within-hillslope variability of key properties (such as

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**Moved down [3]:** As expected, the hillslopes

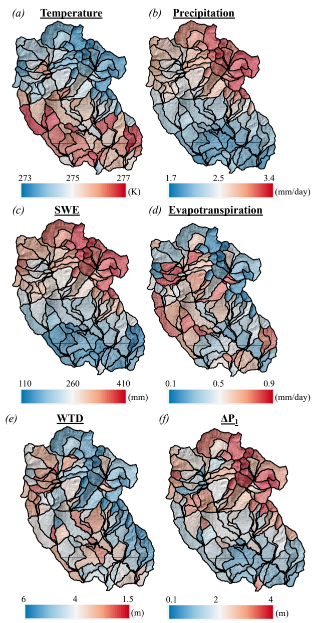


Figure 3: Spatial distributions of hillslope annual average values of (a) temperature, (b) precipitation, (c) snow water equivalent (SWE), (d) evapotranspiration, (e) water table depth (WTD) and (e) $\Delta P_1$

As expected, the hillslopes characterized by high SWE have high precipitation and low temperatures in contrast to the hillslopes with low SWE. However, ET shows a different pattern, because it depends on both water availability and ET demands, which depends on the type of land cover. The mid-elevation zone (i.e., zone 2) with a high coverage of forests has high ET. Hillslope with high $\Delta P_1$ have a deep WTD on average, this is because the WTD increases significantly during baseflow conditions and reaches very large values as quantified by $\Delta P_1$. Hillslopes with high $\Delta P_1$ values generally correspond to hillslopes with high precipitation and low temperature and therefore high SWE values.

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The spatial variability in $\Delta P_1$ and annual average Water Table Depth (WTD) across different hillslopes are also depicted in Figure 3. These two patterns are different from each other, and they are also different from the ones associated with the land surface processes which eventually control the recharge and release of water (SWE and ET). Nevertheless, the spatial distributions of WTD and $\Delta P_1$ provide complementary information, with areas with high $\Delta P_1$ having low WTD because the strong changes in groundwater levels, as

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**Deleted:** We also note that the variabilities of these variables within hillslopes are smaller than the ones across hillslopes, which is consistent with Wainwright et al. (2021).

To better understand the relationship between $\Delta P_1$ and the hillslope physical characteristics and hydrologic processes, we study the Pearson correlation coefficient between $\Delta P_1$ and the elevation, the percent of the dominant land cover, TWI, AI, ET, SWE, and WTD (Figure 4).

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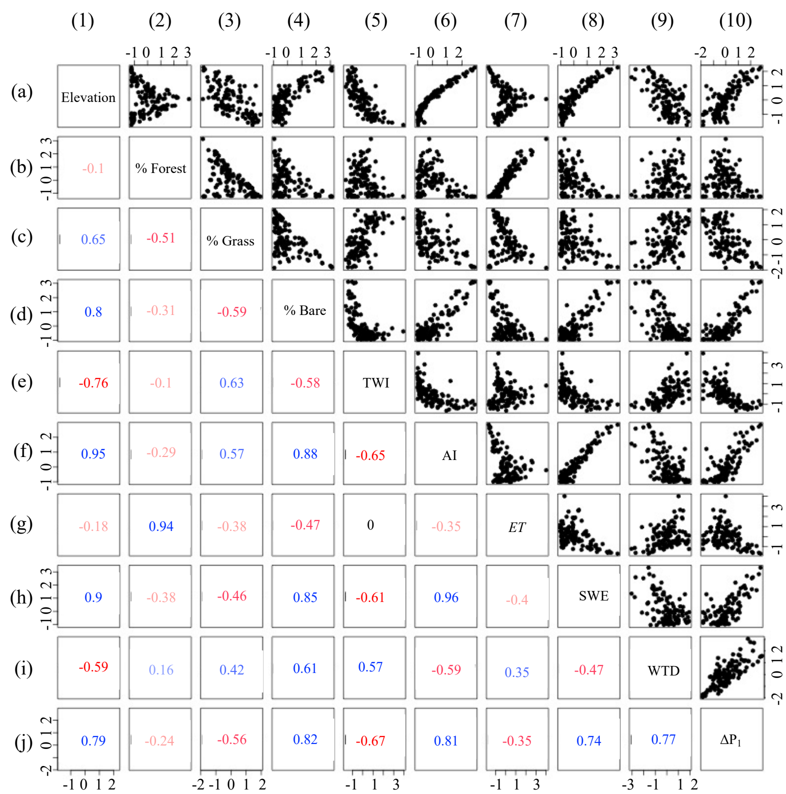


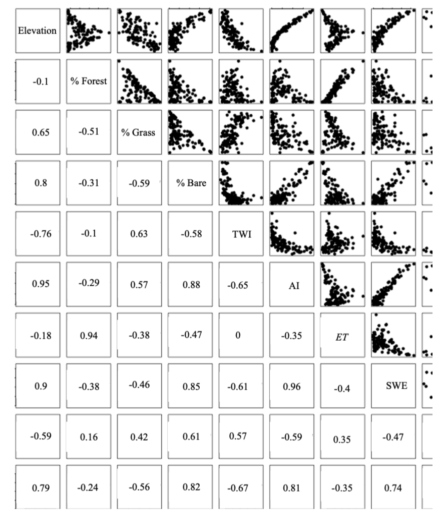


Figure 4: Pearson's correlations between the selected variables for hillslope clustering approaches: elevation, percent of the main land cover type (forest, grassland, and bare soil), topographic wetness index (TWI), aridity index (AI), evapotranspiration (ET), snow water equivalent (SWE), water table depth (WTD), and seasonal changes in groundwater $\Delta P_1$. Note that correlation coefficients are colored coded based on their values.

**Deleted:** similarity classifications

Results for $\Delta P_2$ are not shown because $\Delta P_2$ is strongly correlated to $\Delta P_1$. Bare soil, TWI, AI, SWE, and $\Delta P_1$ are strongly correlated (we define this as Pearson's correlation coefficient higher than 0.7) with elevation (Figure 4, column 1, lines d, e, f, h, and j). In particular, elevation has a dominant control on AI and SWE with a Pearson's correlation coefficient higher than 0.9. We observe nonlinearity such that TWI increases in the lower elevation and that AI becomes constant at the lower elevation. High percentage of forests is only found in mid-elevation (Figure 4, 2a) whereas high percentage of grassland is well correlated to low elevations (Figure 4, 3a). ET is strongly correlated to the percent of forests (Pearson's correlation coefficient is higher than 0.9, Figure 4 2g). $\Delta P_1$ has a Pearson's correlation coefficient higher than 0.7 for 6 out of 9 studied variables (elevation, percent of bare soil, TWI (correlation coefficient equal to 0.67), AI, SWE, and WTD, Figure 4, line j, columns 1, 4, 5, 6, 8 and 9); it, therefore, indicates that changes $\Delta P_1$ can reflect the changes of these variables. The two variables with low correlations with $\Delta P_1$ are ET and the percent of forests (Figure 4, line j, column 2 and 7). ET is related to groundwater dynamics in a nonlinear way (Condon et al., 2013; Ferguson & Maxwell, 2010; Rahman et al., 2016). As shown in these studies, regions with shallow WTDs have the highest ET fluxes and this flux typically decreases significantly with WTD. When WTD reaches a critical depth, the groundwater and the atmosphere disconnect and changes in WTD do not impact ET.

## 3.2. Similar hillslopes identification

For each clustering, we identify three zones (Figure 5). For the $\Delta P_1$, elevation, TWI, and AI clustering approaches, we define the thresholds of each zone by analyzing the distributions of the hillslope values of these indices.

**Deleted:** Results for $\Delta P_2$ are not shown because it is strongly correlated to $\Delta P_1$ and the two variables provide the same information. TWI, AI, SWE, WTD, and $\Delta P_1$ are significantly correlated with elevation. In particular, elevation has a dominant control on AI and SWE with a correlation coefficient higher than 0.9. We observe nonlinearity such that TWI increases in the lower elevation and that AI becomes constant at the lower elevation. The percentage of forest cover has a quadratic relationship with elevation. A high correlation between the percent of forests and the elevation is found in the mid-elevation whereas grassland shows a high correlation in low and high elevations. ET is well correlated to the percent of forests, where hillslopes with high ET have a high percent of forests. $\Delta P_1$ is, in general, well correlated to all these variables; it, therefore, indicates that the selected variable contains valuable information about these variables. Specifically, $\Delta P_1$ shows a high correlation with SWE, elevation, AI, and WTD with a Pearson correlation coefficient greater than 0.7. Changes in groundwater levels in this mountainous watershed are mostly controlled by the snow dynamics. The two variables with low correlations with $\Delta P_1$ are the ET (-0.35) and the percent of forests (-0.24). ET is related to groundwater dynamics in a nonlinear way (Condon et al., 2013; Ferguson & Maxwell, 2010; Maina et al., 2022; Rahman et al., 2016). Regions with shallow WTDs have the highest ET fluxes and this flux typically decreases exponentially with the depth, where after a certain threshold a disconnection between the groundwater and the atmosphere occurs, and changes in WTD do not impact ET.

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1. $\Delta P_1$: Zone 1 comprises hillslopes whose $\Delta P_1$ are less than 1.5 m, $\Delta P_1$ of hillslopes of zone 2 are comprised between 1.5 m and 2.5 m, and Zone 3 group all hillslopes with $\Delta P_1$ greater than 2.5 m.

1. Elevation: Zone 1 characterizes low elevation areas (average hillslope elevation less than 3000 m), Zone 2 mid (average hillslope elevation comprises between 3000 m and 3500 m), and Zone 3 high elevation (hillslope with an average elevation greater than 3500 m).

3. Land Cover: Zone 1 describes hillslopes that have predominantly grasses as land cover, Zone 2 for hillslopes with more than 50% of forest, and Zone 3 for hillslopes where bare soil is the dominant land cover.

4. TWI: We define 3 zones with high (TWI>1, Zone 1), mid (TWI comprises between 1 and 0.2 Zone 2), and low (TWI<0.2, Zone 3) TWI.

5. AI: Zone 1 comprises hillslopes with AI less than 0.45, Zone 2 describes hillslopes with AI between 0.45 and 0.55, and hillslopes of Zone 3 have an AI greater than 0.55.

6. Clustering: the approaches automatically regroup the similar hillslopes into three zones.

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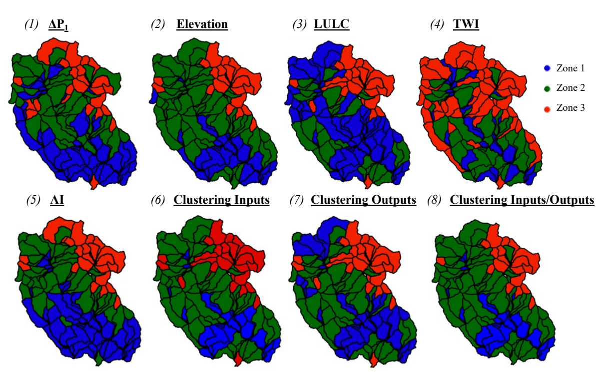


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Figure 5: Spatial distribution of hillslope zones derived from the eight selected clustering approaches (1) $\Delta P_1$, (2) elevation, (3) land cover (LULC), (4) topographic wetness index (TWI),

(5) aridity index (AI), and clustering with (6) inputs, (7) outputs, and (8) inputs and outputs variables.

## 3.3. Comparisons of the eight selected hillslope clustering approaches

Table 1 depicts the mean ($\mu$) and the corresponding coefficient of variation (CV) of hillslope values for each variable, zone, and clustering.

**Variable: Elevation**

| $\Delta P_1$ | Elevation | LULC | TWI |
|---|---|---|---|
| Zone 1: μ=3027 ; CV=0.25 | Zone 1: μ=2884 ; CV=0.02 | Zone 1: μ=3099 ; CV=0.06 | Zone 1: μ=2853 ; CV=0.25 |
| Zone 2: μ=3226 ; CV=0.06 | Zone 2: μ=3233 ; CV=0.06 | Zone 2: μ=3065 ; CV=0.16 | Zone 2: μ=2637 ; CV=0.41 |
| Zone 3: μ=3593 ; CV=0.04 | Zone 3: μ=3641 ; CV=0.04 | Zone 3: μ=3595 ; CV=0.04 | Zone 3: μ=1999 ; CV=0.84 |

| AI | Clustering Input | Clustering Output | Clustering I. O. |
|---|---|---|---|
| Zone 1: μ=2947 ; CV=0.03 | Zone 1: μ=3202 ; CV=0.04 | Zone 1: μ=3029 ; CV=0.07 | Zone 1: μ=3232 ; CV=0.049 |
| Zone 2: μ=3285 ; CV=0.03 | Zone 2: μ=2903 ; CV=0.03 | Zone 2: μ=3175 ; CV=0.04 | Zone 2: μ=2904 ; CV=0.034 |
| Zone 3: μ=3625 ; CV=0.03 | Zone 3: μ=3592 ; CV=0.03 | Zone 3: μ=3605 ; CV=0.03 | Zone 3: μ=3658 ; CV=0.025 |

**Variable: Precipitation**

| $\Delta P_1$ | Elevation | LULC | TWI |
|---|---|---|---|
| Zone 1: μ=2.24 ; CV=0.21 | Zone 1: μ=2.11 ; CV=0.22 | Zone 1: μ=2.42 ; CV=0.22 | Zone 1: μ=2.38 ; CV=0.23 |
| Zone 2: μ=2.68 ; CV=0.18 | Zone 2: μ=2.77 ; CV=0.22 | Zone 2: μ=2.39 ; CV=0.20 | Zone 2: μ=2.37 ; CV=0.22 |
| Zone 3: μ=3.26 ; CV=0.15 | Zone 3: μ=3.55 ; CV=0.09 | Zone 3: μ=3.26 ; CV=0.16 | Zone 3: μ=2.74 ; CV=0.23 |

| AI | Clustering Input | Clustering Output | Clustering I. O. |
|---|---|---|---|
| Zone 1: μ=2.10 ; CV=0.15 | Zone 1: μ=2.68 ; CV=0.18 | Zone 1: μ=2.33 ; CV=0.22 | Zone 1: μ=2.73 ; CV=0.18 |
| Zone 2: μ=2.74 ; CV=0.17 | Zone 2: μ=2.06 ; CV=0.16 | Zone 2: μ=2.63 ; CV=0.18 | Zone 2: μ=2.07 ; CV=0.17 |
| Zone 3: μ=3.39 ; CV=0.12 | Zone 3: μ=3.41 ; CV=0.11 | Zone 3: μ=3.43 ; CV=0.11 | Zone 3: μ=3.56 ; CV=0.06 |

**Variable: Temperature**

| $\Delta P_1$ | Elevation | LULC | TWI |
|---|---|---|---|
| Zone 1: μ=276.5 ; CV=0.001 | Zone 1: μ=276.2 ; CV=0.003 | Zone 1: μ=276.1 ; CV=0.002 | Zone 1: μ=276.3 ; CV=0.001 |
| Zone 2: μ=275.9 ; CV=0.002 | Zone 2: μ=276.0 ; CV=0.003 | Zone 2: μ=276.4 ; CV=0.001 | Zone 2: μ=276.2 ; CV=0.002 |
| Zone 3: μ=274.5 ; CV=0.002 | Zone 3: μ=274.1 ; CV=0.002 | Zone 3: μ=274.4 ; CV=0.002 | Zone 3: μ=275.6 ; CV=0.003 |

| AI | Clustering Input | Clustering Output | Clustering I. O. |
|---|---|---|---|
| Zone 1: μ=276.6 ; CV=0.001 | Zone 1: μ=276.2 ; CV=0.002 | Zone 1: μ=276.2 ; CV=0.002 | Zone 1: μ=276.1 ; CV=0.002 |
| Zone 2: μ=275.8 ; CV=0.002 | Zone 2: μ=276.5 ; CV=0.001 | Zone 2: μ=276.3 ; CV=0.002 | Zone 2: μ=276.5 ; CV=0.001 |
| Zone 3: μ=274.3 ; CV=0.002 | Zone 3: μ=274.4 ; CV=0.003 | Zone 3: μ=274.3 ; CV=0.002 | Zone 3: μ=274.1 ; CV=0.002 |

**Variable: SWE**



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**Moved up [2]:** To test the ability of the eight selected classifications to identify and categorize hillslopes with similar static characteristics and hydrologic functions, we assess each method's ability to describe several characteristics of the hillslope. These include a spectrum of datasets varying from those which are widely available (e.g. LULC and elevation) to those which are time-variant (e.g. hydroclimatic data such as temperature and precipitation), and modeled descriptions (e.g. water and energy fluxes). For each variable, zone, and classification scheme, we compute the mean ($\mu$) of the hillslope values and the corresponding coefficient of variation (CV), see Table 1. We also calculate the mean of the CV of the different zones for each variable and classification scheme. This allows us to determine the classification scheme that categorizes zones with the least variability, an important metric that provides a degree of performance for the method's ability to delineate zones. ¶

**Deleted:** We examine eight different hillslope classifications using the variables listed below. For each method, three functional zones are delineated (see Figure 5). Except for the clustering approaches, grouping was made based on the manual selection of natural grouping in the probability density function.¶

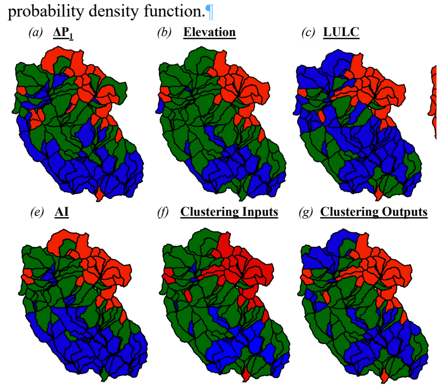


Figure 5: Hillslope zonations based on (a) $\Delta P_1$, (b) elevation, (c) land cover (LULC), (d) topographic wetness index (TWI), (e) aridity index (AI), and clustering with (f) inputs, (g) outputs, and (h) inputs and outputs variables.¶

¶

$\Delta P_1$: a preliminary analysis of the seasonal changes in groundwater levels allows distinguishing three main hillslope categories with similar $\Delta P_1$. Zone 1 comprises hillslopes whose $\Delta P_1$ are less than 1.5 m, $\Delta P_1$ of hillslopes of zone 2 are comprised between 1.5 m and 2.5 m, and Zone 3 group all hillslopes with $\Delta P_1$ greater than 2.5 m.¶ ... [4]

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| $\Delta P_1$ | Elevation | LULC | TWI |
|---|---|---|---|
| Zone 1: μ=152 ; CV=0.30 | Zone 1: μ=149 ; CV=0.38 | Zone 1: μ=181 ; CV=0.34 | Zone 1: μ=169 ; CV=0.50 |
| Zone 2: μ=204 ; CV=0.34 | Zone 2: μ=201 ; CV=0.43 | Zone 2: μ=151 ; CV=0.29 | Zone 2: μ=165 ; CV=0.39 |
| Zone 3: μ=335 ; CV=0.31 | Zone 3: μ=389 ; CV=0.26 | Zone 3: μ=339 ; CV=0.29 | Zone 3: μ=234 ; CV=0.46 |

| AI | Clustering Input | Clustering Output | Clustering I. O. |
|---|---|---|---|
| Zone 1: μ=137 ; CV=0.18 | Zone 1: μ=191 ; CV=0.32 | Zone 1: μ=173 ; CV=0.34 | Zone 1: μ=200 ; CV=0.33 |
| Zone 2: μ=206 ; CV=0.25 | Zone 2: μ=145 ; CV=0.17 | Zone 2: μ=179 ; CV=0.30 | Zone 2: μ=146 ; CV=0.20 |
| Zone 3: μ=360 ; CV=0.24 | Zone 3: μ=359 ; CV=0.25 | Zone 3: μ=365 ; CV=0.23 | Zone 3: μ=396 ; CV=0.18 |

***Variable: ET***

| $\Delta P_1$ | Elevation | LULC | TWI |
|---|---|---|---|
| Zone 1: μ=0.42 ; CV=0.47 | Zone 1: μ=0.35 ; CV=0.75 | Zone 1: μ=0.31 ; CV=0.36 | Zone 1: μ=0.37 ; CV=0.58 |
| Zone 2: μ=0.41 ; CV=0.47 | Zone 2: μ=0.48 ; CV=0.54 | Zone 2: μ=0.61 ; CV=0.27 | Zone 2: μ=0.41 ; CV=0.49 |
| Zone 3: μ=0.17 ; CV=0.74 | Zone 3: μ=0.15 ; CV=0.90 | Zone 3: μ=0.19 ; CV=0.69 | Zone 3: μ=0.35 ; CV=0.56 |

| AI | Clustering Input | Clustering Output | Clustering I. O. |
|---|---|---|---|
| Zone 1: μ=0.40 ; CV=0.46 | Zone 1: μ=0.49 ; CV=0.37 | Zone 1: μ=0.27 ; CV=0.29 | Zone 1: μ=0.48 ; CV=0.38 |
| Zone 2: μ=0.45 ; CV=0.45 | Zone 2: μ=0.25 ; CV=0.32 | Zone 2: μ=0.55 ; CV=0.29 | Zone 2: μ=0.25 ; CV=0.31 |
| Zone 3: μ=0.14 ; CV=0.58 | Zone 3: μ=0.19 ; CV=0.68 | Zone 3: μ=0.18 ; CV=0.65 | Zone 3: μ=0.12 ; CV=0.57 |

***Variable: Saturation***

| $\Delta P_1$ | Elevation | LULC | TWI |
|---|---|---|---|
| Zone 1: μ=0.77 ; CV=0.14 | Zone 1: μ=0.75 ; CV=0.23 | Zone 1: μ=0.75 ; CV=0.14 | Zone 1: μ=0.81 ; CV=0.14 |
| Zone 2: μ=0.69 ; CV=0.10 | Zone 2: μ=0.73 ; CV=0.16 | Zone 2: μ=0.71 ; CV=0.15 | Zone 2: μ=0.72 ; CV=0.12 |
| Zone 3: μ=0.66 ; CV=0.11 | Zone 3: μ=0.67 ; CV=0.13 | Zone 3: μ=0.68 ; CV=0.09 | Zone 3: μ=0.70 ; CV=0.13 |

| AI | Clustering Input | Clustering Output | Clustering I. O. |
|---|---|---|---|
| Zone 1: μ=0.75 ; CV=0.15 | Zone 1: μ=0.72 ; CV=0.11 | Zone 1: μ=0.76 ; CV=0.15 | Zone 1: μ=0.72 ; CV=0.10 |
| Zone 2: μ=0.73 ; CV=0.13 | Zone 2: μ=0.77 ; CV=0.16 | Zone 2: μ=0.72 ; CV=0.10 | Zone 2: μ=0.78 ; CV=0.15 |
| Zone 3: μ=0.68 ; CV=0.11 | Zone 3: μ=0.69 ; CV=0.09 | Zone 3: μ=0.68 ; CV=0.09 | Zone 3: μ=0.66 ; CV=0.08 |

***Variable: WTD***

| $\Delta P_1$ | Elevation | LULC | TWI |
|---|---|---|---|
| Zone 1: μ=2.9 ; CV=0.06 | Zone 1: μ=3.4 ; CV=0.1 | Zone 1: μ=3.0 ; CV=0.06 | Zone 1: μ=2.4 ; CV=0.04 |
| Zone 2: μ=3.7 ; CV=0.05 | Zone 2: μ=3.2 ; CV=0.07 | Zone 2: μ=3.5 ; CV=0.07 | Zone 2: μ=3.3 ; CV=0.04 |
| Zone 3: μ=4.8 ; CV=0.07 | Zone 3: μ=4.6 ; CV=0.08 | Zone 3: μ=4.7 ; CV=0.07 | Zone 3: μ=4.0 ; CV=0.1 |

| AI | Clustering Input | Clustering Output | Clustering I. O. |
|---|---|---|---|
| Zone 1: μ=3.1 ; CV=0.06 | Zone 1: μ=3.2 ; CV=0.04 | Zone 1: μ=2.8 ; CV=0.05 | Zone 1: μ=3.3 ; CV=0.04 |
| Zone 2: μ=3.5 ; CV=0.07 | Zone 2: μ=2.6 ; CV=0.04 | Zone 2: μ=3.2 ; CV=0.04 | Zone 2: μ=2.5 ; CV=0.04 |
| Zone 3: μ=4.7 ; CV=0.08 | Zone 3: μ=4.4 ; CV=0.06 | Zone 3: μ=4.5 ; CV=0.05 | Zone 3: μ=4.8 ; CV=0.05 |

***Variable: $\Delta P_2$***

| Variable | Zone 1 | Zone 2 | Zone 3 |
|---|---|---|---|
| **$\Delta P_1$** | $\mu$=2.9 ; CV=0.06 | $\mu$=3.7 ; CV=0.05 | $\mu$=4.8 ; CV=0.07 |
| **Elevation** | $\mu$=3.4 ; CV=0.1 | $\mu$=3.2 ; CV=0.07 | $\mu$=4.6 ; CV=0.08 |
| **LULC** | $\mu$=3.0 ; CV=0.06 | $\mu$=3.5 ; CV=0.07 | $\mu$=4.7 ; CV=0.07 |
| **TWI** | $\mu$=2.4 ; CV=0.04 | $\mu$=3.3 ; CV=0.04 | $\mu$=4.0 ; CV=0.1 |
| **AI** | $\mu$=3.1 ; CV=0.06 | $\mu$=3.5 ; CV=0.07 | $\mu$=4.7 ; CV=0.08 |
| **Clustering Input** | $\mu$=3.2 ; CV=0.04 | $\mu$=2.6 ; CV=0.04 | $\mu$=4.4 ; CV=0.06 |
| **Clustering Output** | $\mu$=2.8 ; CV=0.05 | $\mu$=3.2 ; CV=0.04 | $\mu$=4.5 ; CV=0.05 |
| **Clustering I. O.** | $\mu$=3.3 ; CV=0.04 | $\mu$=2.5 ; CV=0.04 | $\mu$=4.8 ; CV=0.05 |

Table 1: Mean $\mu$ and coefficient of variation CV of each variable and hillslope zone derived from the 8 clustering approaches.

### 3.1.1. Similarities in hillslope structure

Elevation plays an important role in the hydroclimate of a region especially in mountainous watersheds where it controls snow accumulation and controls the downstream hydrology. Figure 6 shows the elevation frequency distributions associated with the 3 zones derived from the 8 clustering approaches.

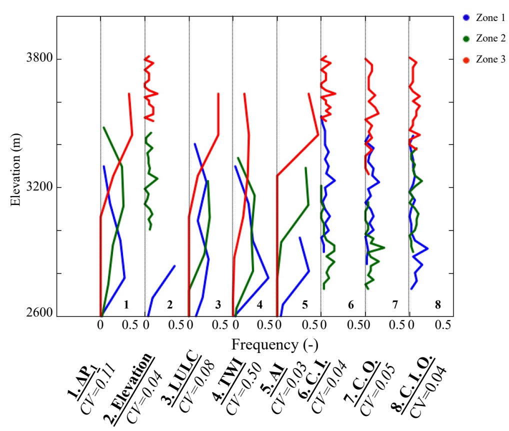


Figure 6: Frequency distributions of hillslope elevation. Clustering approaches are based on $\Delta P_1$, elevation, land cover (LULC), topographic wetness index (TWI), aridity index (AI), and

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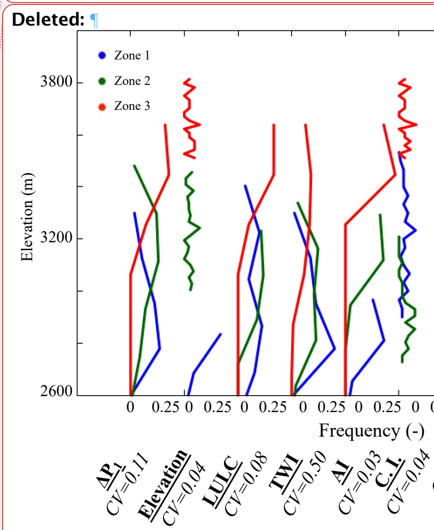


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**Formatted:** Font: 12 pt, Not Italic, Font color: Auto machine-learning approaches (with inputs C.I., outputs C.O., and inputs and outputs C.I.O). Hillslope clustering approaches are located across the x-axis. Note that we plotted the distributions of the 8 clustering approaches on the same graph, between each dotted line (frequency from 0 to 0.5) are plotted the frequency distributions of the three zones derived from the clustering.

By classifying the hillslopes using their similarity in $\Delta P_1$, we observe that hillslopes with low $\Delta P$ have the lowest elevation while the hillslopes of zone 3 (high $\Delta P_1$) have the highest elevation. Unsurprisingly, the second clustering (i.e. elevation) clearly identifies the hillslopes with similar elevation. The AI clustering also identifies hillslopes with similar elevation as shown in Figures 4 and 6. The TWI clustering performs moderately, where zones 1 and 2 are characterized by similar elevation distributions. Hillslopes with lower TWI are mostly located in high elevation areas on the contrary to the low elevation hillslopes. In the land cover clustering, most of the grassed hillslopes (zone 1) are in low elevation, forests (zone 2) in mid-elevation, and hillslopes whose landscape is mainly bare soil (zone 3) are in high elevation areas above the tree line. The three clustering approaches using machine learning allow identifying hillslopes with similar elevation, their coefficients of variation are of the same order as the elevation clustering.

Table 2 describes the average hillslope ratio of land cover type (forests, grassland, and bare soil) for each zone and clustering. The land cover clustering indicates that grassland is the dominant land cover of zone 1, forests Zone 2, and bare soil zone 3. Only the machine learning clustering approaches using outputs lead to a similar conclusion whereas while the other clustering approaches capture the characteristics of zone 1 and 3, they do not identify a distinct forested zone 2. For the $\Delta P_1$ clustering this could be attributed to the disconnection between groundwater dynamics and land surface processes that takes place in certain forested zones. Since clustering

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based on landscape characteristics and $\Delta P_1$ do not identify such a distinct zone, it suggests that this zone may not be indicative of distinct hydrologic behavior.

| **$\Delta P_1$** | **Forest** | **Grassland** | **Bare Soil** |
|---|---|---|---|
| **Zone 1** | 0.35 | 0.55 | 0.10 |
| **Zone 2** | 0.35 | 0.43 | 0.22 |
| **Zone 3** | 0.11 | 0.27 | 0.62 |
| ***CV*** | 0.97 | 0.56 | 0.69 |

| **Elevation** | **Forest** | **Grassland** | **Bare Soil** |
|---|---|---|---|
| **Zone 1** | 0.28 | 0.56 | 0.15 |
| **Zone 2** | 0.41 | 0.42 | 0.17 |
| **Zone 3** | 0.07 | 0.26 | 0.68 |
| ***CV*** | 1.33 | 0.76 | 1.07 |

| **Land Cover** | **Forest** | **Grassland** | **Bare Soil** |
|---|---|---|---|
| **Zone 1** | 0.23 | 0.67 | 0.14 |
| **Zone 2** | 0.72 | 0.26 | 0.12 |
| **Zone 3** | 0.12 | 0.22 | 0.66 |
| ***CV*** | 0.67 | 0.45 | 0.64 |

| **Topographic Wetness Index (TWI)** | **Forest** | **Grasslands** | **Bare Soil** |
|---|---|---|---|
| **Zone 1** | 0.24 | 0.66 | 0.10 |
| **Zone 2** | 0.35 | 0.51 | 0.14 |
| **Zone 3** | 0.32 | 0.35 | 0.33 |
| ***CV*** | 1.47 | 0.49 | 0.95 |

| **Aridity Index** | **Forest** | **Grassland** | **Bare Soil** |
|---|---|---|---|
| **Zone 1** | 0.34 | 0.57 | 0.09 |
| **Zone 2** | 0.37 | 0.41 | 0.22 |
| **Zone 3** | 0.07 | 0.32 | 0.61 |
| ***CV*** | 0.91 | 0.56 | 0.69 |

| **Clustering with input layers** | **Forest** | **Grassland** | **Bare Soil** |
|---|---|---|---|
| **Zone 1** | 0.44 | 0.42 | 0.14 |
| **Zone 2** | 0.11 | 0.83 | 0.06 |
| **Zone 3** | 0.12 | 0.25 | 0.63 |
| ***CV*** | 0.83 | 0.38 | 0.62 |

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**Deleted:** LULC classification allows clearly distinguishing zone 1 (grasses) from zone 2 (hillslopes of these zones have more than 70% of forest). For $\Delta P_1$, elevation, AI, and LULC classifications, zone 3 is mostly comprised of bare soil, as this zone is mostly located in high elevation areas above the tree line. In the TWI classification, zone 1 is characterized by grasses whereas zone 3's land cover located in high elevation with low TWI is bare soil. ¶

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|---|---|---|---|
| **Clustering with output layers** | **Forest** | **Grasslands** | **Bare Soil** |
| **Zone 1** | 0.14 | 0.77 | 0.09 |
| **Zone 2** | 0.52 | 0.34 | 0.15 |
| **Zone 3** | 0.11 | 0.25 | 0.64 |
| ***CV*** | 0.77 | 0.38 | 0.61 |
| [redacted] | | | |
| **Clustering with inputs and outputs** | **Forest** | **Grassland** | **Bare Soil** |
| **Zone 1** | 0.42 | 0.40 | 0.18 |
| **Zone 2** | 0.12 | 0.82 | 0.06 |
| **Zone 3** | 0.05 | 0.24 | 0.70 |
| ***CV*** | 0.87 | 0.41 | 0.65 |

Table 2: Average values of hillslope ratio of forests, grasslands, and bare soils for each zone and clustering.

### 3.1.2. Similarities in hydroclimate

Figures 7a and b depict the distributions of precipitation and temperature obtained with the eight selected clustering approaches. The AI clustering allows identifying hillslope with similar hydroclimate because it has low values of coefficients of variation. Zone 1 located in low elevation has low precipitation and high temperatures, contrary to zone 3. Zone 2 is characterized by a hydroclimate that is in between those of Zone 1 and 3. Our $\Delta P_1$ clustering leads to conclusions similar to the machine learning based clustering and AI. These three clustering approaches have the same average CV and are the only methods that allow identifying hillslopes with similar hydroclimate. Although, we note that in the three machine learning based clustering as well as in the $\Delta P$ clustering, Zones 1 and 2 have similar hydroclimate, which is not the case in the AI clustering. While the land cover clustering approaches clearly identifies the typical hydroclimate of the hillslopes of zone 3, the two remaining zones have the same hydroclimate. The TWI clustering does not identify hillslopes with similar hydroclimates because it relies on the hydrologic processes driven by the topography. TWI shows that clustering that includes only

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hydroclimate would miss important information on distinct hillslope hydrologic processes that strongly affect the response of the hillslope to meteorological forcing.

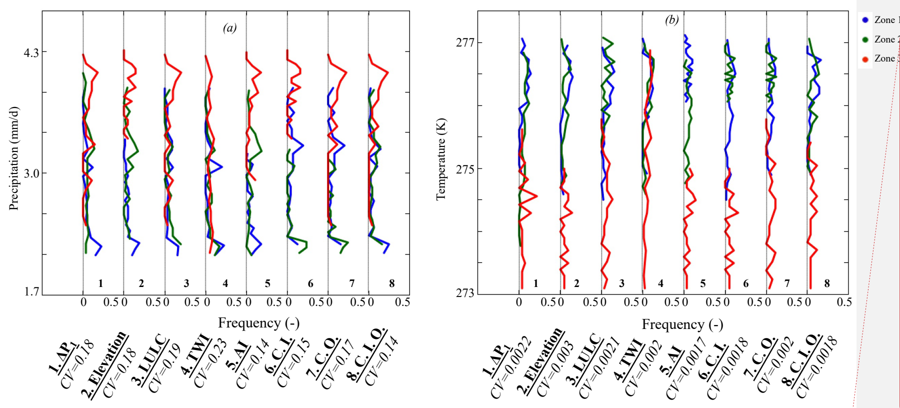


Figure 7: Frequency distributions of hillslope (a) annual average daily rates of precipitation and (b) annual average temperature. Clustering approaches are based on $\Delta P_1$, elevation, land cover (LULC), topographic wetness index (TWI), aridity index (AI), and machine-learning approaches (with inputs C.I., outputs C.O., and inputs and outputs C.I.O). Hillslope clustering approaches are located across the x-axis. Note that we plotted the distributions of the 8 clustering approaches on the same graph, between each dotted line (frequency from 0 to 0.5) are plotted the frequency distributions of the three zones derived from the clustering.

### 3.1.3. Similarities in hydrologic processes

In this section, we study the ability the selected clustering approaches to identify hillslopes with similar hydrologic processes: snow dynamics, evapotranspiration, and WTD values and variations.

#### 3.1.3.1. Land surface processes

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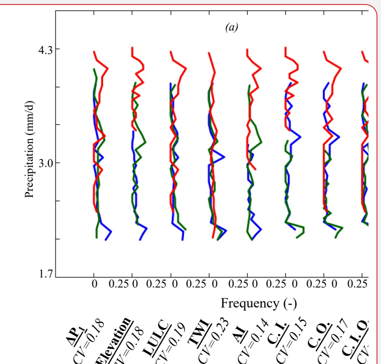

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**Deleted:** Distributions of hillslope (a) annual average daily rates of precipitation and (b) annual average temperature of the three zones derived from $\Delta P_1$, elevation, land cover (LULC), topographic wetness index (TWI), aridity index (AI), and clustering (clustering with inputs C.I., clustering with outputs C.O., and clustering with inputs and outputs C.I.O) hillslope classifications.

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**Deleted:** A hillslope hydrologic function should aim to describe how a hillslope partitions, stores, retains, and releases water. Many hydrologic processes, both at the land surface and in the subsurface, are simultaneously occurring, which typically result in non-linear dynamics.

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A robust clustering in mountainous watersheds should identify hillslopes with similar snow dynamics. Figure 8a illustrates the SWE frequency distribution associated with each zone and clustering. Because SWE dynamics are primarily driven by elevation and the precipitation, the AI and machine learning based clustering have the lowest average of the CV followed by the land cover and the $\Delta P_1$ clustering. The land cover spatial distribution contains information about elevation especially in high elevation areas where some hillslopes are located above the tree line. The $\Delta P_1$ clustering accounts for SWE dynamics because $\Delta P_1$ is highly correlated to SWE as discussed in section 3.1.

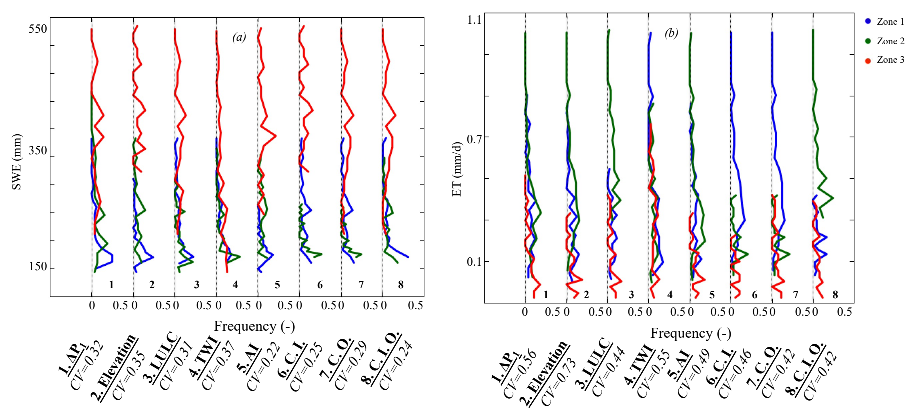


Figure 8: Frequency distributions of hillslope land surface variables (a) annual average SWE and (b) annual average daily rates of ET. Clustering approaches are based on $\Delta P_1$, elevation, land cover (LULC), topographic wetness index (TWI), aridity index (AI), and machine-learning approaches (with inputs C.I., outputs C.O., and inputs and outputs C.I.O). Hillslope clustering approaches are located across the x-axis. Note that we plotted the distributions of the 8 clustering approaches on the same graph, between each dotted line (frequency from 0 to 0.5) are plotted the frequency distributions of the three zones derived from the clustering.

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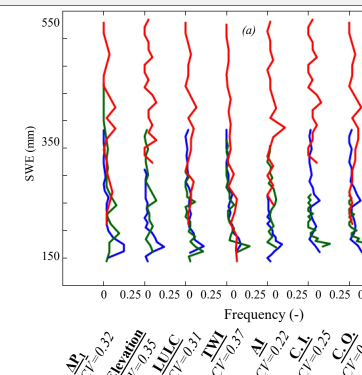

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The spatial distribution of ET is controlled by many factors, including soil moisture, land cover, and subsurface flow. The land cover clustering performs well at identifying hillslopes with similar ET because the latter strongly depends on the land cover (Figure 8b). Consistent with the aforementioned results, the other clustering approaches performing well are the machine learning based clustering and the AI. The TWI and elevation clustering approaches do not separate hillslopes by their ET values because they do not account for varying land cover and soil properties that influence ET. The average CV of the $\Delta P_1$ clustering is close to those of the land cover and AI clustering. As stated in many studies (Ferguson & Maxwell, 2010; Maina & Siirila-Woodburn, 2020, Maina et al., 2022), subsurface flow affects ET, as such information about subsurface flow contains valuable information about the ET even if the correlation between $\Delta P_1$ and ET is nonlinear.

#### 3.1.3.2. Similarities in subsurface hydrodynamics

We investigate the ability of the eight selected clustering approaches to identify hillslopes with similar subsurface hydrodynamics. We study the average saturation of the first 10 cm of the soil throughout the WY, the yearly average of WTD and $\Delta P_2$. Soil saturation is a key feature in both subsurface and atmospheric dynamics; it controls ET and groundwater recharge. The averages CV of the $\Delta P_1$, TWI, AI, land cover, and clustering approaches are very similar (Figure 9a). As the land cover clustering adequately regroup hillslopes with similar ET, it also allows regrouping hillslopes with similar soil saturation. Because the TWI describes the characteristics that drive flow, it serves as a good indicator of soil saturation like the AI. Similar to the results above, the machine learning based clustering perform well. The $\Delta P_1$ clustering has a low average CV due to the strong connection between the changes in WTD and soil saturation. It is only the elevation

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clustering that fails to identify hillslope with similar soil saturation, where the distributions of the three defined zones show overlap.

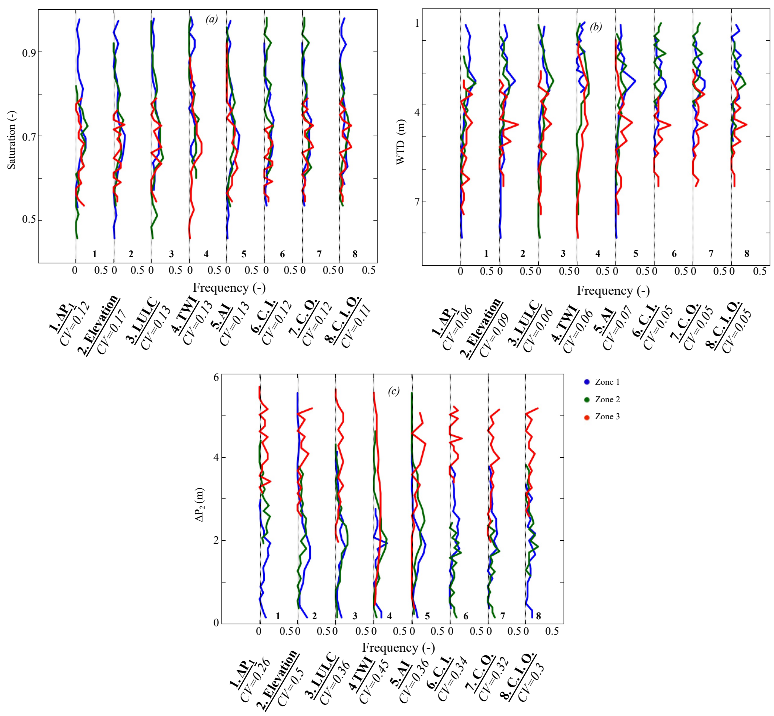


Figure 9: Frequency distributions of hillslope (a) saturation, (b) WTD, and (c) $\Delta P_2$. Clustering approaches are based on $\Delta P_1$, elevation, land cover (LULC), topographic wetness index (TWI), aridity index (AI), and machine-learning approaches (with inputs C.I., outputs C.O., and inputs and outputs C.I.O). Hillslope clustering approaches are located across the x-axis. Note that we plotted the distributions of the 8 clustering approaches on the same graph, between each dotted line (frequency from 0 to 0.5) are plotted the frequency distributions of the three zones derived from the clustering.

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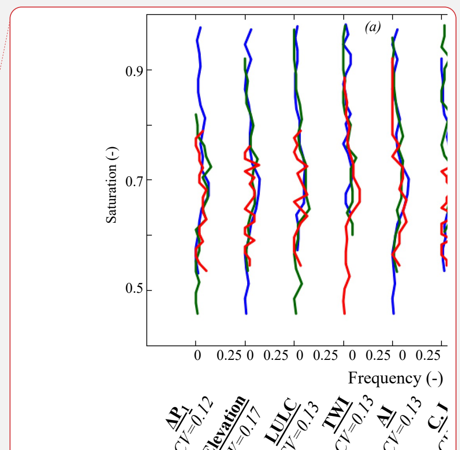

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WTD is an important variable for determining groundwater storage. Here, we rely on the average WTD throughout the year. As expected, the $\Delta P_1$ clustering identifies hillslopes with similar WTD (Figure 9b). Zone 1 located in low elevation has the shallowest WTD and the lowest $\Delta P_1$, contrary to zone 3. Zone 2 exhibits a behavior that is in between those of Zone 1 and 3. The TWI and land cover clustering approaches also are good for identifying hillslope with similar WTD. Hillslopes with low TWI (Zone 3) have the deepest WTD, contrary to the hillslopes of Zone 1. The TWI identifies hillslopes with similar WTD because of the high relief of the watershed that drive its hydrology (Fan et al., 2019). The land cover clustering indicates that most of the forest (Zone 2) and bare soil (Zone 3) hillslopes have deep WTD whereas grasses (Zone 1) hillslopes have the shallowest WTD. The elevation clustering doesn't accurately identify hillslopes with similar WTD, and its average CV remains higher than the 4 other clustering approaches. The AI, like the elevation, isn't a good variable for identifying hillslopes with similar WTD. All their three zones overlap in terms of WTD. Results from the machine learning based clustering are similar to the $\Delta P_1$ clustering with a CV of the same order, yet there isn't a clear distinction between Zone 1 and 2 in these machine learning based clustering approaches.

Figure 9c illustrates the distributions of the $\Delta P_2$ for each clustering approach and zone. $\Delta P_1$ clusters hillslopes with similar $\Delta P_2$ as expected. Another suitable clustering approach for hillslopes with similar $\Delta P_2$ is the land cover. Zone 3 characterizing bare soil hillslopes has the highest $\Delta P_2$, unlike zones 1 and 2. The AI clustering shows that the majority of zone 3 hillslopes have high $\Delta P_2$ whereas zone 2 hillslopes have low $\Delta P_2$, followed by zone 1 hillslopes. In terms of $\Delta P_2$ similarity, the elevation clustering outperforms the TWI. The machine learning based clustering approaches are good for identifying hillslopes with similar $\Delta P_2$ especially the clustering using inputs variables

> **Deleted:** Groundwater storage is mostly quantified in terms of WTD. …TD is an important variable for determining groundwater storage at a hillslope scale… Here, we quantify …ely on the average WTD throughout the year. As expected, the $\Delta P_1$ based classification…lustering groups identifies hillslopes with similar WTD (Figure 9b). Zone 1 located in low elevation has the shallowest WTD and the lowest $\Delta P_1$, contrary to zone 3. Zone 2 exhibits an intermediary… behavior that is in between those of Zone 1 and 3. The TWI and land cover classification…lustering approaches schemes …lso are good methods …or hillslope with similar changes in …TD. Hillslopes with low TWI (Zone 3) have the deepest WTD, contrary to the hillslopes of Zone 1. The TWI classification …dentifies hillslopes with similar WTD because of the high relief of the watershed that drive the…ts hydrology (Fan et al., 2019). (cite Haurko's paper). …he land cover based classification…lustering indicates that most of the forest (Zone 2) and bare soil (Zone 3) hillslopes have deep WTD whereas grasses (Zone 1) hillslopes have the shallowest WTD. The elevation-based…classification …lustering scheme …oesn't accurately regroup …dentify hillslopes with similar WTD, and its average CV remains higher than the 4 other classification …lustering approachesschemes… The AI method… like the elevation method… isn't a good variable for identifying hillslopes with similar WTD. In fact, a…ll their three zones overlap in terms of WTD even if their AIs are distinct… Results from the machine learning based clustering approach …re similar to the $\Delta P_1$ based classification…lustering with a CV of the same order, yet there isn't a clear distinction between Zone 1 and 2 in these approaches ... [12]

> **Deleted:** seasonal changes in groundwater levels …or each classification …lustering approach and zone. The …$P_1$ classification based on $\Delta P_1$ groups …lusters hillslopes with similar $\Delta P_2$ as expected. Another suitable approach clustering approach to …or group …illslopes with similar $\Delta P_2$ is the land cover classification… Zone 3 characterizing bare soil hillslopes has the highest $\Delta P_2$, unlike zones 1 and 2. The AI classification …lustering shows that the majority of zone 3 hillslopes have high $\Delta P_2$ whereas zone 2 hillslopes have low $\Delta P_2$, followed by zone 1 hillslopes. In terms of $\Delta P_2$ similarity, the elevation-based… classification…lustering outperforms the TWI. The machine learning based clustering approaches …pproaches area …re good way of…or identifying with …illslopes with similar $\Delta P_2$ especially the clustering approach based…sing on ... [13]

(CI). The two other machine learning based clustering approaches (outputs and inputs and outputs) do not distinguish zone 1 from zone 2.

## 4. Discussions

In this section, we discuss the advantages of the proposed $\Delta P$ clustering compared to the other clustering approaches and its ability to capture dry and wet hydrologic conditions.

### 4.1. Advantages of the $\Delta P$ clustering

Depending on the purpose of the identification of similar hillslopes, the appropriate clustering may change. Nonetheless, it is important for any clustering approach to identify hillslopes with similar hydrologic processes. As demonstrated here, the advantage of using $\Delta P_1$ to identify similar hillslopes is that many hydrologic processes are embedded in $\Delta P_1$. Our comparisons have shown that by using a $\Delta P_1$ clustering, one is able to identify hillslopes with not only similar subsurface hydrodynamics but also similar land surface processes. Because these processes are intimately linked to the physical characteristics of the hillslope, its hydroclimate, and its land cover, the $\Delta P_1$ clustering also allows for the identification of hillslopes with the aforementioned characteristics similar.

We, however, highlight that other clustering approaches may outperform the $\Delta P_1$ when looking at a single characteristic. For instance, our results show that the elevation and AI clustering approaches may be excellent at identifying hillslopes with similar hydroclimates and snow dynamics. The land cover clustering allows for better identification of hillslopes with similar land surface processes such as ET and soil saturation. Lastly, the TWI clustering allows the identification of hillslopes with similar groundwater dynamics and soil saturation values as it describes the topographic flow. In terms of overall performance, our results show that for the study site considered here, the machine learning based clustering approaches are also a very good at identifying similar hillslopes.

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Wainwright et al., (2022) use an unsupervised clustering method and remote sensing data layers which include elevation, SWE, radiation, resistivity, and Normalized Difference Vegetation Index NDVI to define 7 clusters in the East River watershed. While their clustering method has more zones (7) than ours (3), it leads to similar conclusions as our study where zones 1 and 2 are characterized by low elevation, high TWI, and low SWE values contrary to zones 5 and 6.

Other hillslope clustering approaches based on hydrologic processes relied on the Peclet number (Berne et al., 2005; S. W. Lyon & Troch, 2007; Steve W. Lyon & Troch, 2010) which describes the subsurface hydrological response and is derived from an analytical solution of the subsurface flow (e.g. the Boussinesq storage equation (Steve W. Lyon & Troch, 2010)). However, while the three-dimensional Richards equation has the advantage of better representing the subsurface flow it cannot be solved analytically, hence these indices cannot be applied to integrated hydrologic models. Our approach has demonstrated that the $\Delta P$ helps quantify the subsurface hydrologic responses without using these indices and therefore overcomes the limitation of the use of attributes such as the Peclet number on integrated hydrologic models to categorize hillslopes.

## 4.2. Similarities in hydrologic responses to wet and dry conditions

According to McDonnell & Woods, (2004) and Wagener et al., (2007), any classification should be able to predict the dynamics of the hillslopes. We test the ability of the $\Delta P_1$ clustering to predict the dynamics of the hillslopes in wet and dry conditions. A possible limitation of a clustering based on a hydrologic process is that the latter may be linked to the conditions of the selected year. Hydrologic responses are by essence nonlinear and may strongly change from year to year. In addition, compared to the intrinsic characteristics of the hillslope (elevation, topographic index, and land cover), which are only variable if long periods of time are considered; the scale at which hydrologic processes change is much shorter. Therefore, a clustering based on

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a hydrologic process may be time-dependent. We previously quantified $\Delta P_1$ using an average WY. In this section, we compare the response of each zone to dry and wet conditions. We extend our simulation from the WY 2015 to include the WYs 2016, 2017, and 2018, then we analyze WYs 2017 and 2018. This 4-year simulation covers a relatively wet (2017) and dry (2018) WY. The annual average precipitation in 2017 was ~15% higher than the annual average precipitation in 2015. After this wet WY, the watershed is characterized by a dry climate in 2018, with average precipitation almost 50% below the normal conditions. Figure 10 shows the distributions of hillslope annual average values of precipitation and ET, and the hillslope $\Delta P_2$ associated with the defined $\Delta P_1$ zones and for both the wet WY 2017 and the dry WY 2018. We have selected the key variables describing the hydroclimate (Precipitation), land surface processes (ET), and subsurface hydrodynamics ($\Delta P_2$).

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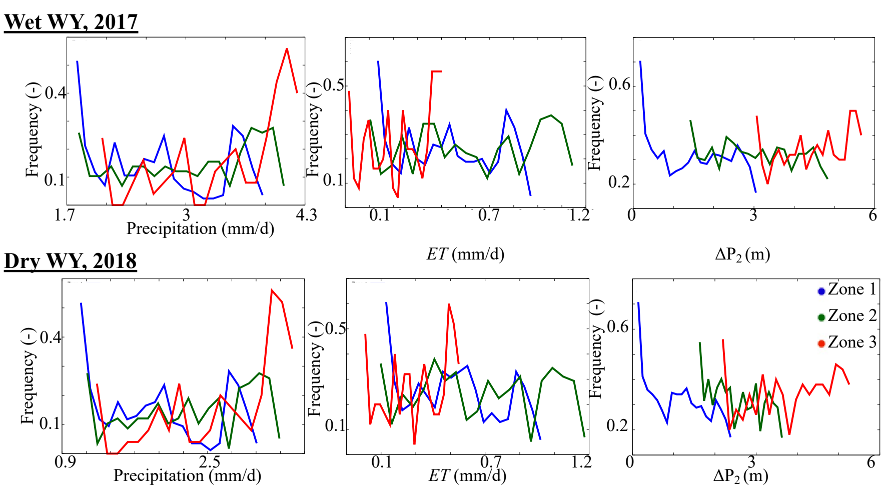


Figure 10: Frequency distributions of hillslope annual average daily rates of precipitation and evapotranspiration (ET), and the hillslope seasonal changes in groundwater levels ($\Delta P_2$) in 2017 (wet WY) and 2018 (dry WY) of the three zones derived from the WY 2015 $\Delta P_1$

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At first glance, for both dry and wet years and selected processes, all zones remain distinct. Zone 1 with hillslopes with low $\Delta P_1$ located in low elevation remains with low precipitation, high ET through both wet and dry years. Zone 3 describing hillslopes with high $\Delta P_1$ has the highest precipitation in the area during both the wet and dry years. Hillslopes of zone 2, located in mid-elevation, have most of their hydrologic dynamics in between those of zone 1 and 3 except their ET, which is the highest in the area due to the presence of forest. Our results show that although we defined hillslopes clustering based on a hydrologic process during an average WY, our clustering approach can predict the similarity of the dynamics of these hillslopes in wet and dry conditions. The $\Delta P_1$ clustering is, therefore, robust in predicting similarity in hydrologic responses under both wet and dry conditions.

# 5. Summary and conclusions

In this study, we use seasonal changes in groundwater levels termed $\Delta P_1$ to identify and categorize similar hillslopes. $\Delta P_1$ is an important variable controlled by many hydrologic processes including land surface processes and hydroclimatic. We defined three zones based on their similarity in $\Delta P_1$. For a test case site in the East River watershed, zone 1 characterizes hillslopes with low $\Delta P_1$; these hillslopes are mostly located in low elevation areas, their main land cover is grassland, and their ET is high because their WTDs are shallow. Zone 3, on the opposite of zone 1 is located in high elevation areas and has high $\Delta P_1$; the hydroclimate leads to high snow accumulation and low ET. Hillslopes of zone 3 are mostly bare soil. Zone 2 is in-between these two zones, most of the hillslopes of this zone are covered by forests.

We tested the performance of the proposed $\Delta P_1$ clustering by comparing it with other existing clustering approaches based on elevation, land cover, aridity index, a topographic wetting

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index, and three clustering approaches based on machine learning which uses multiple data layers, including model inputs and outputs. Our results show that the $\Delta P_1$ clustering is robust, as it reasonably identifies and categorizes hillslopes with similar elevation, land cover, hydroclimate characteristics, land surface processes (ET and SWE), and subsurface hydrodynamics (WTD, soil moisture, and $\Delta P_1$). In general, the other clustering approaches are good in identifying similarity in a single characteristic related to the variable determining the clustering. Our work also demonstrates that a clustering using machine learning, either based on top-down (inputs) or bottom-up (outputs) performs well. Nevertheless, these clustering approaches like the $\Delta P_1$ require multiple datasets, each one with its own associated uncertainty. We further demonstrate the robustness of the proposed $\Delta P_1$ clustering by testing its ability to predict hillslope responses to wet and dry hydrologic conditions. The $\Delta P_1$ values are derived from a model and could be a limitation for sites where simulated outputs are unavailable, or the spatio-temporal resolution of groundwater observations are limited. In addition, one of the main limitations of the proposed clustering is that due to the disconnection between land surface processes and structures and the subsurface dynamics in some regions, this clustering approach cannot be used in these conditions.

Future studies could aim to identify similar hillslopes using $\Delta P_1$ and sophisticated machine learning approaches or optimization procedures. Our results are limited to one catchment, which has snow-dominated hydrology. Future studies could expand the comparison shown here to other watersheds, to include additional clustering approaches, and for different hydroclimate and durations of time (for example, sub-annual or multi-annual clustering).

**Data availability**

Data supporting the findings of this study are freely available on ESS-DIVE: https://ess-dive.lbl.gov

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**Author contribution**

The authors contribute equally to this work.

**Competing interests**

The authors declare that they have no conflict of interest.

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## Appendix A

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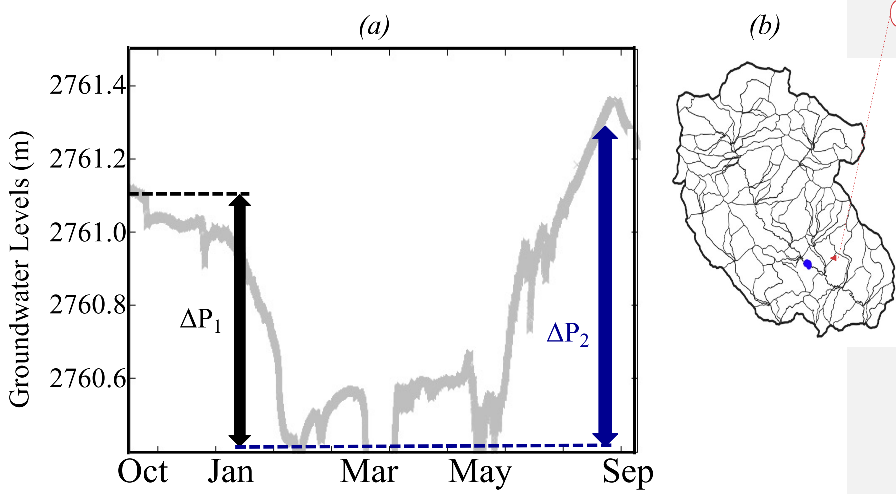


Figure A1: (a) Measured groundwater levels in WY2016 at a station located in blue in (b)

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