Controls of climate, topography, vegetation, and lithology on drainage density extracted from high resolution topography data

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Abstract

Mark Melton in 1957 found that climate, basin morphometry, and surficial variables control drainage density (D_d), but differences observed between field surveyed channels and those mapped on topographic contours or blue lines left doubts on these results. Later, several landscape evolution modeling and observational studies have analyzed the behavior of D_d . However, only a few studies have been performed over a large number of landscapes of different characteristics and have relied on high resolution topography data.

We revisit Melton's hypothesis by using meter resolution digital terrain models (DTMs) in 101 subbasins in the USA. We first propose a dimensionless drainage density (D_{dd}) metric based on the ratio of likely channelized pixels to total number of basin pixels which has the advantage of eliminating the computation of the channel network. Our analysis shows that D_{dd} is a weak scaling function of the input DTM resolution compared to the classic dimensional D_d metric (ratio of total channel length to total basin area). We analyze the correlation of D_{dd} and mean annual precipitation (MAP) with a Gaussian mixture model which identifies two sub-groups displaying different correlation; negative in arid and semi-arid environments, and positive in humid environments. The transition in correlation is around $1100 \pm 100 \text{ mm/yr}$

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of MAP and is accompanied by the occurrence of thick soil layers and high available water capacity that promote dense vegetation cover (V_{cov}) and low D_{dd} . While small variation in D_{dd} is observed across vegetation types, increasing V_{cov} corresponds to decreasing D_{dd} . We also further explore the relationship between D_{dd} and relief R , and D_{dd} and lithology. D_{dd} and R are weakly correlated in arid and semi-arid environments, while they have strong positive correlation in humid environments. No significant correlation is found between D_{dd} and lithology although the results are likely affected by our sample choice.

Keywords: drainage density, climate, topography, lidar

1. Introduction

As a unique property of the landscape, drainage density (D_d) relates the underlying geomorphic processes acting in a catchment to its topography (Moglen et al., 1998). Usually expressed as the ratio of total channel length to total catchment area (Horton, 1932), D_d is controlled by local lithology (Carlston, 1963; Kelson & Wells, 1989; Melton, 1957; Talling & Sowter, 1999), topography (Tucker & Bras, 1998; Oguchi, 1997a), vegetation (Luoto, 2007; Chorley, 1957; Moglen et al., 1998; Melton, 1957; Collins & Bras, 2010; Istanbuluoglu & Bras, 2005) and regional climatic patterns (Melton, 1957; Abrahams, 1984, 1972b; Daniel, 1981; Gregory & Walling, 1968; Madduma Bandara, 1974; Chorley, 1957; Moglen et al., 1998; Smith et al., 2013; Chadwick et al., 2013).

Field studies and modeling efforts have been used to isolate and understand the controls of climate, topography, vegetation, and lithology on D_d . One such extensive field study was conducted by Melton (1957) over 90 basins in Arizona, Colorado, New Mexico and Utah. Topographic contour maps [1:24,000] were used to measure catchment slope, relief (R), and D_d . The Thornthwaite precipitation-evaporation (P-E) index (Thornthwaite, 1931) was used to represent regional climatic patterns, while relative infiltration capacity, soil strength, and percent bare were used to represent soil and vegetation characteristics. Through multivariate regression and correlation analysis, Melton (1957) observed that D_d increased with increasing percent bare and runoff (I) but decreased with increasing P-E index and infiltration capacity. Some variation in D_d by lithology type was also observed; average D_d for shale and schist was well above the observed mean D_d , whereas the

26 values for limestone and acidic volcanic rocks were well below mean D_d .

27 Abrahams (1984) extended this analysis over a wider range of P-E index
28 and observed that D_d varied inversely with P-E index in semi-arid regions
29 while increased with increasing P-E index in humid environments. This
30 reversal in trend was attributed to the local vegetation cover (V_{cov}). The
31 dueling control of vegetation and runoff over D_d with increasing mean an-
32 nual precipitation (MAP) was also studied by Istanbuluoglu & Bras (2005)
33 who showed with numerical experiments that contrasting differences between
34 drainage networks in landscapes with and without vegetation cover existed.
35 For no V_{cov} their simulations generated low relief highly dissected landscapes,
36 while a static V_{cov} produced a less dissected landscape. Collins & Bras (2010)
37 later summarized the feedback of vegetation and runoff under varying MAP
38 in a schematic representation showing an initial increase in drainage density
39 in arid areas, followed by a decrease in semi-arid regions, and an increase in
40 humid environments.

41 Drainage density (D_d) is defined as the ratio of total channel length
42 in a catchment to total catchment area (Horton, 1932). Computation of
43 D_d needs prior knowledge of channel head locations followed by a robust
44 method for channel centerline extraction. Coarse resolution digital elevation
45 models (DEMs) fail to capture first order channels which are essential for
46 the transport of runoff and sediment from hillslopes to valleys. The inabil-
47 ity to accurately detect channel networks in coarse resolution DEMs affects
48 the computation of D_d causing strong discrepancy with field mapped results
49 (Morisawa, 1957, 1961; Schneider, 1961; Li & Wong, 2010; Goulden et al.,
50 2014). With the recent availability of high resolution topography (HRT)
51 data, we have the opportunity to analyze drainage density at spatial reso-
52 lutions commensurate with the underlying process regimes. HRT data have
53 changed the way landscapes are analyzed and have increased our ability to
54 infer processes from landscapes and extract landscape features at scales com-
55 parable to the underlying catchment processes (Lin & Oguchi, 2004; Roering
56 et al., 2013; Glennie et al., 2013; Passalacqua et al., 2014; Tarolli, 2014; Har-
57 pold et al., 2015; Passalacqua et al., 2015).

58 Channel networks and channel heads can be automatically and objectively
59 extracted from HRT data (Lashermes et al., 2007; Tarolli & Dalla Fontana,
60 2009; Passalacqua et al., 2010b,a; Pelletier, 2013; Sangireddy et al., 2016)
61 opening up the possibility of measuring D_d objectively and revisiting the
62 Melton (1957) hypothesis. Similarly, processes such as tree throws and root
63 decay, which control sediment generation in a basin and indirectly influence

the extent of landscape dissection, can be inferred successfully from HRT data (Gabet et al., 2003; Roering et al., 2004; Gabet & Mudd, 2010). Vegetation properties such as mean tree height, canopy density, above ground biomass (AGB) can also be computed from these datasets (Nilsson, 1996; Clark et al., 2011; Pelletier et al., 2011; Hurst et al., 2013).

Basin lithology affects the extent of landscape dissection. *MAP* and available water capacity (*AWC*) are important factors influencing rock weathering and soil thickness (*THICK*). By analyzing the behavior of soil parameters, relief (*R*), and vegetation cover (V_{cov}) with increasing *MAP* we can capture how climate controls these variables and how these variables affect the correlation of D_d and *MAP*. Also, soil physical properties such as porosity, thickness, and pore size are controlled indirectly by climate (Chadwick et al., 2013) and determine water supply that strongly influences plant growth. Similarly, the correlation between topographic relief and D_d is of particular interest as it helps understand the relationship between erosion rates and patterns of channelization critical for testing eco-geomorphic landscape evolution models (Oguchi, 1997a; Howard, 1998; Tucker & Bras, 1998).

Melton’s hypothesis has been cited numerous times in the literature. However, to our knowledge, this hypothesis has not been investigated using high-resolution lidar data and new technologies for data processing and methods for channel identification. This paper presents a new non-dimensional metric of drainage density, illustrates its robustness with respect to data resolution, and uses it for analyzing the relationship between drainage density and its controlling factors. In particular, the goals of this study are to: (i) propose a dimensionless measure of drainage density D_{dd} based on the number of likely channelized basin pixels, eliminating the need for computation of the channel network and reducing the resolution dependence of drainage density, and (ii) by using a large high resolution data set across the USA, revisit Melton’s hypothesis and examine the controls of climate, topography, vegetation, and lithology on drainage density. The underlying hypothesis of our study is that drainage density carries strong, codependent signatures of *MAP*, *R*, V_{cov} , vegetation type, lithology, and rock strength. Such signatures can be objectively determined by analyzing HRT data.

We test this hypothesis by mapping drainage density over meter resolution datasets with the GeoNet method (<https://sites.google.com/site/geonethome>, Passalacqua et al. (2010b); Sangireddy et al. (2016)) in 101 sub-basins across 13 states in the USA in combination with best available spatial resolution maps of precipitation, soil, geology, and land cover. The choice of

102 the subbasins was constrained by the availability of HRT data and the need
103 to cover a wide range of climatic regimes. The availability of spatial maps of
104 precipitation, soil, geology, and land cover was also considered. In addition,
105 we focused our analysis on basins that are not severely urbanized, enforcing
106 this criterion through visual inspection of aerial imagery.

107 The paper is organized as follows. After introducing the datasets used
108 in this work (Section 2), we propose a dimensionless drainage density metric
109 and analyze its behavior through scales, followed by an explanation of the
110 method used to estimate canopy cover (Section 3). We analyze the correlation
111 between drainage density and several climatic, topographic, vegetational,
112 and geologic parameters (Section 4), followed by a discussion of the results
113 (Section 5). Finally, we state the conclusions of this work (Section 6).

114 2. Study areas and data description

115 We analyze a total of 101 subbasins located across 13 states (Figure 1). HRT
116 data were obtained from OpenTopography (<http://www.opentopography.org/>) at 1 m resolution (airborne lidar), except for four basins in Arizona
117 and four basins in Utah, for which HRT data were obtained from the Na-
118 tional Elevation Dataset (NED) at 3 m resolution and re-sampled to 1 m
119 resolution by using the nearest neighbor method. The eight basins from
120 NED were included in our analysis as these regions were analyzed by Melton
121 (1957). Lidar point density varied considerably over the basins depending
122 on the date of the lidar survey as well as the local ground cover. Rasters
123 were generated from the lidar point clouds by creating a TIN (Triangulated
124 Irregular Network) with an interpolation algorithm called TIN streaming
125 (<http://www.cs.unc.edu/~isenburg/tin2dem/>).

126
127 As explained in Section 3.3, the estimation of vegetation density relies on
128 lidar data classified into ground returns (bare earth DTMs) and non-ground
129 returns (Digital Surface Models DSMs). The ground and non-ground returns
130 are only available for the datasets obtained from OpenTopography.

131 The subbasins analyzed are all of size 0.12 km^2 . A larger box of data
132 of size 2 km^2 was cut around each subbasin to perform operations such as
133 filtering and computation of topographic attributes without creation of edge
134 effects at the subbasin boundary. Information on the lithology, vegetation
135 type, and climate for each of the sub basins included in our analysis is avail-
136 able in the Supplementary Information.

Figure 1: Location of study areas (red circles) with outline of available lidar datasets on OpenTopography (grey polygons). The $MAP(mm/yr)$ in the United States is also shown in the background.

137 Mean annual precipitation (MAP) was downloaded from the gridded
 138 PRISM climate dataset (<http://prism.oregonstate.edu>) available at 800
 139 m resolution for the period 1981 - 2010. Runoff intensity (I) was computed
 140 as $I = P - f + 5$ (Melton, 1957), where P are 5 year, 1 hour precipita-
 141 tion frequency depths (inches), f is infiltration capacity (in/hr), and 5 is
 142 a constant added to keep the runoff intensity positive. The precipitation
 143 frequency depths (PFD) available as gridded GIS datasets and prepared
 144 from partial duration series for 1hr duration storms with 5 year return pe-
 145 riod, were downloaded from the NOAA precipitation frequency data server
 146 (<http://hdsc.nws.noaa.gov/hdsc/pfds/index.html>). The basins from
 147 Washington, Oregon and Idaho were excluded from the correlation analysis
 148 between D_d and I as 5 year 1 hour duration $PFDs$ were not available.

149 Rock strength and lithology were determined from state geological maps
 150 downloaded from the Mineral Resources On-Line Spatial Data hosted by

151 the U.S. Geological Survey (USGS) at <http://mrdata.usgs.gov/geology/>
152 **state**. The dominant rock type and age of the rocks were obtained for
153 each analyzed basin. The Uniaxial Compressive Strength (*UCS*) (MPa)
154 reported by the International Society for Rock Mechanics (ISRM) was used
155 as a measure of rock strength (Ulusay & Hudson, 2007). The low, average,
156 and high *UCS* (MPa) values for each rock type were recorded and the average
157 *UCS* was used for arranging basins by rock strength.

158 Soil parameters such as available water capacity (*AWC*) (amount of water
159 that a soil can store, measured in inches/inch), soil permeability (*PERM*)
160 (in/hr), and soil thickness (*THICK*) (in) were obtained from the USDA
161 STATSGO soil database (SoilSurveyStaff, 2014). All soil and geological
162 maps were accessed at the available scale of 1:250,000. The soil perme-
163 ability (*PERM*) reported in inches/hr was converted to mm/hr and used as
164 infiltration capacity (mm/hr) (*f*) in the estimation of runoff (*I*). The map
165 of North American Land Cover (2010) at the available spatial resolution of
166 250 m was used to derive land cover information (<http://www.cec.org/>).
167 The North American Land Cover Database has 19 level II land cover classes
168 defined using the land cover classification system developed by the Food
169 and Agriculture Organization of the United States. The data was prepared
170 from monthly aggregates of the 2010 Moderate Resolution Imaging Spectro-
171 radiometer (MODIS) satellite imagery. We use the defined classes within
172 this dataset to identify vegetation types in our subbasins.

173 3. Methods

174 3.1. Dimensionless drainage density

175 Drainage density is commonly defined as the ratio of total length of channels
176 to total basin area (Horton, 1932). This drainage density metric is scale-
177 dependent; as the data become coarser, D_d decreases since channels below
178 the grid resolution cannot be detected. In addition, the extraction of the
179 channel network is required to compute the total channel length. To address
180 these issues, we propose a dimensionless drainage density metric based on
181 a recently developed approach to detect likely channelized pixels from the
182 deviation of the curvature [*C*] distribution from normal behavior (quantile-
183 quantile plot) (Lashermes et al., 2007; Passalacqua et al., 2010b) (Figure 2a).
184 The deviation in the statistical behavior of *C* is interpreted as transition from
185 hillslopes to valleys and used to compute a curvature threshold C_{th} :

$$C_{th} = \mu_c + T_{qq} * \sigma_c \quad (1)$$

186 where μ_c and σ_c are the mean and standard deviation of the catchment
 187 curvature values and T_{qq} is the value of the standard normal variate at the
 188 deviation point (red dot in Figure 2a). Based on C_{th} , we can identify the
 189 skeleton $[S]$ of likely channelized pixels defined as:

$$S = \begin{cases} 1 & C \in C > C_{th} \\ 0 & C \in C < C_{th} \end{cases} \quad (2)$$

190 The set of points with $S = 1$ are the likely channelized pixels in the land-
 191 scape (Figure 2b). T_{qq} , C , and S are automatically computed within GeoNet.
 192 The skeleton captures the extent of channelization in the basin and appears
 193 disrupted in correspondence of road crossings and other similar features de-
 194 tected in the HRT data. The skeleton is used within GeoNet to identify
 195 channel initiation points (as the upstream end points of the skeleton) and
 196 trace channel centerlines as geodesics.

197 Based on the skeleton S , a dimensionless drainage density $[D_{dd}]$ metric
 198 can be defined as:

$$D_{dd} = \frac{P_{ch}}{P_b} \quad (3)$$

199 where P_{ch} indicates the total number of channelized pixels within the basin
 200 and P_b the total number of basin pixels. This definition allows the estimation
 201 of drainage density without extracting the actual channel network centerline
 202 (Figure 2b).

Figure 2: Identification of likely channelized pixels. (a) Comparison of curvature (C) distribution to Normal distribution on a quantile-quantile plot for the Paso del Norte basin in New Mexico. The point at which the curvature distribution deviates from normal behavior is automatically identified within GeoNet (T_{qq} , red dot) and used to compute a curvature threshold C_{th} . All the basin pixels with $C \geq C_{th}$ are identified as likely channelized pixels. (b) Hillshade of the Paso del Norte basin in New Mexico, skeleton of likely channelized pixels (blue), and basin area (yellow).

3.2. Scaling analysis of drainage density

We compare the behavior of D_{dd} through scales to the classic drainage density metric:

$$D_g = \frac{P_c * \delta}{P_b * \delta^2} \quad (4)$$

where δ is the input digital terrain model (DTM) resolution, and P_c is the total number of pixels along the channel centerline. Depending on the flow direction at any given pixel, δ is $\sqrt{2}\delta$ (when flow direction is along the diagonal of a grid cell) or just δ (when flow direction is along the horizontal or vertical faces of a grid cell).

The scaling analysis of D_d is performed on 12 large watersheds. Lidar datasets of box size $\approx 5 \text{ km}^2$ were downloaded and subbasins of size 0.9 km^2 extracted from them. A larger area ensured the availability of enough pixels to extract D_{dd} and D_g at coarser resolutions. Each input lidar DTM was resampled to coarser resolutions (2, 3, 4, 5, 6, 8, 10 m) by using the nearest neighbor (NN) method. Resolutions greater than 10 m were not considered as at coarse resolutions first and second order channels were not

218 captured. Channel centerlines were extracted with the GeoNet method as
 219 curves of minimum cost (Passalacqua et al., 2010b) and D_g (m/km^2) was
 220 then calculated (equation 4).

221 The scaling analysis of D_g and D_{dd} shows that D_g decreases with decreas-
 222 ing resolution (Figure 3a) as channels smaller than the grid size cannot be
 223 detected. D_{dd} instead shows a slight increase with data resolution (Figure
 224 3b) which can be explained as follows. P_{ch} (number of channelized pixels)
 225 and P_b (number of basin pixels) decrease with decreasing resolution (Figure
 226 3 c,d). The analysis of the quantile-quantile plot of curvature across various
 227 input resolutions (δ) shows that as the input data are coarsened, the stan-
 228 dard deviation of curvature (σ_c) decays faster than the mean curvature (μ_c).
 229 Thus, the combined effect of σ_c and μ_c forces the curvature threshold (C_{th})
 230 to decrease with δ which causes more pixels to exceed C_{th} and be identified
 231 as possible channel pixels at coarser resolutions. Furthermore, the conver-
 232 gent topography of the datasets used in our analysis facilitates this behavior
 233 as the skeleton widens with decreasing resolution (coarser data). It should
 234 also be noted that filtering and the geodesic global minimization approach
 235 of GeoNet to centerline extraction prevent the artificial increase of channel
 236 centerline length usually observed when channels are extracted from HRT
 237 data with a steepest descent approach. In that case, the decreasing behavior
 238 of D_g with data resolution would be more pronounced than what shown here.

239 We model the relationship between D_d and δ with a model of the form
 240 (Rodríguez-Iturbe & Rinaldo, 2001):

$$D_d = a\delta^\alpha \quad (5)$$

241 where D_d is the drainage density measure (D_{dd} or D_g), δ is the input DTM
 242 pixel resolution, and α is the slope of the model in log space ($\log(D) =$
 243 $\log(a) + \alpha * \log(\delta)$). The regressed values for the D_{dd} model are $a = 0.072$
 244 $[m^{-\alpha}]$ and $\alpha = 0.195$, while for the model D_g are $a = 1.882e+04 [m^{1-\alpha}/km^2]$
 245 and $\alpha = -0.435$. The values of α indicate that D_g is approximately twice
 246 as strongly dependent on the input dataset resolution as D_{dd} . This analysis
 247 suggests that D_{dd} is a better drainage density metric due to its dimensionless
 248 formulation, the ability to extract it objectively from lidar datasets without
 249 the need to extract channel centerlines, and a weaker scaling dependency on
 250 input data resolution (δ).

Figure 3: Scaling analysis of drainage density metrics. (a) Variation of D_g ($m^1 km^{-2}$) with input data resolution (δ) (m). For $D_g = a\delta^\alpha$ the regressed values are $a = 1.882e + 04$ [$m^{1-\alpha}/km^2$] and $\alpha = -0.435$. (b) Variation in D_{dd} with DTM resolution (δ) (m). For $D_{dd} = a\delta^\alpha$ the regressed values are $a = 0.072$ [$m^{-\alpha}$] and $\alpha = 0.195$. D_{dd} is less dependent on input DTM resolution compared to D_g . (c) Number of channelized pixels (P_{ch}) identified for each landscape at each resolution (δ) (m). (d) Number of basin pixels (P_b) identified for each landscape at each resolution (δ) (m).

3.3. Estimation of vegetation density

To estimate vegetation density, we use lidar data classified into ground returns (bare earth DTMs) and non-ground returns which we refer to here as Digital Surface Models (DSMs). Vegetation height at each pixel ($1 m^2$) is computed as the difference between the DSM and DTM for each study re-

gion. We express (DSM - DTM) as a percentage by comparing the number of pixels (P_{diff}) with elevation greater than 3 m (only positive) to total number of basin pixels (P_b):

$$V_{cov} = \frac{P_{diff}}{P_b} * 100 \quad (6)$$

A value of $V_{cov} = 100\%$ indicates that all the pixels in the DTM are above ground and the basin is completely covered with canopy (trees taller than 3 m), while $V_{cov} = 0\%$ indicates no vegetation above 3 m. The height difference of 3 m avoids the erroneous identification of vegetation due to errors in the DTM interpolation method in the case of low point density of the lidar survey. All the derived canopy density estimates compared visually well with satellite imagery. Since we restricted our analysis to non-urbanized landscapes, the simple difference of DSM - DTM can capture the extent of vegetation cover appropriately.

4. Results

4.1. Correlation between D_{dd} , mean annual precipitation, and runoff intensity

We analyze the correlation of D_{dd} and MAP with a Gaussian mixture model (McLachlan & Peel, 2004). This model assigns a posterior probability to each point indicating the probability to belong to a cluster or sub population type. This approach is often preferred over the K-means clustering model as it is more general and also able to handle clusters of different size and that are correlated. In our analysis we used the *gmdistribution* class available in the MATLAB statistics toolbox.

The Gaussian mixture model of D_{dd} and MAP identifies two groups of subbasins with different trends. D_{dd} initially decreases and then increases with increasing MAP (Figure 4a; the contour lines represent the posterior probability of a basin to belong to a cluster; the orientation of the contours indicates possible trends in each group but trends cannot be inferred solely based on the contours). The transition point between negative and positive correlation groups is identified visually at about 1050 mm/yr MAP (indicated by an arrow symbol in Figure 4a). We refer to all the basins with a MAP lower than 1050 mm/yr as group A and the rest as group B.

We quantify the correlation with the non parametric Kendall's τ_k . The null hypothesis is of no correlation among the two measured variables. We

289 reject the null hypothesis when the p -value (a measure of the likelihood of
 290 the null hypothesis) is less than a significance level of 0.05. Both trends are
 291 significant (group A: $\tau_k = -0.423$, $p = 1.4773e - 06$, group B: $\tau_k = 0.246$,
 292 $p = 0.03$) (Figure 4b) and agree with the results of Collins & Bras (2010)
 293 and previous observational studies (Gregory & Walling, 1968; Melton, 1957;
 294 Abrahams, 1972a; Abrahams & Ponczynski, 1984; Moglen et al., 1998), in
 295 semi-arid (group A) and humid environments (group B).

296 Correlation between D_{dd} and runoff intensity (I)(mm/hr) quantified with
 297 the non parametric Kendall's τ_k shows no significant correlation (τ_k : -0.0323,
 298 $p = 0.69$) (Figure S4(a) in the Supplementary Information). Same result is
 299 obtained when analyzing group A and group B separately (Figure S4(b));
 300 (Group A: (τ_k : -0.00179, $p = 0.99$); Group B: (τ_k : -0.00741, $p = 0.98$)).

Figure 4: Confirming Melton's hypothesis using high resolution data. (a) Correlation analysis between D_{dd} and MAP with a Gaussian mixture model. The colors on the contours are estimates showing posterior probabilities that indicate the probability of each point to belong to a cluster. All datasets that have less than 1050 mm/yr of MAP are labeled as group A, while all other datasets are labeled as group B. (b) The correlation changes from negative in group A to positive in group B. Both trends are significant (group A: $\tau_k = -0.423$, $p = 1.4773e - 06$, group B: $\tau_k = 0.246$, $p = 0.030$). The non parametric Theil-Sen linear trend line for each group is also shown for illustration. For group A the slope of the trend line is $-5.344e-05$ ($p = 1.1943e - 05$) and for group B is $9.582e-06$ ($p = 0.01$).

301 4.2. Soil parameters, relief, and vegetation cover as a function of climate

302 First we analyze the variation in $THICK$ and AWC with increasing MAP
 303 for the entire USA (Figure 5a,b). The values of $THICK$ and AWC reported

304 in the STATSGO database for each rock unit polygon as rasters were re-
 305 sampled at 800 m spatial resolution to match the spatial resolution of *MAP*
 306 obtained from the PRISM climate dataset. The data were then binned into
 307 75 regularly spaced bins in *MAP* and for each bin the median and standard
 308 deviation in *THICK* and *AWC* were estimated and plotted. Two change
 309 points and three distinct zones (T1, T2, and T3) can be detected (Figure 5a).
 310 In zone T1 (arid landscapes with *MAP* < 300 mm/yr) the median soil thick-
 311 ness gradually decreases with increasing *MAP* (τ_k : -0.799, $p = 2.7358e - 09$).
 312 In semi-arid and sub-humid landscapes (T2: $300 < MAP < 1700$ mm/yr)
 313 the correlation is positive and median soil thickness increases with *MAP*
 314 (τ_k : 0.892, $p = < 2.22e - 16$). In very humid landscapes (T3: *MAP* >
 315 1700 mm/yr) the correlation remains positive (τ_k : 0.4, $p = 0.015$). A sharp
 316 transition in median soil thickness is observed between zones T2 and T3.
 317 Significant amount of variation in soil thickness is observed throughout the
 318 range of *MAP*.

319 Soil thickness and climate determine the amount of water that is available
 320 for vegetation at any given location. The analysis of *AWC* and *MAP* for
 321 the entire USA (Figure 5b) shows that the correlation between these two
 322 variables transitions from positive (AWC1: $\tau_k = 0.801$, $p = < 2.22e - 16$)
 323 to negative (AWC2: $\tau_k = -0.635$, $p = 1.4297e - 06$) with increasing *MAP*.
 324 The transition between positive and negative correlation occurs at a *MAP*
 325 of 1050 mm/yr (visually identified from Figure 5b).

Figure 5: Change in soil thickness ($THICK$) and available water capacity (AWC) as a function of MAP . (a) Variation of soil thickness ($THICK$)(mm) with MAP (mm/yr) for the entire USA. Three different groups are identified visually from the plot (T1, T2, T3). (b) Variation of available water capacity (AWC) (in/in) with MAP (mm/yr) for the entire USA. Two different groups are identified visually from the plot (AWC1, AWC2). Data are binned into regularly spaced bins in MAP (see text for further discussion).

326 We perform a similar analysis on relief R and vegetation cover V_{cov} only
 327 for the 101 lidar datasets as the estimation of V_{cov} requires the availability
 328 of HRT data (Figure 6). The data shows that in general higher topographic
 329 relief is associated with increasing MAP (Figure 6a). The second order
 330 polynomial fit to the data is significant ($p = 4.899e - 10$). Vegetation cover
 331 (V_{cov}) increases gradually with increasing MAP until about 2500 mm/yr
 332 and then appears to decrease (second order polynomial fit: $p < 2.2e - 16$),
 333 although few data points are available for MAP above 3000 mm/yr.

Figure 6: Relief and vegetation cover versus MAP . (a) Variation of relief R (m) with MAP (mm/yr) for the lidar datasets. The solid lines represent a second order polynomial fit ($p = 4.899e - 10$). (b) Plot of vegetation cover (V_{cov}) (%) with MAP (mm/yr) for the lidar datasets. The predicted second order relationship between V_{cov} and MAP is significant ($p \leq 2.2e - 16$). The shaded region in grey around the solid lines represents the 95% confidence interval.

334 4.3. Correlation analysis of D_{dd} and soil parameters

335 The analysis of D_{dd} and soil thickness ($THICK$) shows no significant correla-
 336 tion (group A: $\tau_k = -0.0719$, $p = 0.43$, group B: $\tau_k = -0.185$, $p = 0.11$; Figure
 337 S5(a) in supplementary information). A similar result is obtained from the
 338 analysis of D_{dd} and AWC (group A: $\tau_k = -0.145$, $p = 0.12$, group B: $\tau_k =$
 339 -0.098 , $p = 0.41$; Figure S5(b) in supplementary information)). Inadequate
 340 representation of AWC and $THICK$ at comparable scales to D_{dd} could be
 341 one of the reasons for the lack of statistical significance.

342 4.4. Correlation between D_{dd} and relief

343 The relief for each basin is measured as the maximum elevation above the
 344 basin outlet. In arid and semi-arid environments (group A) the correlation
 345 between topographic relief R and D_{dd} is barely significant (τ_k : -0.179 , $p =$
 346 0.04), while it is strong and positive in humid environments (group B; τ_k :
 347 0.312 , $p = 0.005$; Figure 7a).

348 Without considering the regional climate, we identify three subgroups of
 349 landscapes (R1, R2, R3) (Figure 7b) by using a Gaussian mixture model
 350 for D_{dd} and R . The first transition point between positive and negative

correlation is observed at a relief of ≈ 140 m (indicated by a solid arrow in Figure 7b), while the second transition from negative to positive correlation is observed at a relief of ≈ 500 m (indicated by a solid arrow in Figure 7b). Group R1 shows positive correlation (τ_k : 0.368, $p = 0.0009$) while group R2 shows negative correlation (τ_k : -0.315, $p = 0.008$), both statistically significant, while the correlation in group R3 is not statistically significant (τ_k : 0.209, $p = 0.27$) (Figure 7c). These trends are consistent with the study of Howard (1997) in which a change in correlation between D_{dd} and R was reported from positive to negative with increasing relief in the badlands on the Colorado Plateau (USA).

Figure 7: Correlation analysis of D_{dd} and relief. (a) Plot of relief $R(m)$ above the basin outlet and D_{dd} for groups A and B. The solid line represents a linear relationship between D_{dd} and R (group A: $p = 0.03$; group B: $p = 0.03$). (b) Gaussian mixture model applied to D_{dd} and R . Datasets with $R < 140m$ are labeled as R1, $140m < R < 400m$ as R2, and $R > 400m$ as R3. Solid arrows indicate the visually identified transition points. (c) Scatterplot of D_{dd} and R for the three different groups (R1, R2, and R3). Correlations in R1 and R2 are statistically significant, while correlation in R3 is not. Solid lines represent the linear relation between D_{dd} and R (R1: $p = 0.003$; R2: $p = 0.08$; R3: $p = 0.78$). Shaded regions in grey represent 95 % confidence intervals.

361 4.5. *Changes in soil thickness, available water capacity, and vegetation cover* 362 *with relief*

363 Correlations between *THICK*, *AWC*, and *V_{cov}* with topographic relief *R*
364 are analyzed for the three sub groups R1, R2, and R3 (Figure S6 (a)). Soil
365 thickness first decreases with increasing *R* for low and medium relief land-
366 scapes (group R1; τ_k : -0.289, $p = 0.008$), while in moderate relief landscapes
367 no significant correlation is observed (group R2: $\tau_k = 0.0461$, $p = 0.70$).
368 Very high relief landscapes show positive correlation between soil thickness
369 and topographic relief (group R3: $\tau_k = -0.289$, $p = 0.008$).

370 *AWC* shows negative correlation with *R* in low and medium relief land-
371 scapes (group R1: τ_k : -0.451, $p = 3.9083e - 05$) while the correlation in
372 moderate (group R2: $\tau_k = 0.172$, $p = 0.14$) and high relief landscapes (group
373 R3: $\tau_k = -0.133$, $p = 0.50$) is not significant (Figure S6 (b)). Similarly, *V_{cov}*
374 shows negative correlation with *R* in group R1 ($\tau_k = -0.324$, $p = 0.004$) and
375 positive correlation in group R2 ($\tau_k = 0.316$, $p = 0.007$) and group R3 (not
376 significant: $\tau_k = 0.126$, $p = 0.52$) (Figure S6 (c)).

377 4.6. *Correlation between D_{dd} and vegetation cover*

378 Two opposite correlations are observed between *D_{dd}* and *V_{cov}* (Figure 8a)
379 when the basins are subdivided based on climate. In group A the correlation
380 between *D_{dd}* and *V_{cov}* is negative (τ_k : -0.333, $p = 0.0004$), while in group B
381 it is weakly positive (τ_k : 0.241, $p = 0.04$). The analysis of *D_{dd}* and *V_{cov}* for
382 the whole range shows that *D_{dd}* decreases with increasing *V_{cov}* (τ_k : -0.186,
383 $p = 0.009$; Figure 8b).

384 While the maximum vegetation cover observed in arid and semiarid en-
385 vironments (group A) does not exceed $\approx 55\%$ with a mean canopy height
386 of $\approx 3.51m$, a wider range of vegetation cover is observed in humid environ-
387 ments (group B; $\approx 1\% - 99\%$) with a mean canopy height ≈ 12.1 m (Figure
388 8c).

389 We group vegetation by type into barren lands, grasslands, shrubs, broad
390 leaf forests, needle leaf forests, and mixed forests and analyze the variation
391 in *D_{dd}* as boxplots for each land cover type (Figure 8d). Except for barren
392 lands, the median *D_{dd}* remains fairly constant for each land cover type. We
393 note that the sample size for three of the vegetation types analyzed is small.

Figure 8: Correlation of D_{dd} and vegetation cover. (a) D_{dd} and vegetation cover V_{cov} (%) for group A and B. The solid line represents the linear relationship between D_{dd} and V_{cov} (Group A: $p = 7.852e - 06$, Group B: $p = 0.023$).

Figure 8: (Continued..) (b) D_{dd} and vegetation cover V_{cov} (%) for the whole dataset ($p = 0.01$). (c) Mean height distribution (DSM-DTM) for each group with sample means (dotted lines). Group A mean height is 3.51 m and group B mean height is 12.1 m. (d) D_{dd} variation within each class of vegetation type arranged by increasing V_{cov} . The numbers indicate the sample size of each group.

394 4.7. Correlation between D_{dd} and lithology

395 The analysis of D_{dd} and rock type arranged in increasing order of mean
 396 UCS (Figure 9) shows that D_{dd} is lowest for the unconsolidated sediments
 397 (sand and clay) compared to other rock types. Overall D_{dd} decreases with
 398 increasing uniaxial compressive rock strength, however, the small sample size
 399 of three of the rock types analyzed likely affects the results.

400 We analyze the relationship between D_{dd} and rock strength after group-
 401 ing rock types in three groups: sand and clay (group L1: $UCS < 0.25$ MPa),
 402 strong rock basins (group L2: $50 \text{ MPa} < UCS < 100 \text{ MPa}$), and very strong
 403 rock basins (group L3: $100 \text{ MPa} < UCS < 250 \text{ MPa}$) (Figure S7). No sig-
 404 nificant correlation between D_{dd} and UCS is observed in group L1 (less than
 405 12 sample points) and L2 (τ_k : 0.106, $p = 0.46$). A weak negative correlation
 406 between D_{dd} and UCS is observed in group L3 (τ_k : -0.183, $p = 0.047$), indi-
 407 cating decreasing D_{dd} with increasing uniaxial compressive strength (as rock
 408 hardness increases). The control of lithology (UCS) on D_{dd} is also analyzed
 409 within climate groups A and B. Correlations between D_{dd} and UCS are not
 410 statistically significant for either group (group A: τ_k : 0.0409, $p = 0.66$; group
 411 B: τ_k : -0.0358, $p = 0.78$; Figure S7).

Figure 9: D_{dd} for different rock types arranged by increasing mean uniaxial compressive strength (MPa). The boxplot shows the first and third quartiles. The number of samples for each group are indicated. The rock types are U- Unconsolidated sediment, S- Sedimentary rock, P- Plutonic rock, V- Volcanic rock, MM- Metamorphic rock, MS- Metasedimentary rock.

5. Discussion

The analysis presented here revisits and supports the hypothesis of Melton (1957) that climate, topography, vegetation, and lithology affect drainage density. We tested this hypothesis over natural landscapes across a wide range of MAP for which HRT data are available.

Objective extraction of drainage density is essential in hydro-geomorphic analyses such as the one here performed. Our proposed dimensionless drainage density (D_{dd}) metric provides a simple and elegant way to estimate the extent of channelization in natural landscapes using HRT data. D_{dd} has the advantage of eliminating the need for channel network extraction. Furthermore, the scaling analysis of D_{dd} shows weak dependence on the input DTM resolution compared to the classic dimensional drainage density metric (D_g), allowing the computation of D_{dd} from coarser resolution DEMs with reduced bias. We also showed that a power law exists between the dimensionless drainage density and the input DEM resolution, offering the opportunity to estimate drainage density at finer resolutions based on a coarser DEM.

428 The current study offers insight into the role of climate, soil parameters,
 429 topographic relief, vegetation, and lithology on the extent of landscape dis-
 430 section. Previous studies have either shown an inverse relationship between
 431 D_d and MAP (Melton, 1957) or a non-monotonic relation in which drainage
 432 density decreases with MAP in arid and semiarid climates and increases
 433 in humid environments (Gregory & Walling, 1968; Collins & Bras, 2010).
 434 The Gaussian mixture model used in our analysis identifies two subgroups of
 435 landscapes; in group A basins (arid environments) the correlation between
 436 D_{dd} and MAP is negative, while in group B basins (humid environments)
 437 it is positive. The transition between the two groups occurs around MAP
 438 of 1000 - 1100 mm/yr and coincides with transitions in soil thickness and
 439 available water capacity. In group A (arid and semi-arid environments) the
 440 increasing thickness of soil layers and available water capacity with MAP
 441 promote dense plant cover and reduce erosion due to runoff, decreasing the
 442 overall drainage density. In humid regions (group B) the available water ca-
 443 pacity decreases accompanied by a sudden drop in soil thickness by ≈ 400
 444 mm, which causes a gradual decrease in vegetation cover (Figure 6b) and
 445 boosts erosion due to overland flow resulting in increased drainage density.
 446 Changes in soil properties with varying climate conditions have also been
 447 observed by Chadwick et al. (2003) for catchments in Hawaii, where a dom-
 448 inant threshold in saturation of base cation was predicted at $MAP \approx 1400$
 449 mm/yr. Although our analysis did not consider soil chemical properties, we
 450 observed their effect in the correlation of AWC and $THICK$ with MAP .
 451 By using a Gaussian mixture model we recognized similar transition zones
 452 to those observed by Chadwick et al. (2003).

453 The results obtained from the analysis of D_{dd} and MAP are similar to the
 454 results of Collins & Bras (2010) for steady state modeled landscapes and field
 455 measurements from northern Colorado. Their analysis showed a transition
 456 in correlation at about 300 mm/yr but was restricted to soil mantled water
 457 limited equilibrium landscapes characterized by low-medium relief. This dif-
 458 ference may explain the mismatch between the transition point in our study
 459 and Collins & Bras (2010). Furthermore Collins & Bras (2010) noted that
 460 the identified transition point was likely too low.

461 The analysis of natural landscapes offers valuable insights to inform land-
 462 scape evolution models and provides results from landscapes that are not at
 463 steady state. For example, the correlation between D_{dd} and various con-
 464 trolling factors change (only some are significant trends) upon decoupling
 465 the analysis from the effect of MAP . This result highlights the extent to

466 which individual factors control landscape dissection under similar climatic
 467 regimes. Similarly, the strong influence of *MAP* over *AWC* and soil thick-
 468 ness allows ranges of soil thickness and soil moisture to be identified within
 469 similar climatic regimes. Such estimates may be helpful in soil production
 470 and vegetation growth models.

471 Previous studies based on slope models by Kirkby (1978, 1992) predicted
 472 that D_d increases in humid climates with increasing relief R , while it is
 473 independent of R in semi-arid environments. Oguchi (1997b), instead, found
 474 an inverse relationship between D_d and R for mountainous terrain in Japan
 475 prone to landsliding and other mass wasting processes. In this study, D_{dd}
 476 shows weak negative correlation with R in arid and semi-arid environments
 477 while it shows strong positive correlation in humid environments.

478 Geomorphic transport laws used in landscape evolution models predict a
 479 power law relationship between D_d and R ($D \propto R^{-\xi}$) such that the corre-
 480 lation between the variables is positive in creep dominated landscapes and
 481 negative in landslide prone ones (Tucker & Bras, 1998). Similar behavior
 482 emerges in our analysis as indicated by the Gaussian mixture model applied
 483 to D_{dd} and R (Figure 7c). We observe that for low - medium relief land-
 484 scapes (group R1) soil thickness, *AWC*, and V_{cov} decrease with increasing
 485 relief resulting in increased landscape dissection in the basins. At around
 486 $R \approx 140$ m the correlation between D_{dd} and R changes from positive to neg-
 487 ative as the increase in plant cover aided by thick soil layers and high *AWC*
 488 reduces drainage density (Figure 7c for group R2). No significant correlation
 489 between D_{dd} and R is observed for group R3. Howard (1997) observed a sim-
 490 ilar change in correlation between D_{dd} and relative relief ratio and suggested
 491 that the transition from positive to negative correlation is due to a change
 492 from diffusion mass wasting to threshold dominated mass wasting processes.
 493 The results presented here may indicate dominant process signatures. Field
 494 observations are needed to confirm these results.

495 Our analysis shows that vegetation cover changes with *MAP*; canopy
 496 density increases with increasing *MAP* until 2000 mm/yr and then starts
 497 decreasing. As we decouple the climatic signature and look at correlations
 498 between D_{dd} and V_{cov} within each group A and B, we observe opposite trends
 499 (Figure 8a). Istanbulluoglu & Bras (2005) observed similar behaviors and
 500 reported that for equilibrium landscapes with relatively moderate ratio of
 501 uplift to diffusivity (U_*) vegetation controlled erosion processes at channel
 502 heads unlike landscapes with high and low U_* values. Negative correlation
 503 between D_{dd} and V_{cov} implies that V_{cov} increases the threshold for channel

initiation resulting in decreasing drainage density. A positive correlation between D_{dd} and V_{cov} is difficult to understand (weakly significant in our analysis). As suggested by other field based studies (Dunne et al., 2010; Jahn, 1991), this behavior can occur when landscapes are experiencing constant rates of uplift and dense vegetation cover is hindering hillslope diffusivity (Istanbulluoglu & Bras, 2005). To keep up with increasing uplift rates and decreasing hillslope diffusivity (reduced by increasing vegetation cover), D_d will gradually increase. We observe that mean canopy height for group B is 4 times higher than group A and the average canopy cover is also higher in group B than group A (Figure 8c) which might decrease the hillslope diffusivity in these basins. Such process signatures are not seen when group A and B are combined into a single dataset. In this case, D_{dd} decreases with increasing V_{cov} as observed by Melton (1957).

The dominant plant communities observed in the 101 subbasins are shrubs, grasslands, broad leaf deciduous trees, needle leaf and mixed forests (Figure 8d). Only basins with barren land had significantly different median D_{dd} , while all the other vegetation types had similar median D_{dd} values. These results may be influenced by the uneven sample size for each vegetation type analyzed.

Most basins included in our study have lithology dominated by strong rocks (Figures 9 and S7). Our results indicate that D_d spans over variable yet similar ranges for the rock types (Figure 9). Mueller & Pitlick (2013) showed similar trends for various rock types in the Northern Rocky Mountains, USA. Day (1980) observed in six small rural catchments in Southern New England that drainage density was highest for sedimentary rocks compared to granite rocks. Our results also show that D_{dd} is relatively higher for sedimentary rocks compared to other groups.

No significant correlation between D_d and UCS is observed when the signature of climate is removed (Figure S7 (b)). Similarly, no significant correlation is observed when basins are clustered by rock strength except for a weak correlation in group L3 (very strong rocks). Since most of the rocks in the areas analyzed are either strong rocks or very strong rocks, our sample choice may prevent us from observing any dominant trend. There is significant spread around the mean uniaxial compressive strength used for each rock type preventing the mean from representing appropriately the rock strength in the basin. The lack of any significant correlation across different rock types may also be due to the coarse resolution of the lithology datasets. The same analysis repeated on a larger dataset may highlight

542 significant relationships between D_d and UCS . Based on our results, climate
543 and vegetation appear to have a more dominant impact on drainage density
544 than rock strength and geology.

545 Our statistical analysis has consisted of the exploration of one to one
546 relationships among D_{dd} and climate and other factors and of these factors
547 with each other. The results of preliminary multivariate statistical analyses
548 (correlation analysis and Principal Component Analysis; Figure S1, S2, and
549 S3 in supplementary information) supported the choice of investigating mul-
550 tiple one-to-one relationships. The first PC component (PC1), for example,
551 explained only 40% of the variance. Future work will include further multi-
552 variate statistical analysis of these datasets. In addition, while the current
553 study has looked at fairly small non urbanized basins, future work could in-
554 clude larger basins representative of more rock types. Urbanized catchments
555 could also be analyzed to test the performance of the dimensionless drainage
556 density metric.

557 6. Conclusions

558 In this work we proposed a dimensionless drainage density metric (D_{dd}) based
559 on the number of likely channelized pixels in a basin. The proposed metric
560 D_{dd} is less dependent on the input DTM resolution when compared to the
561 classic drainage density metric (D_g). We measured D_{dd} on HRT data across
562 the USA and analyzed its correlation with climate, topography, vegetation,
563 and lithology. Two subgroups of landscapes are identified by a Gaussian
564 mixture model of D_{dd} and mean annual precipitation MAP (group A: arid
565 and semi-arid; group B: humid environments). The analysis of D_{dd} and MAP
566 shows a transition from negative to positive correlation at MAP 1000-1100
567 mm/yr. The changeover range coincides with variations in vegetation cover,
568 soil thickness, and available water capacity.

569 D_{dd} shows weak negative correlation with relief in arid and semi-arid
570 environments and strong positive correlation in humid environments. The
571 analysis of D_{dd} and vegetation cover shows that D_{dd} increases with decreas-
572 ing vegetation cover. No significant correlation is observed between rock
573 characteristics (lithology and rock strength) and D_{dd} in the analyzed data,
574 although the lack of correlation may be due to our sample choice.

575 Our results capture the effect of runoff, vegetation, soil thickness, avail-
576 able water capacity, topographic relief, and rock strength on drainage density
577 across varying MAP regimes in natural landscapes.

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Table 1: Principal component loading matrix of the variables analyzed

Parameters	PC1	PC2	PC3	PC4	PC5	PC6	PC7
V_{cov}	0.55	-0.01	0.12	-0.04	-0.13	0.51	-0.64
D_{dd}	-0.14	-0.49	0.62	-0.38	-0.42	-0.16	-0.02
Relief	0.39	-0.27	0.28	0.67	0.17	-0.47	-0.05
UCS	0.19	-0.48	-0.63	0.11	-0.54	0.01	0.17
AWC	0.43	0.27	-0.19	-0.52	-0.02	-0.65	-0.14
THICK	0.15	0.60	0.25	0.25	-0.63	0.03	0.31
MAP	0.53	-0.14	0.15	-0.25	0.29	0.29	0.67

third component indicates that variance in rock strength and drainage density are also inversely proportional.

Label	State	BasinName	NLCD	UnitAge	lithology
1	California	Badlands I	8	Cenozoic	sedimentary
2	California	Badlands II	16	Cenozoic	sedimentary
3	California	Badlands III	16	Cenozoic	sedimentary
4	California	Badlands IV	16	Cenozoic	sedimentary
5	California	Badlands V	16	Cenozoic	sedimentary
6	California	Badlands VI	16	Cenozoic	sedimentary
7	California	Earthscope I	7	Mesozoic	plutonic rock
8	California	Earthscope II	7	Mesozoic	plutonic rock
9	California	Earthscope III	7	Mesozoic	plutonic rock
10	California	Earthscope IV	7	Mesozoic	plutonic rock
11	California	Earthscope V	7	Mesozoic	plutonic rock
12	California	Earthscope VI	7	Mesozoic	plutonic rock
13	California	Earthscope VII	7	Mesozoic	plutonic rock
14	California	Earthscope VIII	7	Cenozoic	sedimentary
15	California	Earthscope IX	7	Cenozoic	sedimentary
16	California	Earthscope X	7	Cenozoic	unconsolidated
17	California	Earthscope XI	7	Cenozoic	unconsolidated
18	California	Earthscope XII	7	Cenozoic	sedimentary
19	California	Earthscope XIII	7	Cenozoic	sedimentary
20	California	Earthscope XIV	7	Cenozoic	sedimentary
21	Idaho	Salmon Creek I	8	Mesozoic	plutonic rock
22	Idaho	Salmon Creek II	8	Mesozoic	plutonic rock
23	Idaho	Salmon Creek III	8	Mesozoic	plutonic rock
24	Idaho	Salmon Creek IV	8	Mesozoic	plutonic rock
25	Idaho	Salmon Creek V	8	Mesozoic	plutonic rock
26	Idaho	Salmon Creek VI	8	Mesozoic	plutonic rock
27	Idaho	Salmon Creek VII	8	Mesozoic	plutonic rock
28	Idaho	Salmon Creek VIII	8	Mesozoic	plutonic rock
29	Idaho	Salmon Creek IX	8	Mesozoic	plutonic rock
30	Utah	Little Salt lake I	1	Cenozoic	volcanic rock
31	Utah	Little Salt lake II	1	Cenozoic	volcanic rock
32	Utah	Little Salt lake III	1	Cenozoic	volcanic rock
33	Utah	Little Salt lake IV	1	Mesozoic	sedimentary
34	Utah	Little Salt lake V	8	Mesozoic	sedimentary
35	Utah	Little Salt lake VI	8	Mesozoic	sedimentary

Table 2: Land cover and lithology groups of study sites. The NLCD are the class value in national land cover database http://www.mrlc.gov/nlcd06_leg.php

Table 2: Continued... Land cover and lithology groups of study sites. The NLCD are the class value in national land cover database http://www.mrlc.gov/nlcd06_leg.php

Label	State	BasinName	NLCD	UnitAge	lithology
36	Utah	Dairy Hill I	8	Cenozoic	sedimentary
37	Utah	Dairy Hill II	8	Cenozoic	sedimentary
38	Utah	Dairy Hill III	8	Cenozoic	sedimentary
39	Utah	Dairy Hill IV	8	Cenozoic	sedimentary
40	Utah	Dairy Hill V	8	Cenozoic	sedimentary
41	North Carolina	Smoky Mnts I	5	Proterozoic	metamorphic rock
42	North Carolina	Smoky Mnts II	5	Proterozoic	metamorphic rock
43	North Carolina	Smoky Mnts III	5	Proterozoic	metamorphic rock
44	North Carolina	Nantahala NF I	5	Proterozoic	metamorphic rock
45	North Carolina	Nantahala NF II	5	Proterozoic	metamorphic rock
46	North Carolina	Nantahala NF III	5	Proterozoic	metamorphic rock
47	North Carolina	Nantahala NF IV	5	Proterozoic	metamorphic rock
48	North Carolina	Nantahala NF V	5	Proterozoic	metamorphic rock
49	Alabama	Malone Creek	1	Mesozoic	unconsolidated
50	Alabama	Malone Creek I	5	Mesozoic	unconsolidated
51	Alabama	Malone Creek II	5	Mesozoic	unconsolidated
52	Alabama	Malone Creek III	5	Mesozoic	unconsolidated
53	Indiana	PPT1080 I	5	Paleozoic	sedimentary
54	Indiana	PPT1080 II	5	Paleozoic	sedimentary
55	Indiana	PPT1080 III	5	Paleozoic	sedimentary
56	Pennsylvania	Shale Hills I	15	Paleozoic	sedimentary
57	Pennsylvania	Shale Hills II	5	Paleozoic	sedimentary
58	Pennsylvania	Shale Hills III	5	Paleozoic	sedimentary
59	Indiana	PPT1100 I	5	Paleozoic	sedimentary
60	Indiana	PPT1100 II	5	Paleozoic	sedimentary
61	Indiana	PPT1100 III	5	Paleozoic	sedimentary
62	Indiana	PPT1200 I	5	Paleozoic	sedimentary
63	Indiana	PPT1200 II	5	Paleozoic	sedimentary
64	Indiana	PPT1200 III	5	Paleozoic	sedimentary
65	Washington	West Rainier I	8	Cenozoic	sedimentary
66	Washington	West Rainier II	8	Cenozoic	sedimentary
67	Washington	West Rainier III	1	Cenozoic	sedimentary
68	Washington	West Rainier IV	8	Cenozoic	sedimentary
69	Washington	West Rainier V	1	Cenozoic	sedimentary
70	Washington	West Rainier VI	8	Cenozoic	sedimentary

Table 2: Continued... Land cover and lithology groups of study sites. The NLCD are the class value in national land cover database http://www.mrlc.gov/nlcd06_leg.php

Label	State	BasinName	NLCD	UnitAge	lithology
71	Washington	West Rainier VII	8	Cenozoic	sedimentary
72	Washington	West Rainier VIII	1	Cenozoic	sedimentary
73	Oregon	Basaltic basin part1 - I	8	Cenozoic	volcanic rock
74	Oregon	Basaltic basin part1 - II	8	Cenozoic	volcanic rock
75	Oregon	Basaltic basin part1 - I	1	Cenozoic	volcanic rock
76	Oregon	Basaltic basin part1 - I	8	Cenozoic	volcanic rock
77	Oregon	Basaltic basin part2 -I	1	Cenozoic	volcanic rock
78	Arizona	Finley and Adams Canyon I	1	Mesozoic	volcanic rock
79	Arizona	Finley and Adams Canyon II	1	Mesozoic	volcanic rock
80	Arizona	Sycamore canyon I	1	Mesozoic	plutonic rock
81	Arizona	Sycamore canyon II	1	Mesozoic	plutonic rock
82	Colorado	Delonde gulch	1	Proterozoic	plutonic rock
83	Colorado	Hicks gulch	1	Proterozoic	metamorphic rock
84	New Mexico	Paso del Norte Basin	1	Cenozoic	volcanic rock
85	New Mexico	Paso del Norte Basin I	1	Cenozoic	volcanic rock
86	New Mexico	Paso del Norte Basin II	1	Cenozoic	volcanic rock
87	Utah	Maple hollow	8	Paleozoic	sedimentary
88	Utah	Mercer hollow	10	Cenozoic	volcanic rock
89	Oregon	Basaltic basin part3 -I	8	Cenozoic	volcanic rock
90	Oregon	Basaltic basin part3 -II	8	Cenozoic	volcanic rock
91	Oregon	Basaltic basin part3 -III	8	Cenozoic	volcanic rock
92	Oregon	Basaltic basin part4 -I	6	Cenozoic	volcanic rock
93	Oregon	Basaltic basin part4 -II	6	Cenozoic	volcanic rock
94	Oregon	Basaltic basin part4 -III	1	Cenozoic	volcanic rock
95	Oregon	Basaltic basin part4 -IV	1	Cenozoic	volcanic rock
96	Virginia	Piedmont I	5	Paleozoic	metamorphic rock
97	Virginia	Piedmont II	5	Paleozoic	metamorphic rock
98	Virginia	Piedmont III	5	Paleozoic	metamorphic rock
99	California	NAPA I	10	Cenozoic	sedimentary
100	California	NAPA II	10	Cenozoic	sedimentary
101	New Mexico	Crater basin I	1	Cenozoic	volcanic rock

Table 3: Climate and soil parameters of the study sites

Label	MAP [mm/yr]	D_{dd} [-]	D_g [m/km ²]	AWC [-]	Clay [%]	KFFACT	PERM [in/hr]	THICK [in]	PFD	RUNOFF
1	76	0.076	22499.56	0.04	9.7	0.15	4.79	1447.8	11.2522	16.5862
2	76	0.114	30191.40	0.04	9.7	0.15	4.79	1447.8	11.684	17.018
3	76	0.099	23127.10	0.04	9.7	0.15	4.79	1447.8	11.2522	16.5862
4	79	0.090	23665.75	0.04	9.7	0.15	4.79	1447.8	11.2522	16.5862
5	81	0.109	26640.15	0.04	9.7	0.15	4.79	1447.8	11.4808	16.8148
6	82	0.092	25034.27	0.04	9.7	0.15	4.79	1447.8	11.684	17.018
7	172	0.061	9878.87	0.05	12.9	0.14	2.61	1013.46	11.4808	72.1868
8	177	0.075	13549.02	0.05	12.9	0.14	2.61	1013.46	11.5951	72.3011
9	172	0.046	9415.57	0.05	12.9	0.14	2.61	1013.46	11.4808	72.1868
10	172	0.063	11994.57	0.05	12.9	0.14	2.61	1013.46	11.4808	72.1868
11	165	0.086	8247.02	0.05	12.9	0.14	2.61	1013.46	11.4046	72.1106
12	172	0.078	13703.45	0.05	12.9	0.14	2.61	1013.46	11.4808	72.1868
13	167	0.064	8893.14	0.05	12.9	0.14	2.61	1013.46	11.3792	72.0852
14	148	0.096	16887.39	0.05	12.9	0.14	2.61	1013.46	11.0998	71.8058
15	148	0.102	13621.39	0.05	12.9	0.14	2.61	1013.46	11.0998	71.8058
16	143	0.080	14425.30	0.05	12.9	0.14	2.61	1013.46	11.0998	71.8058
17	140	0.098	9680.33	0.05	12.9	0.14	2.61	1013.46	10.9982	71.7042
18	161	0.090	12681.01	0.05	12.9	0.14	2.61	1013.46	11.2776	71.9836
19	162	0.101	12304.50	0.05	12.9	0.14	2.61	1013.46	11.303	72.009
20	161	0.079	10526.60	0.05	12.9	0.14	2.61	1013.46	11.3284	72.0344
21	646	0.058	5536.12	0.07	6	0.21	11.43	1549.4	NA	NA
22	646	0.070	8845.24	0.07	6	0.21	11.43	1549.4	NA	NA
23	646	0.079	14793.17	0.07	6	0.21	11.43	1549.4	NA	NA
24	641	0.037	8035.19	0.07	6	0.21	11.43	1549.4	NA	NA
25	646	0.077	13310.10	0.07	6	0.21	11.43	1549.4	NA	NA
26	646	0.089	14522.58	0.07	6	0.21	11.43	1549.4	NA	NA
27	645	0.069	11079.47	0.07	6	0.21	11.43	1549.4	NA	NA
28	644	0.056	8412.51	0.07	6	0.21	11.43	1549.4	NA	NA
29	641	0.031	6066.53	0.07	6	0.21	11.43	1549.4	NA	NA
30	500	0.109	21997.50	0.15	35	0.29	0.47	1564.64	25.7556	140.8176
31	562	0.080	11420.70	0.15	35	0.29	0.47	1564.64	27.432	142.494
32	526	0.076	11114.08	0.15	35	0.29	0.47	1564.64	26.7208	141.7828
33	440	0.121	16493.17	0.15	35	0.29	0.47	1564.64	24.6888	139.7508
34	490	0.104	17552.64	0.15	35	0.29	0.47	1564.64	26.0096	141.0716
35	490	0.127	17467.16	0.15	35	0.29	0.47	1564.64	26.0096	141.0716
36	323	0.079	12733.62	0.09	26.6	0.21	1.19	960.12	20.193	116.967
37	322	0.108	21278.70	0.09	26.6	0.21	1.19	960.12	20.2946	117.0686
38	324	0.070	9233.93	0.09	26.6	0.21	1.19	960.12	20.2692	117.0432
39	321	0.101	12783.20	0.09	26.6	0.21	1.19	960.12	20.2438	117.0178
40	320	0.089	14159.42	0.09	26.6	0.21	1.19	960.12	20.0914	116.8654

Table 3: Continued... Climate and soil parameters of the study sites

Label	MAP [mm/yr]	D_{dd} [-]	D_g [m/km ²]	AWC [-]	Clay [%]	KFFACT	PERM [in/hr]	THICK [in]	PFD	RUNOFF
41	1626	0.032	5276.38	0.12	10.9	0.23	3.81	1374.14	51.8922	82.1182
42	1626	0.061	9837.93	0.12	10.9	0.23	3.81	1374.14	52.324	82.55
43	1626	0.088	14611.60	0.1	14.5	0.21	2.97	1559.56	51.9176	103.4796
44	1972.5	0.071	14932.64	0.13	17.1	0.23	2.72	1493.52	51.1302	109.0422
45	2009	0.068	9841.97	0.13	17.1	0.23	2.72	1493.52	51.7398	109.6518
46	2009	0.071	16431.73	0.13	17.1	0.23	2.72	1493.52	51.7398	109.6518
47	2006	0.072	15392.58	0.13	17.1	0.23	2.72	1493.52	51.7398	109.6518
48	2006	0.065	13243.95	0.13	17.1	0.23	2.72	1493.52	51.6636	109.5756
49	1388	0.032	10422.86	0.15	28.3	0.29	2.32	1874.52	53.2892	121.3612
50	1389	0.066	18630.62	0.15	28.3	0.29	2.32	1874.52	53.3146	121.3866
51	1388	0.021	6406.63	0.15	28.3	0.29	2.32	1874.52	53.2892	121.3612
52	1388	0.036	14463.07	0.15	28.3	0.29	2.32	1874.52	53.2892	121.3612
53	1097	0.066	18690.25	0.16	26	0.28	1.43	1696.72	45.9994	136.6774
54	1097	0.056	15006.12	0.16	26	0.28	1.43	1696.72	46.0248	136.7028
55	1096	0.069	17986.80	0.16	26	0.28	1.43	1696.72	45.9994	136.6774
56	1016	0.042	10774.77	0.11	34.5	0.26	1.93	1036.32	38.1	116.078
57	1013	0.064	18734.61	0.11	34.5	0.26	1.93	1036.32	38.0746	116.0526
58	1013	0.054	16537.59	0.11	34.5	0.26	1.93	1036.32	38.1	116.078
59	1180	0.050	10827.02	0.11	22.2	0.3	2.31	1089.66	45.4152	113.7412
60	1179	0.057	11329.32	0.11	22.2	0.3	2.31	1089.66	45.4406	113.7666
61	1179	0.070	12072.16	0.11	22.2	0.3	2.31	1089.66	45.4152	113.7412
62	1241	0.081	8042.08	0.14	24.1	0.35	1.37	1318.26	44.5516	136.7536
63	1241	0.071	9142.05	0.14	24.1	0.35	1.37	1318.26	44.5008	136.7028
64	1241	0.068	6312.46	0.14	24.1	0.35	1.37	1318.26	44.5008	136.7028
65	1999	0.076	13249.97	0.08	4	0.21	7.69	1470.66	NA	NA
66	1963	0.058	11363.06	0.08	4	0.21	7.69	1470.66	NA	NA
67	2070	0.069	18222.80	0.08	4	0.21	7.69	1470.66	NA	NA
68	2070	0.106	22259.90	0.08	4	0.21	7.69	1470.66	NA	NA
69	2102	0.085	24886.42	0.08	4	0.21	7.69	1470.66	NA	NA
70	2102	0.095	22191.87	0.08	4	0.21	7.69	1470.66	NA	NA
71	2107	0.039	10886.40	0.08	4	0.21	7.69	1470.66	NA	NA
72	1977	0.077	13945.35	0.08	4	0.21	7.69	1470.66	NA	NA
73	461	0.068	24353.11	0.14	32.8	0.3	0.85	1181.1	NA	NA
74	454	0.049	15520.24	0.14	32.8	0.3	0.85	1181.1	NA	NA
75	535	0.049	13019.88	0.14	32.8	0.3	0.85	1181.1	NA	NA
76	418.5	0.061	9868.93	0.14	32.8	0.3	0.85	1181.1	NA	NA
77	835	0.066	20216.19	0.14	19.9	0.35	1.53	1216.66	NA	NA
78	539	0.079	10892.80	0.07	18.9	0	0.54	744.22	44.704	157.988
79	539	0.074	9234.06	0.07	18.9	0	0.54	744.22	44.831	158.115
80	549	0.068	7912.13	0.07	18.9	0	0.54	744.22	45.31995	158.60395

Table 3: Continued... Climate and soil parameters of the study sites

Label	MAP [mm/yr]	D_{dd} [-]	D_g [m/km ²]	AWC [-]	Clay [%]	KFFACT	PERM [in/hr]	THICK [in]	PFD	RUNOFF
81	549	0.084	9726.11	0.07	18.9	0	0.54	744.22	45.3898	158.6738
82	604	0.049	20064.61	0.06	19.5	0.3	2.95	1363.98	22.1488	74.2188
83	727	0.054	13950.63	0.06	10.6	0.18	5.16	1478.28	22.225	18.161
84	668	0.058	9189.83	0.07	14.3	0	5.46	1450.34	31.4833	19.7993
85	668	0.057	8059.04	0.07	14.3	0	5.46	1450.34	31.5468	19.8628
86	668	0.045	8518.98	0.07	14.3	0	5.46	1450.34	31.5468	19.8628
87	583	0.067	10382.60	0.08	24.9	0.26	2.29	1584.96	18.415	87.249
88	590	0.057	9673.37	0.08	24.9	0.26	2.29	1584.96	18.4912	87.3252
89	3611	0.055	14622.03	0.17	20	0.28	1.2	1168.4	NA	NA
90	3620	0.067	11955.13	0.17	20	0.28	1.2	1168.4	NA	NA
91	3741	0.086	15502.97	0.17	20	0.28	1.2	1168.4	NA	NA
92	2729	0.065	15859.17	0.19	19.4	0.25	1.4	1226.82	NA	NA
93	2729	0.077	19419.05	0.19	19.4	0.25	1.4	1226.82	NA	NA
94	2739.5	0.053	13751.85	0.19	19.4	0.25	1.4	1226.82	NA	NA
95	2729	0.093	18525.39	0.19	19.4	0.25	1.4	1226.82	NA	NA
96	1056	0.052	12683.56	0.12	28.1	0.26	2.38	1747.52	46.482	113.03
97	1056	0.051	9400.29	0.12	28.1	0.26	2.38	1747.52	46.482	113.03
98	1055	0.065	18829.53	0.12	28.1	0.26	2.38	1747.52	46.5328	113.0808
99	673	0.048	8278.27	0.15	37.2	0.35	0.31	1272.54	17.7546	136.8806
100	673	0.065	11617.63	0.15	37.2	0.35	0.31	1272.54	17.8562	136.9822
101	712	0.064	11602.59	0.07	14.3	0	5.46	1450.34	33.0708	21.3868