Beyond Total Impervious Area: A New Lumped Descriptor of Basin-Wide Hydrologic Connectivity for Characterizing Urban Watersheds

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Abstract. Urbanization impacts on hydrologic response are typically indexed as a function of the fraction of total impervious area (TIA), i.e., the proportion of impervious areas in a basin. This implicitly assumes that changes in flood characteristics are somehow proportional to the extents of land-development, without considering that such impacts may vary widely depending on the location of the developed areas with respect to each other, the less-developed land patches, the stream network, and the

10 basin outlet. In other words, TIA is blind to the spatial arrangement of the different types of land patches within a basin, and to the nuanced ways in which runoff volumes are differentially generated over them and then subsequently retained or detained, as they are routed towards the stream network and then the outlet. To overcome such limitations, we propose a new lumped index that measures the impacts of urbanization on basin response in terms of the emerging hydrologic connectivity, the distributed, directional basin property driven by topographically induced runoff pathways and locally affected by the different

15 land-use/land-cover types present in a watershed. This alternative, hydrologic-connectivity-based index of urbanization (HCIU) displays sensitivity to the spatial arrangement of both fully developed as well as less developed or undeveloped patches, each with different degrees of imperviousness, roughness, and other characteristics affecting their abilities to either generate or else retain/detain runoff, reflecting their distinct localized effects on hydrologic connectivity. The proposed HCIU can be readily obtained in a GIS environment from easily available raster geospatial data. We found that HCIU improves the

20 predictive power of regional equations for peak flow in three large case-study homogeneous regions, when used in place of the traditional TIA.

1 Introduction

The ongoing expansion in land development across many regions of the world is a major driver of alterations in the hydrologic response of watersheds (Nirupama and Simonovic, 2007; Sillanpää and Koivusalo, 2015), with subsequent impacts

25 on urban stream ecosystems (Walsh et al., 2005; Vietz, et al., 2016a, 2016b). Along with climate change, this trend in urbanization is expected to pose formidable challenges for water resources management in the years to come (Praskievicz & Chang, 2009; Bell et al., 2017; Zölch et al., 2017). Because developed land patches have quite different infiltration and interception capacities, as well as surface roughness characteristics, than undeveloped sectors, they have strong effects on stormwater runoff dynamics; this is why quantifications of the level of urbanization based on a basin's impervious area are

30 widely used in the domains of engineering hydrology and urban river ecology (Bauer et al., 2007; Roy & Shuster, 2009; Lee et al., 2018; Gong et al., 2020; Liang et al., 2022). Urbanization descriptors specified as a fraction of the total watershed area (Bell et al., 2016) are extensively adopted in a range of stormwater management (Kong et al., 2017; Sultana et al., 2020) as well as flood risk assessment and mitigation practices (Suharyanto et al., 1997; Loperfido et al., 2014; Sohn et al., 2020). Popular applications of these metrics include the study of stormwater runoff dynamics (Meierdiercks et al., 2010; Fletcher et

35 al., 2013; Yao et al., 2016), water quality assessments (Fletcher et al., 2014; Lee et al., 2012; Li et al., 2021), and peak flow prediction in ungauged (urban) basins (PUBs; Kennedy & Paretti, 2014; Southard, 2010), also involving urban planning and regulation (Smucker et al., 2016).

The total impervious area of a basin (TIA) has been historically the most widely adopted urbanization metric in hydrology (Shuster et al., 2005). Other representations of the level of urbanization are the directly connected impervious area (DCIA, i.e.,

40 the subset of TIA connected to the stream network through constructed drainage or other fully impervious pathways; Han & Burian, 2009; Sytsma et al., 2020) and the effective impervious area (EIA, i.e., an indirect estimate of DCIA; Boyd et al., 1993, 1994; Ebrahimian et al., 2016a, 2016b, 2018). Despite their widespread use, these methods have intrinsic limitations, as highlighted by a growing body of research (Shuster et al., 2005; Law et al., 2009; Beck et al., 2016; Bell et al., 2016). One drawback relates to their inability to account for differences in the spatial arrangements of impervious patches (Shuster et al.,

45 2005; Beck et al., 2016; Bell et al., 2016). However, basins with similar levels of land development can exhibit distinct hydrologic behaviors, because the actual locations of the developed sectors within a watershed significantly impact surface runoff dynamics (Corbett et al., 1997; Pappas et al., 2008). Another issue with this kind of descriptors is that they are not able to capture the complex, distributed interactions between urbanized patches (with varying land-development intensities, depending on location) and undeveloped sectors with heterogenous hydrologic characteristics (Bell et al., 2016; Law et al.,

50 2009), even though different spatial configurations will significantly affect a watershed's hydrologic response (Loperfido et al., 2014).

Despite the conceptual limitations of TIA and similar indices used to depict a watershed's impervious areas, this kind of simple descriptors are needed to characterize the degree of urbanization in lumped hydrologic models, with their inherent trade-offs between basin representation detail versus the spatial heterogeneity of the captured hydrologic processes

55 (Hrachowitz and Clark, 2017). More recent urbanization metrics try to incorporate information on the spatial distribution and geometric fragmentation of developed and undeveloped patches (Yang et al., 2011; Beck et al., 2016). These indices implicitly attempt to capture the degree of contiguity and interconnection of different land-use/land-cover (LULC) sectors based on their spatial density and granularity (Yang et al., 2011; Beck et al., 2016), but overlook the effects of basin relief on runoff routing. However, spatial contiguity does not fully explain the hydrologic connectivity of patches with distinct LULC types, as this

60 property is ultimately determined by water pathways induced by topographic gradients. Following a conceptually different approach, Zhang & Shuster (2014) proposed the following two indices: 1) the average distance of impervious patches to the outlet, measured along topographic pathways, and 2) the mean number of pervious cells along those routes, regarded as a proxy for hydrologic disconnection. These metrics do consider the effects of topography but fall short in accounting for the heterogeneity across different LULC types and their varying effects on surface runoff dynamics, as they adopt a binary,

65 simplified pervious-vs-impervious LULC classification. Undeveloped areas located downstream of urbanized land patches can mitigate their adverse hydrologic impacts to varying degrees and through different mechanisms, depending on specific factors such as soil infiltrability and vegetation type (and its effects on interception and roughness; Law et al., 2009). The fact that Zhang & Shuster's (2014) indices cannot account for this continuum of behaviors likely explains their poor correlation with simulated stormwater runoff volumes in their two case-study basins.

70 In summary, ongoing efforts in urban watershed characterization have brought to light the limitations of traditional impervious-area-based indicators like TIA as proxies for the effects of land development on stormwater hydrologic processes. Researchers have proposed alternative approaches that shift the focus towards hydrologic or geometric properties, considering either the degree of dispersion and granularity of patches with different LULC types, or else the interconnections of pervious and impervious patches as driven by topographic gradients. However, despite these advances, existing methods have yet to

75 simultaneously address the synergistic impacts of topography and of the existence of a wide spectrum of LULC types with heterogeneous effects on stormwater runoff dynamics.

We propose a conceptual approach for deriving lumped urbanization metrics starting from the DEM and LULC map of a watershed, by measuring the impacts of land-development on hydrologic response in terms of its distributed effects on hydrologic connectivity (Hooke et al., 2021). Hydrologic connectivity is a spatially distributed, directional property induced

80 by topographic gradients and influenced by the spatial arrangement of LULC patches with different hydrologic properties,

such as roughness and infiltrability (Hooke et al., 2021). Distinct LULC patches intensify or mitigate a basin's hydrologic response to varying extents, depending on the hydrologic processes that take place under specific LULC conditions (e.g., high canopy and litter interception as well as detention due to high surface roughness in densely vegetated areas, increased runoff volumes and peaks because of negligible infiltration losses as well as shorter travel times due to low roughness in urbanized

85 sectors, enhanced retention due to higher infiltrability in undisturbed areas, etc.). Hence, basin cells with different land-use/land-cover types contribute to hydrologic connectivity in different ways. Conceptually, highly urbanized, fully impervious patches represent one extreme in the continuous spectrum of LULC potentials for generating runoff and increasing connectivity, with their smooth surfaces and absence of infiltration losses. On the other extreme instead, are forested areas and other natural LULC types with high vegetation densities, because of their ability for reducing runoff volumes and travel speeds

90 through interception, temporary canopy storage, high surface roughness, and soil infiltration.

Because it displays sensitivity to both the topographic structure and the heterogenous mosaic of LULC types of a basin, hydrologic connectivity provides a methodological framework for a conceptual, yet quantitative and comprehensive assessment of the impacts of land development, that not only considers the spatial arrangement of urban sectors with distinct land-development intensities, but also their interactions with undeveloped patches, with their range of flood-mitigating

95 capabilities. Connectivity analyses have gained popularity in recent years within hydrology and geomorphology (Bordoni et al., 2018; Heckmann et al., 2018; Husic and Michalek, 2022; Martini et al., 2022). These methods define a connectivity index (Eq. 1) for each basin cell, that can be interpreted as a measure of its potential for affecting runoff and sediment fluxes (Hooke et al., 2021), depending on its location within the watershed. However, a map of connectivity values, with possible local peaks induced by the presence of fully developed patches, does not represent a lumped measure of the impacts of land development

100 per se, nor does it allow for a straightforward comparison of the effects of urbanization across basins, or of different urbanization scenarios within a given watershed; thus, further conceptualizations are required.

In the next section, we explain in detail our conceptual methodology for deriving a lumped metric of urbanization effects on hydrologic response, incorporating hydrologic connectivity. We then test our hydrologic-connectivity-based index of urbanization HCIU against the traditional fraction of TIA as a predictor of peak flows in regional equations, for three case-

105 study regions with urbanized watersheds, described in Section 3. We conclude by showing and discussing the performance of HCIU as compared to TIA (in Sections 4 and 5, respectively), highlighting strengths and weaknesses of the proposed conceptual framework, and outlining possible future research directions.

2 Methodology

Of the many types of connectivity indices proposed in the literature (see, e.g., Bracken et al., 2013, for a comprehensive

110 review), we adopt a formulation (Eq. 1) first introduced by Borselli et al. (2008), which measures the potential hydrologic connectivity based on a weighted topographic analysis (Bracken et al., 2013). We consider two alternatives for the weights, as a function of either the Manning's surface roughness coefficient n (Eq. 2) or else the Curve Number CN (Eq. 3) of each basin pixel. Conceptually, both n and CN are distributed basin properties that consistently vary across LULC types with different surface runoff dynamics, e.g., due to their distinct water retention/detention capacity or infiltrability.

115 Below, we recall established formulations based on Eq. (1), including recommendations for the weighting factors. These methods provide a measure of the hydrologic connectivity at each basin cell, resulting in a connectivity map for the watershed. We then propose hydrologically driven criteria to obtain a lumped, hydrologic-connectivity-based index of urbanization (HCIU), able to summarize the effects of the spatial arrangement of the varied LULC patches in a watershed, in terms of their distributed impacts on connectivity. Two alternative indices, $HCIU(n)$ and $HCIU(CN)$ (depending on whether n or CN is

120 chosen as weighting coefficient) are derived in this work and tested against the traditional TIA as explanatory variables in predictive peak-flow equations.

2.1 Connectivity-Index Formulations

Borselli et al. (2008) proposed a widely used GIS-based index of connectivity to assess sediment erosion and transport, which was then modified by Cavalli et al. (2013), Persichillo et al. (2018), Zanandrea et al. (2019), Hooke et al. (2021), and

125 Husic & Michalek (2022), among others, to focus on other basin dynamics, such as runoff generation (Hooke et al., 2021) or landslide occurrence (Husic and Michalek, 2022). In general, irrespective of the formulation, computing the index of connectivity requires assigning a flow direction (by either the D8 or D-infinity algorithm; Hooke et al., 2021) and slope value S to each basin cell, from the DEM, as well as a weighting coefficient W that varies across formulations depending on some additional hydrologic properties of interest (e.g., potential for erosion or runoff generation).

130 The index of connectivity (IC_k) is estimated for each raster cell k of the basin hillslope component (i.e., excluding cells corresponding to the stream network) as the logarithm of the ratio of the upslope ($D_{up,k}$) and downslope ($D_{dn,k}$; Fig. 1a) components, as shown in Eq. (1) (Hooke et al., 2021).

$$IC_k = \log_{10}\left(\frac{D_{up,k}}{D_{dn,k}}\right) = \log_{10}\left(\frac{\overline{W}_k\,\overline{S}_k\,\sqrt{A_k}}{\sum_{i=k}^{n_k}\frac{d_i}{W_i\,S_i}}\right) \tag{1}$$

The upslope component $D_{up,k}$ relates to cell k's upstream area (determined from the flow direction raster), and is

135 proportional to its length scale $\sqrt{A_k}$ (where A_k is the area draining to cell k), its average slope $\overline{S}_k$, and its average weighting coefficient $\overline{W}_k$. On the other hand, the downslope component $D_{dn,k}$ accounts for the effects along the topographically determined flow path between cell k and the stream network, obtained as the summation of runoff travel distances d_i (weighted by their respective coefficient W_i and slope S_i) across cells $1, …, i, …, n_k$, moving from cell k down to the pour point where the runoff pathway eventually meets the stream network.

140 In the literature, the cell weighting factor W depends on the type of analysis. Some examples include: 1) the RUSLE C-factor (Renard et al., 1997), i.e., a measure of the potential for erosion, adopted in sediment transport studies (Borselli et al., 2008); 2) measures of topographic roughness, often used for morphologic characterization (Cavalli and Marchi, 2008) or landslide risk assessment (Husic and Michalek, 2022), and 3) quantifications of the hydrologic characteristics of different LULC types, typically expressed as a function of Manning's surface roughness coefficient n, to study, e.g., anthropogenic

145 effects on landscape and sediment transport changes (Persichillo et al., 2018), landslide occurrence (Zanandrea et al., 2019), or runoff generation (Hooke et al., 2021).

In general, independently of the choice of W, the index of connectivity IC_k (Eq. 1) is higher at cells with a larger and/or steeper contributing area, reflecting that such conditions are associated to the generation of potentially larger runoff volumes, that can concentrate faster at cell k. $D_{up,k}$ shows some similarity with the well-known topographic wetness index (TWI, Beven

150 & Kirkby, 1979; Riihimäki et al., 2021), often regarded as a proxy for soil moisture (Riihimäki et al., 2021); both are proportional to the size of the upstream contributing area, but TWI only considers the local (at-the-cell) slope, instead of the average slope of the area draining to the cell. In turn, longer travel distances to the stream network, as well as runoff paths with milder slopes, both increase the value of the downslope component $D_{dn,k}$ (in the denominator of IC_k), resulting in reduced connectivity values, to reflect the lower potential of distant (upstream) hillslope locations to readily contribute the upland

155 runoff (or sediment) to the stream network.

2.2 Recommended weighting coefficients for deriving HCIU

Among the options discussed above, when deriving HCIU we recommend choosing W values that primarily depend on the LULC type of each basin cell. In this way, the effects of pixels with different surface characteristics can be differentially weighted depending on their potentials for either generating and quickly transmitting surface runoff or else retaining, detaining,

160 or infiltrating water, depending on the distinct hydrologic dynamics associated with different LULC types. In turn, this incorporates sensitivity to the presence and spatial arrangement of the wide spectrum of LULC patches, from natural to fully

developed. Specifically, land development will locally increase connectivity at those locations that receive runoff water from urbanized pixels upstream, as well as those sectors that contribute runoff volumes to the stream network through impervious water pathways, proportionally to the intensity of land development; in a similar way, cells with more natural LULC types,

165 characterized by a lower range for the weights (i.e., reflecting higher capacity for interception, detention, retention, infiltration, or some other runoff-mitigation mechanism), will locally decrease connectivity.

A candidate LULC-sensitive expression for the weighting coefficient W is the n-dependent function given by Eq. (2) (Persichillo et al., 2018; Zanandrea et al., 2019; Hooke et al., 2021), which assigns larger weights to urbanized cells, with small roughness coefficients, as compared to vegetated (undisturbed) cells, which typically display greater roughness (Liu & De

170 Smedt, 2004; Hooke et al., 2021).

$$W(n) = 1 - n \qquad (2)$$

Another candidate could be a weighting specified as a function of the Curve Number (CN; Rallison, 1980), which accounts for LULC and soil characteristics with synergistic effects on surface runoff dynamics. In this work, we propose the expression $W(CN)$ given by Eq. (3).

175 $$W(CN) = CN/100 \qquad (3)$$

In what follows, we assess both weighting approaches (i.e., based on either n or CN) for deriving a hydrologic-connectivity-based index of urbanization, indicating the resulting metrics as either $HCIU(n)$ or $HCIU(CN)$, respectively. A table of the Manning's surface roughness coefficients associated with different LULC types, adapted from Hooke et al. (2021) and Liu and De Smedt (2004), is reported in Appendix B. Similarly, CN values adapted from Wu et al. (2024) are tabulated in

180 Appendix C, for different combinations of LULC types and hydrologic soil groups (HSGs, Rallison, 1980; Ross et al., 2018).

2.3 From distributed connectivity to a lumped, hydrologic-connectivity-based index of urbanization $HCIU$

We seek to obtain a meaningful, lumped basin urbanization metric that conceptually encapsulates the impacts of the spatial arrangement of land development and other land-use/land-cover types into a single number, starting from a basin's connectivity map. To achieve this, we propose to first determine a relative measure of the effects of urbanization on the connectivity at each

185 basin cell, by normalizing with respect to a benchmark. This is done by computing the ratio between the connectivity of each cell in the actual basin and the connectivity at the same cell but for a virtual, totally developed copy of the watershed (see Fig. 1b and 1c), with the same shape, relief, and stream network, but fully urbanized conditions. It is clear that connectivity in this virtual, "fully paved" basin takes the highest possible value at each cell, for a given watershed's shape, topography, and stream network. To normalize consistently positive quantities, we suggest a change to the traditional connectivity given by

190 Eq. (1), by computing the hydrologic connectivity index HCI_k of cell k simply as the ratio of the upslope over the downslope component (Eq. 4), without considering the logarithmic transform, so that connectivity is always positive. HIC_k differs from the traditional IC_k (Eq. 1) only in the scale and sign but maintains all other properties of the original formulation, including the sensitivity to topographic characteristics and to the spatial arrangement of patches with different LULC types.

$$HIC_k = \frac{D_{up,k}}{D_{dn,k}} = \frac{\bar{W}_k \, \bar{S}_k \, \sqrt{A_k}}{\sum_{i=k}^{n_k} \frac{d_i}{W_i \, S_i}} \qquad (4)$$

195 The imposed change in land cover in the totally developed benchmark basin involves forcing a Manning roughness value n of 0.02 (or a CN value of 99) and a consequent $W(n)$ of 0.98 (or 0.99 in the case of $W(CN)$), at each hillslope cell. To distinguish the weighting coefficients of actual basin cells from the corresponding ones in its virtual, fully developed copy, we indicate the latter as W_{imp} in what follows (for "impervious"). The resulting connectivity map for the totally impervious basin (Fig. 1c) is a benchmark for the localized effects of the varied land-use/land-cover characteristics in the actual basin. The connectivity

200 values for the totally developed watershed represent a theoretical upper limit for the level of connectivity that could be achieved at each pixel in the study watershed, for its given, fixed shape, topography, and stream network. Using the proposed, non-negative formulation of the connectivity index given by Eq. (4) ensures that the normalization is operated on non-negative

values, so that the resulting normalized variable is in the interval]0; 1]. Eq. (5) provides the expression of the normalized connectivity index $\widehat{HIC}_k$ for reference cell k (see also Fig. 1d).

205

$$\widehat{HIC}_k = \frac{HCI_k}{HCI_{imp,k}} = \frac{\overline{W}_k}{\overline{W}_{k,imp}} \cdot \frac{\sum_{i=k}^{n_k} \frac{d_i}{W_{i,imp} S_i}}{\sum_{i=k}^{n_k} \frac{d_i}{W_i S_i}} = \frac{\overline{W}_k}{W_{imp}} \cdot \frac{\frac{1}{W_{imp}} \sum_{i=k}^{n_k} \frac{d_i}{S_i}}{\sum_{i=k}^{n_k} \frac{d_i}{W_i S_i}}$$

(5)

In Eq. (5), $\overline{W}_{k,imp}$ and $W_{i,imp}$ both refer to the totally impervious benchmark basin, indicating the mean weighting coefficient of the drainage area upstream of cell k, and the coefficient of the generic cell i downstream of k, respectively. Since all upstream cells will have a constant coefficient value W_{imp} in the impervious basin, $\overline{W}_{k,imp}$ is equal to W_{imp}, for any k. Similarly, $W_{i,imp} = W_{imp}$, for any i.

210   The normalized connectivity index $\widehat{HIC}_k$ in Eq. (5) is equal to the product of the ratio of the average weighting coefficients from the upslope components, $\overline{W}_k/W_{imp}$, and the ratio of the weighted distances of reference cell k to its pour point along the stream network, $\frac{1}{W_{imp}} \sum_{i=k}^{n_k} \frac{d_i}{S_i} / \sum_{i=k}^{n_k} \frac{d_i}{W_i S_i}$, measured in the totally impervious and the actual basin, respectively. For both factors, the numerator is always smaller than or equal to the denominator. In what follows, to emphasize the distinction between HIC_k and $\widehat{HIC}_k$ whenever these two are compared, we will refer to the former as "absolute connectivity", instead of simply

215   "connectivity," while the latter will be termed "normalized connectivity."

With the normalized connectivity map of a watershed, we can derive HCIU for the basin, as a weighted average of the normalized connectivity indices at each pixel. We consider a weighted average, instead of a straightforward arithmetic mean, because there is still one aspect that the connectivity index does not account for, by construction, i.e., the distance of each cell to the basin's outlet. As shown in Fig. 1a, the connectivity index considers the distance from each cell k to its pour point along

220   the stream network. However, different pour points along the network are located at different distances from the basin outlet; hence, hillslope cells with similar levels of connectivity (e.g., because they are at similar distances to some segment of the stream network) but at different locations with respect to the basin's main channel and its outlet will display strong variability in their potential for contributing runoff to the outlet, and also in their timing. To account for these differences, we consider, for each hillslope cell k, its corresponding "along-the-stream-network" distance $d_{SN,k}$ to the outlet, measured starting from the

225   pour point SN_k of cell k (see Fig. 1e). Then, we assign a weight w_k to each hillslope cell k in a way such that pixels whose pour point is closer to the outlet receive a larger weight than those which are further away from it. In this work, we propose the weighting function $f_{w,HCIU}(d_{SN,k})$ given by Eq. (6), which assigns weights in the interval [0.5; 1]. Those basin cells pouring at stream locations with the minimum distance d_{min} to the outlet receive a weight of 1, while cells that drain to stream locations at the maximum distance d_{max} to the outlet get a weight of 0.5. All other basin cells with distances $d_{SN,k}$ between d_{min} and

230   d_{max} receive intermediate weights that vary linearly with $d_{SN,k}$ in the interval]0.5; 1[. It is worth noting that d_{max} varies across basins, while d_{min}, the distance between that channel pixel adjacent to the outlet and the outlet, is clearly equal to one pixel, for any basin.

$$w_k = f_{w,HCIU}(d_{SN,k}) = 1 - 0.5 \frac{d_{SN,k} - d_{min}}{d_{max} - d_{min}}$$

(6)

In Eq. (6), the weight assigned to the generic cell k is indicated as w_k. Once a weight is assigned to each cell, depending

235   on its "along-the-stream-network" distance $d_{SN,k}$ to the outlet, a lumped hydrologic-connectivity index of urbanization $HCIU$ can be obtained as the weighted average of the normalized connectivity indices of each basin cell, using Eq. (7), where the normalized connectivity of the generic cell k is indicated as $\widehat{HCI}_k$ (also see Fig. 1f).

$$HCIU = \frac{\sum_k w_k \widehat{HCI}_k}{\sum_k w_k}$$

(7)
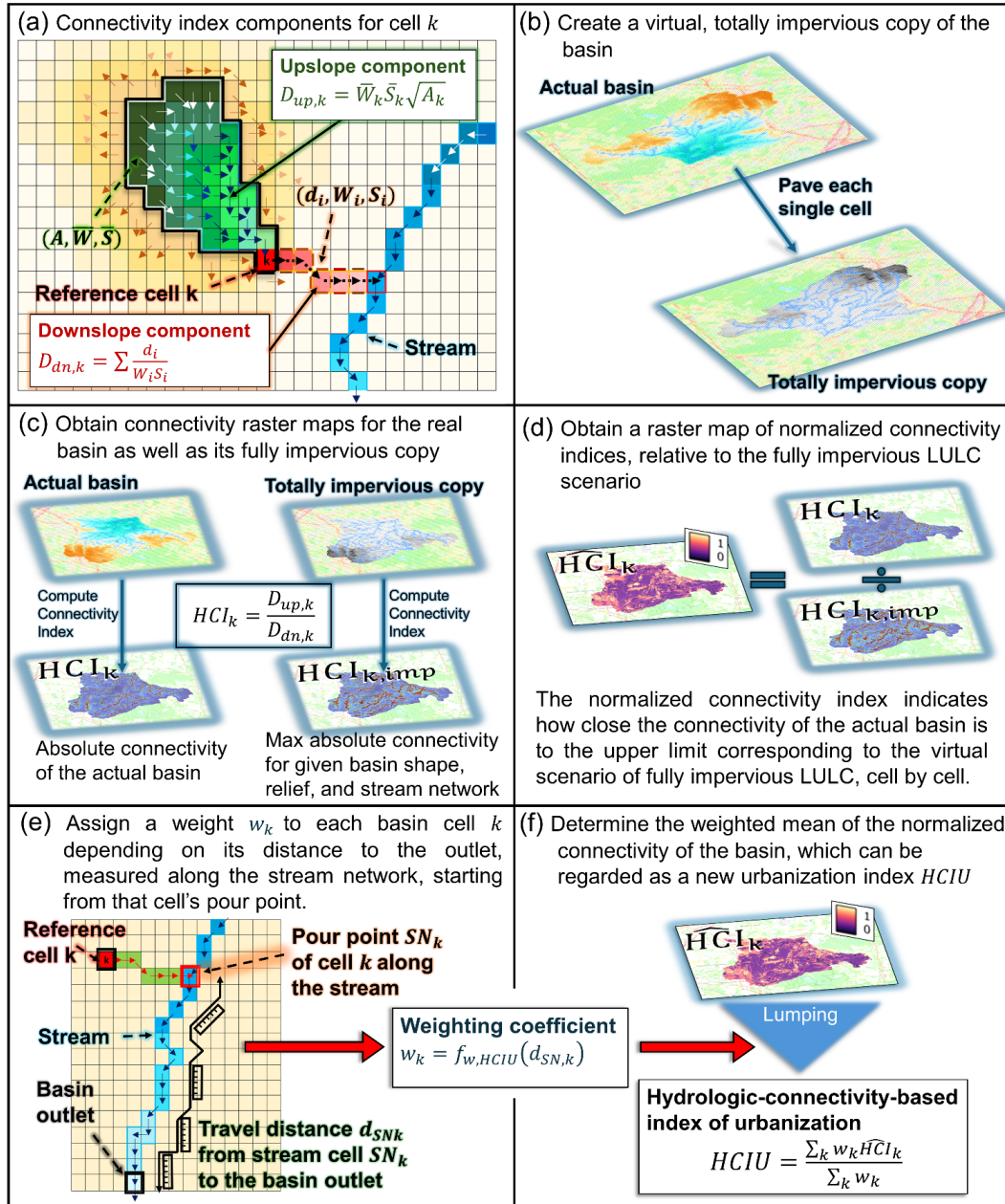
Figure 1: Methodological steps for obtaining the hydrologic-connectivity-based index of urbanization ($HCIU$).

3 Data and case studies for testing $HCIU$

3.1 Hydrologically homogenous regions

To test the proposed connectivity-based urbanization index $HCIU$ against the traditional TIA fraction as a predictive variable in regional peak flow equations, we considered three distinct hydrologically homogeneous regions, as determined by the U.S. Geological Survey (Southard, 2010; Austin, 2014; Feaster et al., 2014; see Fig. 2). One homogenous region encompasses all major metropolitan areas in Missouri (MO) and surroundings, including 34 urbanized watersheds (Southard,

2010). The second involves urban centers in Virginia (VA), with a total of 112 developed basins (Austin, 2014). The third homogenous region (Feaster et al., 2014) is the largest, spanning parts of three states – Georgia, North, and South Carolina; it includes 79 urbanized watersheds, encompassing the "Piedmont" and part of the "Ridge and Valley" ecoregions defined by the U.S. Environmental Protection Agency (USEPA), resulting in a long band of land, moving from Georgia to North Carolina, with consistent flood frequency characteristics (Feaster et al., 2014). For brevity, in what follows we will refer to this third homogeneous region as EPA ecoregion (or EPAE). The VA and EPAE case studies only include basins with at least 10% of TIA (Austin, 2014; Feaster et al., 2014), while the MO study considers a lower threshold, with all basins above 5% TIA, except for one, with only 2.33% (Southard, 2010).
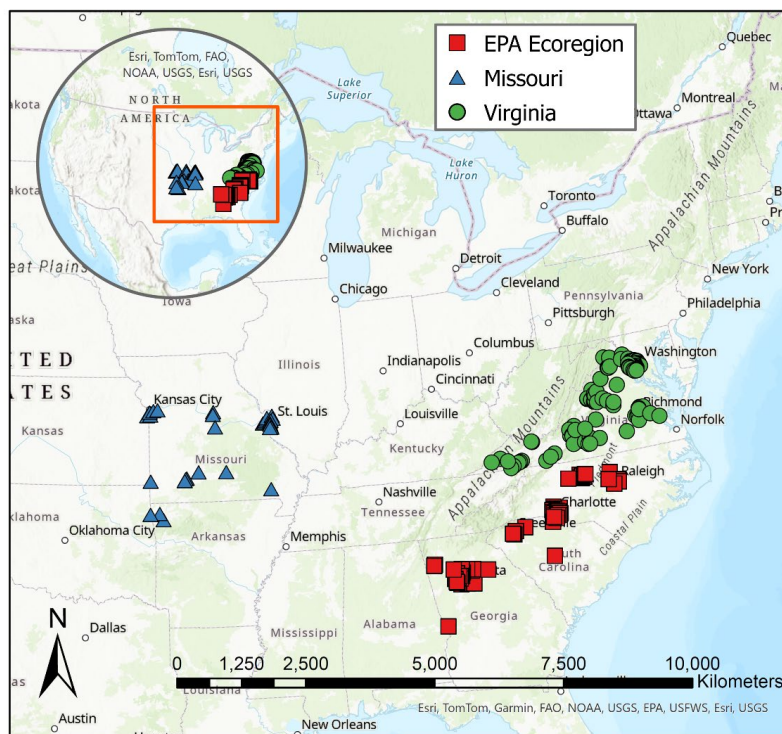
Figure 2: Case-study regions (basin locations are reported in Appendix E; map created with ArcGIS Pro; ESRI, 2024).

For each basin in their case-study regions, Southard (2010), Austin (2014), and Feaster et al. (2014) performed flood frequency analyses and estimated peak flow values for a range of return periods (see Appendix A), following the U.S. national guidelines provided in Bulletin 17B (Interagency Advisory Committee on Water Data, 1982). Southard (2010) and Austin (2014) obtained the fraction of TIA from the National Land Cover Dataset (NLCD) 2001 (Homer et al., 2020), for the MO and VA case studies, respectively. On the other hand, for the EPA ecoregion Feaster et al. (2014) considered the 2006 version.

Regional peak flow equations proposed for these regions all include basin area A and the percentage of TIA (simply referred to as TIA in what follows) as explanatory variables for predicting the flood Q_T with return period T. Southard (2010) and Feaster et al. (2014) adopted the functional form given by Eq. (8), with TIA as the generic urbanization metric U, while Austin (2014) considered a different form, where the peak flow per unit area (Q_T/A) is modeled as a function of A and TIA. For convenience and consistency, in this work we systematically consider the simple linear model given by Eq. (8) to test the predictive power of the hydrologic-connectivity-based index of urbanization $HCIU$ against the traditional TIA. We alternatively use TIA or $HCIU$ as the generic urbanization metric U in Eq. (8), each time fitting the regression model on A-

TIA-Q_T and A-$HCIU$-Q_T data, respectively. The explanatory power of these competing variables would change if we considered other functional dependencies, but from a qualitative standpoint, the superiority of one variable over the other to explain peak flows should not be affected by this change.

$$\log Q_T = \beta_0 + \beta_1 \log A + \beta_2 U \tag{8}$$

Figure 3 plots all the A-TIA pairs for the three case studies, considering basin areas in logarithmic scale. The datasets span four orders of magnitude of basin sizes, and a wide range of land-development conditions. A table with all the basins considered in the different case study regions, and related information, is provided in Appendix A.
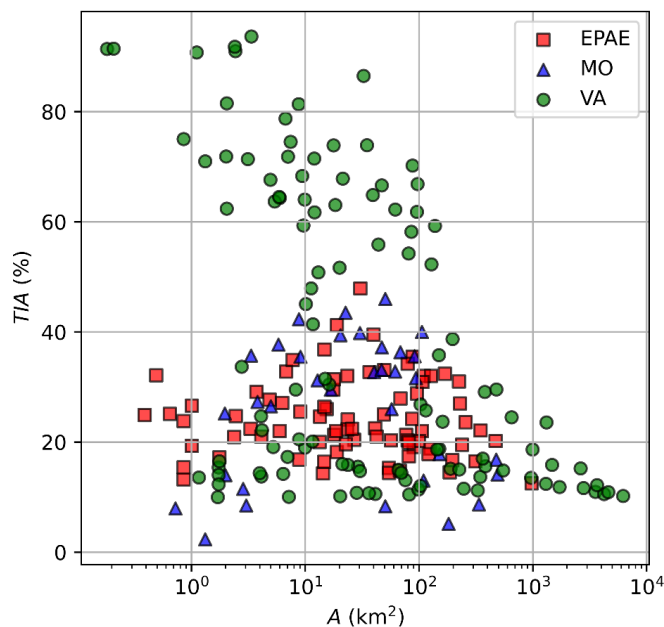
Figure 3: Case-study basins from the EPAE, MO, and VA homogeneous regions, characterized by their area (A) and percentage of total impervious area (TIA). Areas are plotted in logarithmic scale.

3.1 DEM, LULC, and HSG data

For consistency in the comparisons across the different case studies, we used the same DEM and LULC data across all homogenous regions. Because of its fine resolution and thorough coverage across the U.S. territory, we selected the 1/3rd arc-second DEMs by the USGS (U.S. Geological Survey, 2023), while for LULC we adopted the same NLCD maps (Homer et al., 2020) to obtain TIA as in the original studies, thus using the 2001 version for the MO (Southard, 2010) and VA (Austin, 2014) case studies, and the 2006 version for the EPAE case study (Feaster et al., 2014). The original NLCD maps do not distinguish between needleleaf and broadleaf dominant species within the forest categories, even though these two types of tree cover have very different runoff retention capabilities and should thus be modeled using different Manning roughness coefficients (Liu and De Smedt, 2004). This information was obtained from the global, 300-m-resolution LULC maps produced by the European Space Agency (ESA, 2017), by overlapping information from the two sources. Making this distinction results in the expansion of the two original NLCD forested LULC categories "evergreen" and "deciduous" into four classes: "deciduous needleleaf", "deciduous broadleaf", "evergreen needleleaf", and "evergreen broadleaf" forest. To generate Curve-Number-based urbanization metrics $HCIU(CN)$ for our case studies, we also needed information about the hydrologic soil group for each basin cell, for which we considered the HYSOGs250m global dataset (Ross et al., 2018), providing worldwide HSGs over a 250-meter grid.

Information from the DEM, (expanded) LULC, and HSG maps was extracted for each case-study basin using the
295 watershed boundaries obtained from the USGS data repository by Krstolic (2006), for the VA case study, and from the
StreamStats web application developed and maintained by the USGS (U.S. Geological Survey, 2019), for the MO and EPAE
case studies. Then, LULC types and LULC-HSG pairs at each basin pixel were mapped into values of Manning's roughness
coefficient n and Curve Number CN, respectively, following the tables given in Appendices B (adapted from Liu & De Smedt,
2004; Hooke et al., 2021) and C (adapted from Wu et al., 2024), respectively.

300 For each basin, the stream network was obtained from the flow accumulation raster (using the D8 algorithm), by setting
a minimum threshold for the number of upstream cells. Instead of following the traditional procedure of considering a constant
threshold for the whole basin (Tarboton and Ames, 2001), we locally selected the threshold for each headwater to closely
match its location as per the National Land Cover Dataset Plus High Resolution (NHDPlus HR; Moore et al., 2019), outlining
a digital stream network as similar as possible to the official blue lines provided in that dataset. We found this approach a
305 preferable alternative to DEM-burning procedures that would enforce the NHDPlus stream network onto the DEM by locally
lowering the elevations and introducing preferential flow directions (Getirana et al., 2009), because our method is better at
preserving the actual connectivity patterns between the hillslope component and the stream network. DEM-burning algorithms,
on the other hand, could have led to issues such as the occurrence of parallel streams arising from the non-alignment of the
original DEM channels and the corresponding network links coming from the external source (Lindsay, 2016), with the
310 consequent risk of diffused runoff pathway disruptions or alterations before reaching the stream.

Figure 4 shows the frequency distribution of the Manning's surface roughness coefficient n (Fig. 4a, 4b, and 4c), the CN
(Fig. 4d, 4e, and 4f), and the slope (Fig. 4g, 4h, and 4i), observed both at the pixel and basin scales (considering basin averages
in the latter case), for the three case-study regions. Based on the functional dependency of HCI_k outlined by Eq. (4), the
connectivity-based urbanization index $HCIU$, in its two versions $HCIU(n)$ and $HCIU(CN)$, is expected to display sensitivity
315 to those distributed basin characteristics. We note that the VA case study presents a wider spectrum of n values (Fig. 4c) as
compared to the other two (Fig. 4a and 4b), which is imputable to differences in the vegetated areas, with VA more dominated
by the presence of broadleaf tree species, both deciduous and evergreen. While VA also presents a higher frequency of low
CN-value pixels (Fig. 4f), as compared to the other two case studies (Fig. 4d and 4e), the difference in the spread of CN values
is not as noticeable as is the case with n. This is because, in contrast to our n values, the CN for different combinations of
320 LULC types and hydrologic soil groups do not weigh broadleaf and needleleaf tree vegetated areas differently (Wu et al.,
2024). The VA case study also differs from the other two in its relief characteristics, with a wider range of point and basin-
averaged slopes (Fig. 4i, as compared with Fig. 4g and 4h), associated with basins from the Appalachian region.
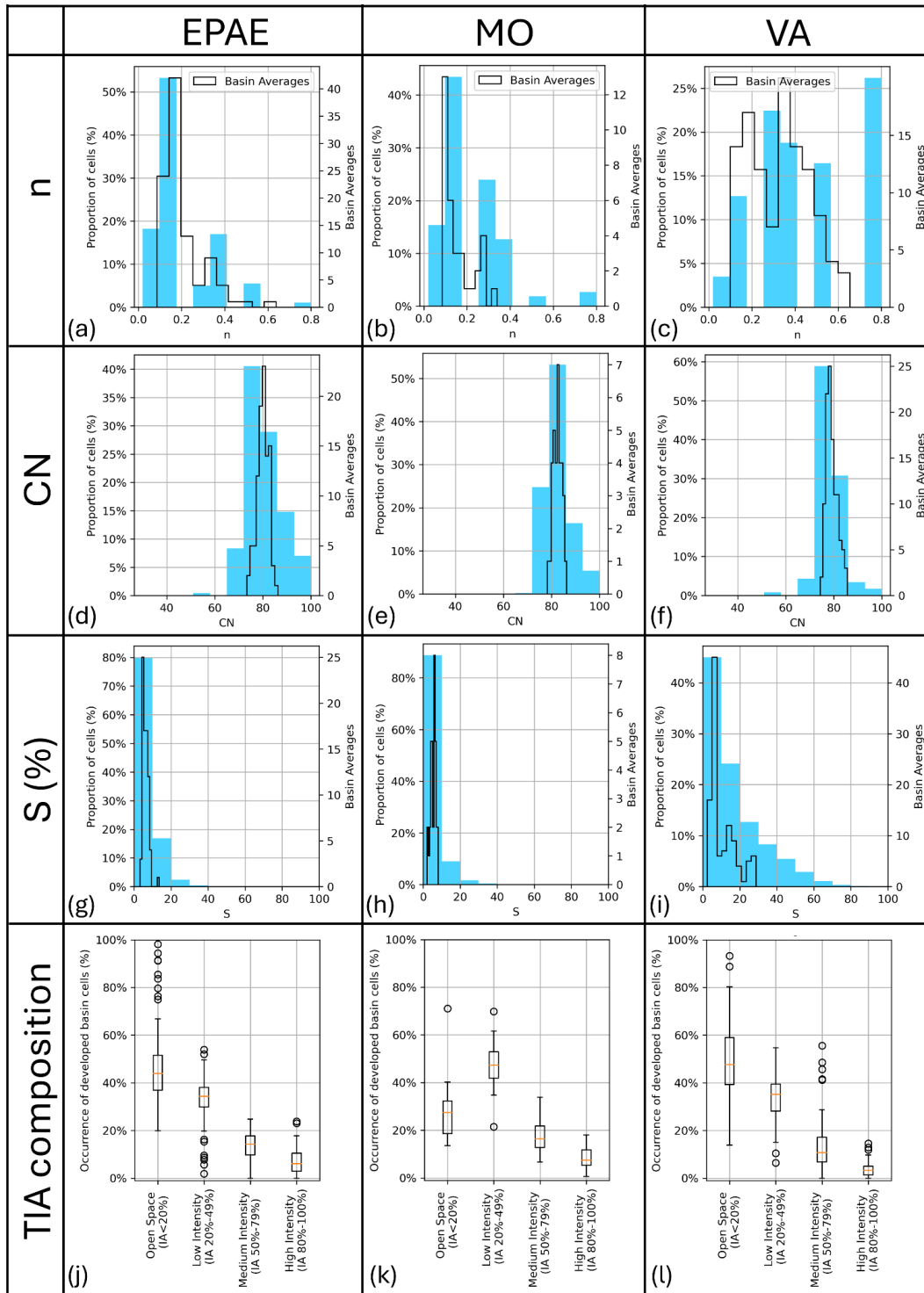
Figure 4: Frequency distribution of the Manning surface roughness coefficient n (a, b, and c), curve number CN (d, e, and f), and slope S (g, h, and i), for the three case studies, both those observed at each basin pixel across all watersheds (filled bars) and as basin averages (empty bars); (j, k, and l): mix of the four NLCD developed LULC types (associated with different amounts of impervious area IA) for all basins in the three case studies, respectively, expressed as percentages of the total extent of developed areas.

Figure 4 also illustrates the mix of developed LULC types in the basins, by showing the distributions (boxplots) of the extents of the four developed NLCD categories (i.e., "Developed, Open Space", "Developed, Low Intensity", "Developed, Medium Intensity", and "Developed, High Intensity") in each watershed, for the three homogenous regions (Fig. 4j, 4k, and 4l, respectively). For each watershed, Fig. 4 provides developed LULC extents as percentages of the number of basin pixels with given developed LULC category (say, "Low Intensity") with respect to the total number of developed LULC cells in that watershed (i.e., the sum of the numbers of "Developed, Open Space", "Low Intensity", "Medium Intensity", and "High Intensity" cells).

The four urbanized LULC categories are associated with distinct levels of imperviousness. For instance, "Open Space" is the least developed LULC category, with each pixel having less than 20% impervious area (IA), while highly urbanized cells, with impervious areas from 80% to 100%, fall in the "High Intensity" category. Because of these differences, moderately developed areas contribute less to the overall TIA of a basin, as compared to highly impervious ones. In other words, larger areas of "Developed, Open Space" and "Developed, Low Intensity" patches are needed, as compared to "Developed, Medium Intensity" and "Developed, High Intensity" ones, to contribute the same proportion of TIA in a watershed.

It is evident from Fig. 4j, 4k, and 4l that each region has its own characteristic mix of basin urbanized areas, even though with a clear dominance of moderately developed LULC categories (i.e., "Open Space" and "Low Intensity") over the more urbanized types, across all the case studies. VA (Fig. 4l) is the region with the smallest relative extents of highly urbanized areas (with respect to the total extent of land development), with most basins having less than 10% "High Intensity" pixels (i.e., with IA between 80% and 100%) and wider (relative) extents of "Open Space" areas (i.e., with IA less than 20%), as compared to basins from the other two case studies (Fig. 4j and 4k). MO, on the other hand (Fig. 4k), contains many watersheds with more concentrated urbanized areas, as indicated by the higher proportion of both "Medium" and "High Intensity" areas, and low-urbanization environments more dominated by "Low Intensity" (i.e., with IA between 20% and 50%), than "Open Space" areas (i.e., with IA below 20%). The EPAE region (Fig. 4j) displays intermediate conditions between those observed for VA (Fig. 4l) and MO (Fig. 4k), both in terms of the more (i.e., "Medium" and "High Intensity") and the less urbanized LULC categories (i.e., "Open Space" and "Low Intensity").

4 Results

4.1 Interpretation of the intermediate raster data products

To get a qualitative understanding of how the new connectivity-based urbanization index works and examine differences between the n-based and CN-based formulations, Fig. 5 shows the intermediate raster products generated by applying the proposed methodology at one of the MO watersheds. Basin 06894000 (Fig. 5a) is characterized by a quite heterogeneous mosaic of land-cover patches, with many parks and forested areas, as well as neighborhoods and parking lots. A zoom on a portion of the basin, in the circular window in Fig. 5a (obtained from OpenStreetMap; OpenStreetMap contributors, 2015), offers a more detailed glimpse into the variety of urbanized and vegetated areas.

Figures 5c and 5e show the HCI raster maps for basin 06894000, obtained from the n- and CN-based formulations, respectively. The pairs of circular windows in Fig. 5c and 5e both depict the same enlarged portion of absolute connectivity maps obtained for the actual basin (HCI) and the totally developed virtual copy (HCI_{imp}), respectively. In all cases, absolute connectivity increases for cells located closer to the stream network. Slope also controls both formulations of HCI, with higher gradients of absolute connectivity observed in steeper valleys, as compared to flatter riverine zones (see Fig. 5b). This is clear when looking at the floodplain for the basin's main channel (the darker buffer area around the main channel in Fig. 5b), which is characterized by lower absolute connectivities than many of the riverine zones of its tributaries, with steeper slopes.

The raster maps of normalized connectivity $\widehat{HCI}$ (Fig. 5d and 5f), on the other hand, display low sensitivity to topographic gradients, as there is no correlation with local spatial patterns in slopes (Fig. 5b). For instance, the floodplain of the main

channel displays higher normalized connectivity $\widehat{HCI}(n)$ than many of the tributary valleys, even though the latter show higher

370   absolute connectivity $HCI(n)$ (compare Fig. 5c and 5d). This is because the n-based normalized connectivity is most sensitive to differences in land-cover, as captured by $W(n)$ (also see Eq. 5). This is easy to notice from the $\widehat{HCI}(n)$ raster (Fig. 5d), where cells with lower normalized connectivities coarsely correspond to green patches in the map of Fig. 5a, while cells with high values of $\widehat{HCI}(n)$ are typically associated to developed areas of the basin.

While spatial patterns in $\widehat{HCI}(n)$ are easy to interpret retrospectively, because n only reflects differences in land-cover

375   types, spatial patterns in $\widehat{HCI}(CN)$ (Fig. 5f) correlate less with the spatial arrangement of land-cover types. This is expected, as $W(CN)$ reflects differences not only in LULC types, but also in hydrologic soil groups. Depending on the specific soil group, some pervious cells with lower soil infiltrability can get CN values as high as those of urbanized cells (Wu et al., 2024), which may result in similar normalized connectivity values for some of the pervious patches, as compared to impervious sectors.

380   In summary, the two types of normalized connectivity raster maps, $\widehat{HCI}(n)$ and $\widehat{HCI}(CN)$ (Fig. 5d and 5f, respectively), may look very different from each other even though the absolute connectivity maps, $HCI(n)$ and $HCI(CN)$ (Fig. 5c and 5e, respectively), present similar spatial patterns. This is because local topography and the proximity to the stream network both are strong controls for the absolute connectivity, but not necessarily so for the normalized connectivity.
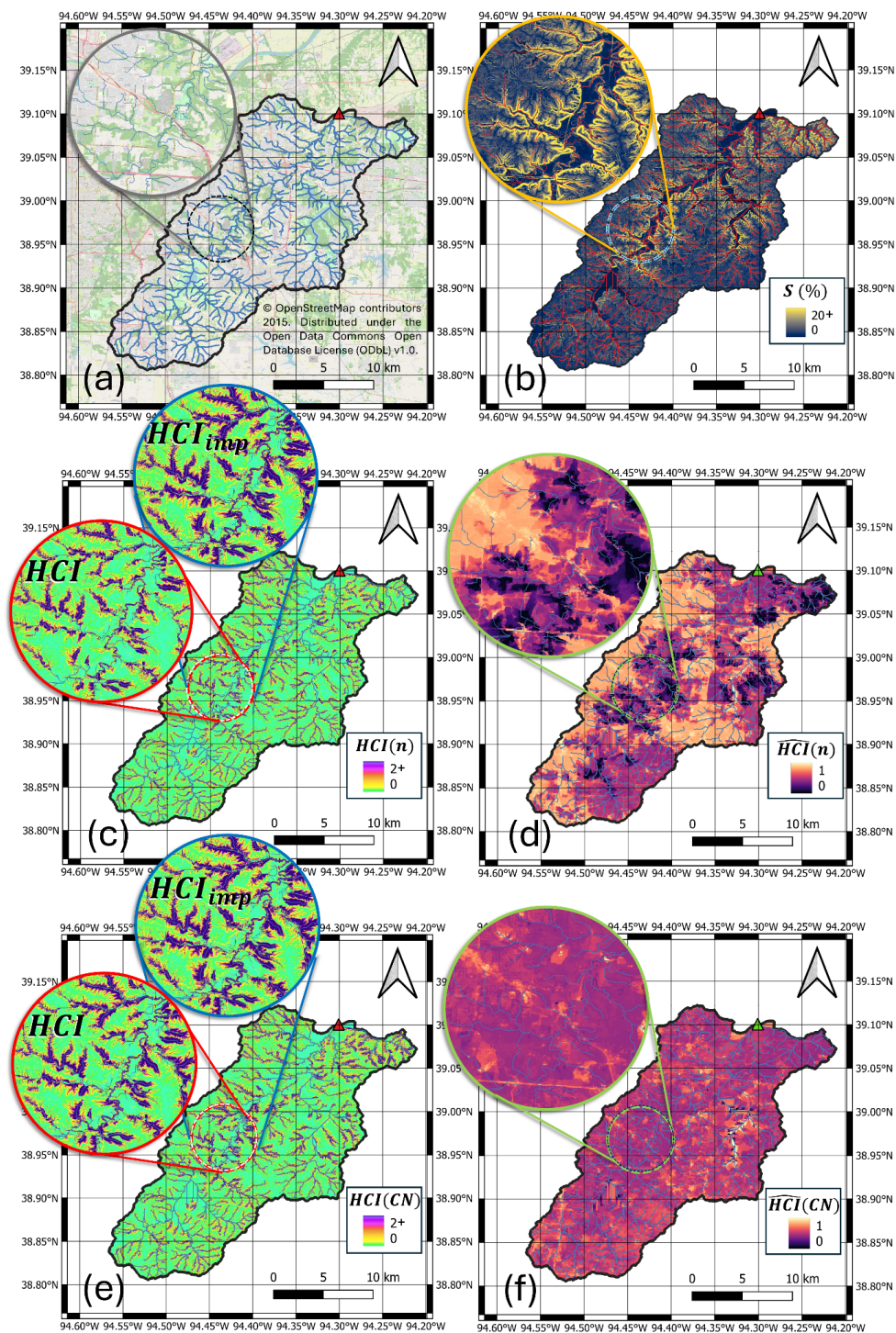
Figure 5. a) Basin 06894000 (MO); b) raster map of slopes S; c) raster map of absolute hydrologic connectivity indices $HCI(n)$ obtained as a function of Manning roughness coefficient (n); d) raster map of normalized connectivity indices $\widehat{HCI}(n)$ obtained as a function of Manning roughness coefficient (n); e) raster map of absolute hydrologic connectivity indices $HCI(CN)$ obtained as a function of curve number (CN); f) raster map of normalized connectivity indices $\widehat{HCI}(CN)$ obtained as a function of curve number (CN). Background map in Fig. a) was retrieved from OpenStreetMap (OpenStreetMap contributors, 2015).

390 **4.2 Conceptual differences between $HCIU$ and TIA**

The new proposed urbanization metric expresses the relative degree of hydrologic connectivity – with respect to the fully developed benchmark – that arises from the spatial arrangement of the spectrum of developed and undisturbed LULC patches present in a basin, with different hydrologic characteristics, contingent upon the topographic structure of the hillslopes and stream network. As such, it is expected to index the effects of land development differently, as compared to TIA, which is

395 simply the proportion of impervious surfaces. This means that different basins with similar percentages of TIA will display variability in their associated $HCIU$ values, because of the heterogeneous effects on connectivity (as captured by W) of distinct spatial arrangements of the urban sectors (with different land-development intensities) and the undeveloped patches in the watershed. Figure 6 shows, in two separate subplots (6a and 6b), the variability in $HCIU$ obtained for our case studies for various levels of TIA, considering $HCIU(n)$ and $HCIU(CN)$, respectively. We include example basins with distinct spatial

400 arrangements of natural and developed areas (Fig. 6c to 6i) to clearly illustrate the sensitivity of $HCIU$ to LULC configurations. For the sake of simplicity, for this visualization we adopt a simplified, four-category LULC classification: "Highly Impervious", "Moderately Impervious", "Moderately Pervious", and "Highly Pervious". We label developed pixels with impervious areas equal to or above 50% (i.e., the NLCD "Medium" and "High Intensity" classes), as "Highly Impervious", while those with imperviousness below 50% (i.e., the NLCD "Open Space" and "Low Intensity" classes) are classified as

405 "Moderately Impervious". On the other hand, the "Moderately Pervious" category encompasses those undeveloped cells with moderate values of Manning's coefficient n, equal to or below 0.3 (see Appendix B), such as herbaceous, hay/pasture, and barren land LULC, while the "Highly Pervious" category covers the remaining undeveloped LULC types, including forested and other densely vegetated areas.
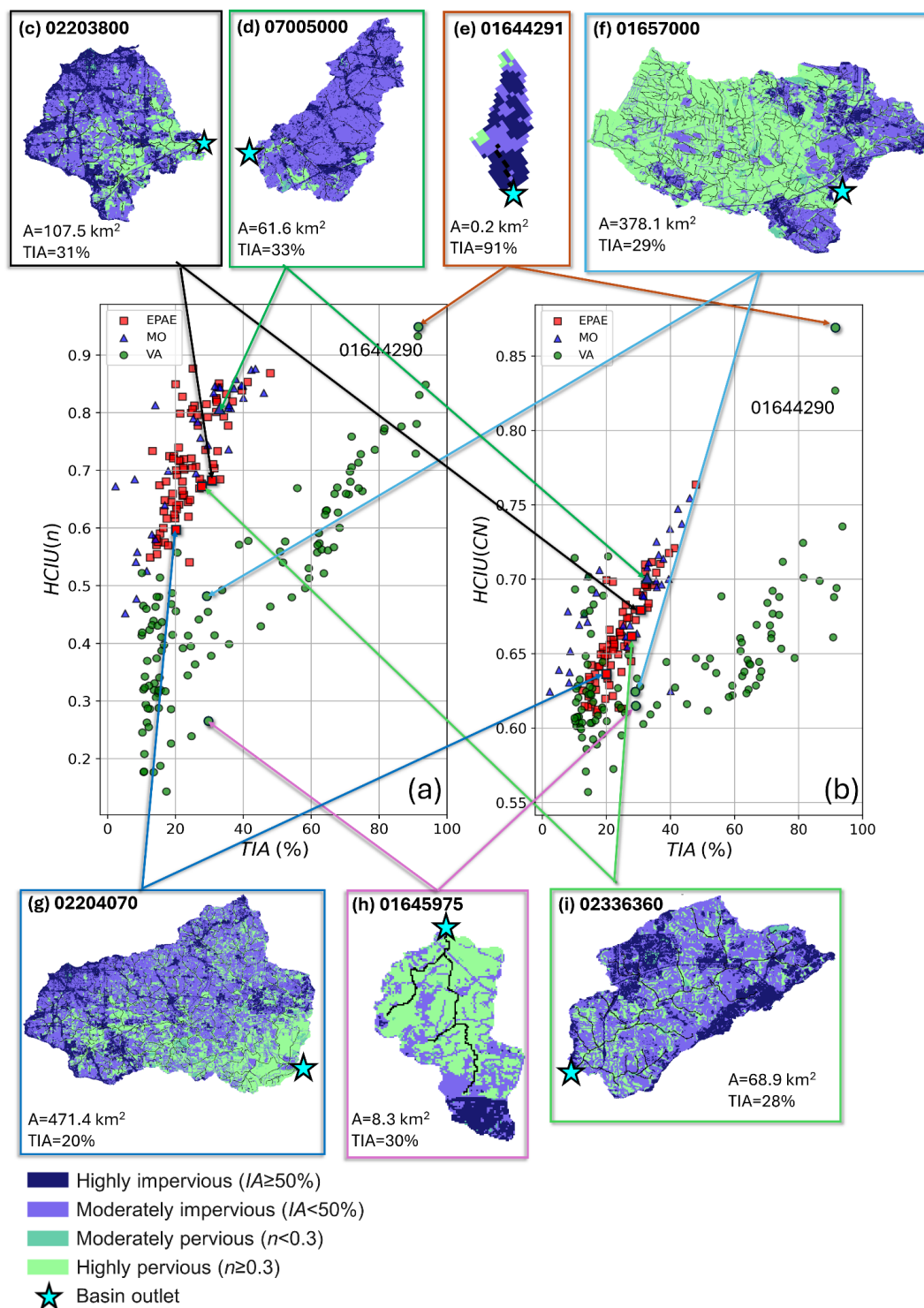
Figure 6. Case-study basins for the EPAE, MO, and VA homogenous regions in the TIA-$HCIU$ plane, considering a) $HCIU(n)$ and b) $HCIU(CN)$, respectively. Seven specific basins (c–i) are used as examples to visualize the sensitivity of $HCIU$ to different spatial arrangements of LULC patches, even for basins with similar TIA; a simplified, four-category LULC classification is adopted, as indicated in the legend.

In general, a wide range of $HCIU$ values is associated to any given TIA, across all case studies; this is expected, since

415 similar relative amounts of impervious areas can have different effects on hydrologic connectivity, depending on their spatial arrangement with respect to each other and also with respect to the less developed and undeveloped patches (Fig. 6a and 6b). However, we also note general positive trends, both within and across all the case studies considered, suggesting that basins with increasingly larger TIA are characterized by overall higher $HCIU$ values, as should also be expected.

Figures 6a and 6b also show that $HCIU(n)$ and $HCIU(CN)$ have different ranges of variability. Both have a lower bound

420 greater than 0; this is intrinsic to the formulation of $HCIU$ itself as a (weighted) average of the relative degree of connectivity of the watershed. The absolute connectivity of a basin with totally pervious land-cover type, which can be regarded as a lower-bound, yet realistic scenario, is small (or very small), compared to the connectivity of the corresponding totally impervious virtual basin, but not zero. Therefore, the fact that $HCIU$'s lower bound is greater than zero comes from physical (or at least conceptual) considerations, depending on the range of variability of the weighing coefficient W, specifically on its minimum

425 value (see Eq. 5). Since $HCIU(n)$ and $HCIU(CN)$ use different weighting coefficients $W(n)$ and $W(CN)$, with different lower limits, their lower bounds will differ.

Figures 6a and 6b display another interesting characteristic of $HCIU$, i.e., its sensitivity to the heterogeneity in the undeveloped LULC types in a basin. Compared to the other two case studies, VA watersheds got overall smaller $HCIU$ values for similar levels of TIA. This is because VA basins are characterized by pervious land-cover types with generally greater

430 flood-mitigating capabilities (larger n values and smaller CN values), as indicated by the wider spread of Manning's coefficients in the range of small values (Fig. 4c), as well as the stronger positive skewness in the frequency distribution of CN values (Fig. 4f), as compared to the other two case studies (Fig. 4a-4b, and 4d-4e, respectively). As a result, VA basins have lower $HCIU$ values as compared to those from the MO and EPAE case studies with similar relative amounts of developed areas, because the pervious fraction in VA basins is more effective in reducing the hydrologic connectivity of the urbanized

435 patches. This effect is more evident with the n-based formulation for $HCIU$, where a clear separation exists also for the smallest TIA values. This is modulated by the diverse ways in which the effects on hydrologic connectivity of distinct undeveloped LULC types are differentially weighted by $W(n)$ and $W(CN)$.

Distinct spatial arrangements of pervious and impervious patches (see examples in Fig. 6c to 6i) get $HCIU(n)$ and $HCIU(CN)$ values (Fig. 6a and 6b, respectively) in agreement with our expectations, irrespective of the weighting approach

440 (based on either n or CN). For instance, focusing on watersheds with similar TIA levels (around 30%), basin 01645975 (Fig. 6h), with predominant "Highly Pervious" land cover and most urbanized areas concentrated in a limited area far upstream from its outlet, gets significantly lower $HCIU$ values (both in the $HCIU(n)$ and $HCIU(CN)$ scales) than basins 01657000 (Fig. 6f) and 02203800 (Fig. 6c), both of which display spatial arrangements of impervious areas that would be expected to cause stronger hydrologic effects.

445 Basin 01657000 (Fig. 6f) has a proportion of pervious and impervious LULC patches similar to basin 01645975 (Fig. 6h), but its urbanized areas (including a considerable extent of "Highly Impervious" patches) are all concentrated downstream, where they can contribute impervious runoff more effectively to the outlet, hence having a stronger impact on the overall hydrologic connectivity of the watershed. Basin 02203800 (Fig. 6c) shows even worse conditions, with a significantly larger proportion of "Moderately Impervious" areas than pervious patches, which impact a wider extent of the watershed, including

450 areas near its outlet. These LULC conditions, even though they are associated with locally lower levels of imperviousness as compared with the highly impervious but spatially concentrated areas of basin 01657000 (Fig. 6f), systematically increase distributed connectivity, hence decreasing the overall response time of the watershed. Consistently, basin 02203800 (Fig. 6c) gets higher $HCIU(n)$ and $HCIU(CN)$ values than basin 01657000 (Fig. 6f).

These comparisons indicate that large developed areas, even with locally low levels of imperviousness, can have stronger

455 effects on $HCIU$, as compared to highly urbanized but spatially concentrated patches. Because of this, basins that get the highest $HCIU$ values are those where developed patches are dominant and uniformly spread. Basins 07005000 (Fig. 6d) and

01644291 (Fig. 6e), both in the higher end of the TIA-$HCIU$ plots (Fig. 6a and 6b), exemplify this case, with their surfaces entirely covered by a mix of "Moderately" and "Highly Impervious" land-cover, and negligible presence of "Moderately" or "Highly Pervious" patches.

460   The stronger effects on $HCIU$ of large extents of moderately impervious patches, as compared with highly urbanized but concentrated areas, hold true also when comparing watersheds with different TIA levels. For instance, basin 02204070 (Fig. 6g) has TIA of 20%, lower than the 30% TIA of 01657000 (Fig. 6f) and 01645975 (Fig. 6h); yet the $HCIU$ value of the former is higher than the $HCIU$ values of the latter two, both for the n- and CN-based formulations. This is, again, because the spatial arrangement of its impervious patches covers a wider (even though less dense) spatial extent, resulting in a more
465   widespread increase in connectivity.

The examples above indicate that $HCIU$ displays sensitivity to the spatial arrangement of the heterogeneous LULC patches in a watershed, irrespective of basin size and shape. However, $HCIU$ can also capture similarities in these spatial arrangements, across basins with different shapes and sizes. For instance, basins 02203800 (Fig. 6c) and 02336360 (Fig. 6i), with areas of 108 and 70 km^2, respectively, both display a preponderance of "Moderately Impervious" LULC types, with few, more intensely
470   developed patches located far upstream with respect to the outlet, and a finely dispersed pervious fraction, that tends to condense into larger pervious patches moving towards the outlet. Because of these similarities in the LULC spatial configurations, these two basins get similar $HCIU$ values, both when using $HCIU(n)$ and $HCIU(CN)$, despite their differences in size and shape.

Two highly urbanized VA basins, 01644290 and 01644291 (Fig. 6e), have unusually higher $HCIU(CN)$ values, as
475   compared to all others (Fig. 6b), because of their peculiar LULC conditions. Both are very small in size (< 0.20 km^2) and are almost totally characterized by highly impervious LULC ("Developed, High Intensity" NLCD type). Furthermore, the few, small undeveloped patches are unable to mitigate the connectivity of the developed areas, since they are located far upstream, close to the water divide (see Fig. 6e for basin 01644291). Both aspects lead to LULC conditions almost identical to those for the virtual, totally impervious scenario considered for normalizing absolute connectivity, hence justifying the large $HCIU(CN)$
480   values for these two watersheds, which are the highest among all basins and case studies. These two watersheds are outliers on the set of $HCIU(CN)$ values for VA (Fig. 6b), while they are the highest in the TIA-$HCIU(n)$ plane (Fig. 6a), but still clustered with other VA basins with high TIA.

4.3 Performance of $HCIU$ in regional peak-flow equations

We tested the predictive power of $HCIU$ as an alternative to TIA, to be used as urbanization metric in the development of
485   regional peak flow equations for the three case studies. Figure 7 shows the performance of the regional model (Eq. 8) fitted on basin area A, $HCIU$, and a range of flood quantiles Q_T (with return periods T of 2, 5, 10, 25, 50, 100, and 500 years; see Appendix A), comparing it to the benchmark model with the same functional dependency, but with TIA as the urbanization metric. The adjusted R^2 is considered as error metric.
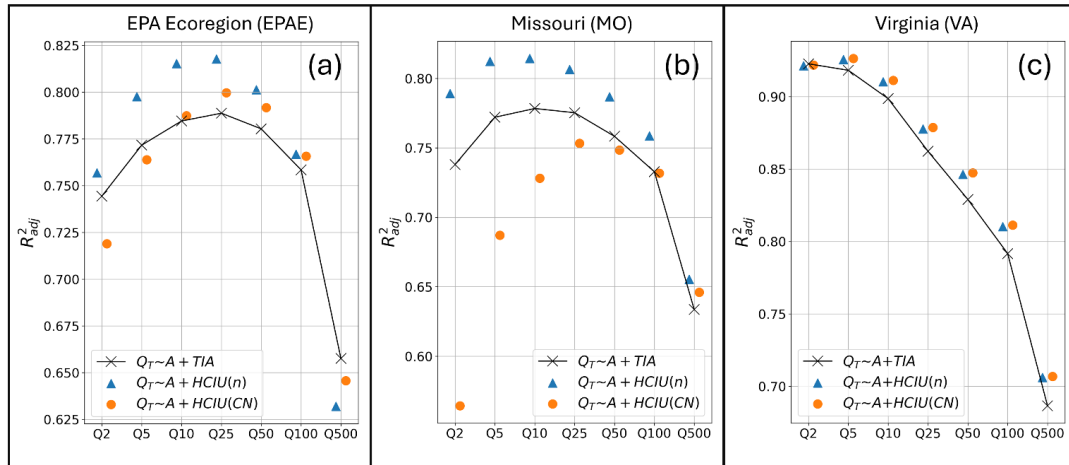
Figure 7. Comparison of the performance of regional peak-flow equations calibrated on 1) A, TIA, and Q_T data (i.e., $Q_T \sim A + TIA$ benchmark model), 2) A, $HCIU(n)$, and Q_T data ($Q_T \sim A + HCIU(n)$ model), and 3) A, $HCIU(CN)$, and Q_T data ($Q_T \sim A + HCIU(CN)$ model), for the a) EPAE, b) MO, and c) VA case studies. Quantiles Q_T associated with return periods T of 2, 5, 10, 25, 50, 100, and 500 years are considered (data in Appendix A).

Our results indicate that not only is $HCIU$ a strong peak flow predictor in combination with A, it also systematically outperforms TIA when the n-based formulation is considered. Improvement is strongest for the EPAE and MO cases studies, while for VA, where the performance of the benchmark model (with A and TIA) was already the highest among case studies, only a marginal gain is obtained. On the other hand, the CN-based formulation for $HCIU$ seems to be overall less robust, with varying behaviors depending on the specific case study. For the EPAE homogeneous region, $HCIU(CN)$ outperforms the benchmark (but not its n-based counterpart) when fitting extreme flood values with return periods between 10 and 100 years, while it slightly underperforms for other flood quantiles. On the other hand, for the MO case study $HCIU(CN)$ displays a noticeably worse performance as compared to the benchmark, except for the two largest flood quantiles (Q_{100} and Q_{500}). VA is the only region where the CN-based $HCIU$ performs similarly to the n-based $HCIU$, systematically outperforming the benchmark, even though only marginally, as all models perform well. In the Discussion section we hypothesize about what might explain the lower performance of $HCIU(CN)$, as compared to $HCIU(n)$.

Figure 7 also shows that, regardless of the urbanization metric considered, model performance decreases with increasing return period T of the flood quantile. This may be due to a combination of two aspects. First, for such extreme events, differences across distinct LULC patches in the basin become increasingly negligible from a hydrologic perspective (Ogden et al., 2011), as wetter pervious patches infiltrate a smaller fraction of precipitation, causing any land-cover descriptor to lose predictive power. The second reason lies in the inevitable uncertainties associated with the estimation of such extreme quantiles from short flow records (Klemeš, 2000), which means that the models are fitted on highly uncertain data points. Because of these reasons, we suggest that improvements in prediction accuracy of urbanization metrics should be only pursued in the range of more frequent floods (say, below the 100-year return period).

The main hydrologic application of regional peak-flow equations fitted on data from gauged basins is to extrapolate the relationships to other, ungauged basins. Therefore, a more informative way of testing the two competing urbanization metrics is to consider a k-fold validation framework, where the full dataset is split into a training and a test set, for fitting and evaluating the model, respectively. Following an approach similar to Dell'Aira et al. (2022), we produced a distribution of test errors (shown in Fig. 8) by repeatedly fitting the peak-flow equation (Eq. 8) and evaluating model performance on separate subsets of the full dataset. For each case study, we alternately considered a 66-33%, 75-25%, and 80%-20% proportion for the training and test-set sizes, respectively, associated with 3, 4, and 5 alternative training-test subset splits, respectively, in a way that all the obtained test sets together span the full dataset without having duplicate basins. For each of these proportions, we repeated

19

the k-fold procedure 10 times, considering 10 different random samplings to populate the folds, to avoid any potential bias associated with a single sampling. This procedure resulted in 120 blind assessments of the performance of the peak-flow equations, each time fitted and tested on different subsets, for each case study.
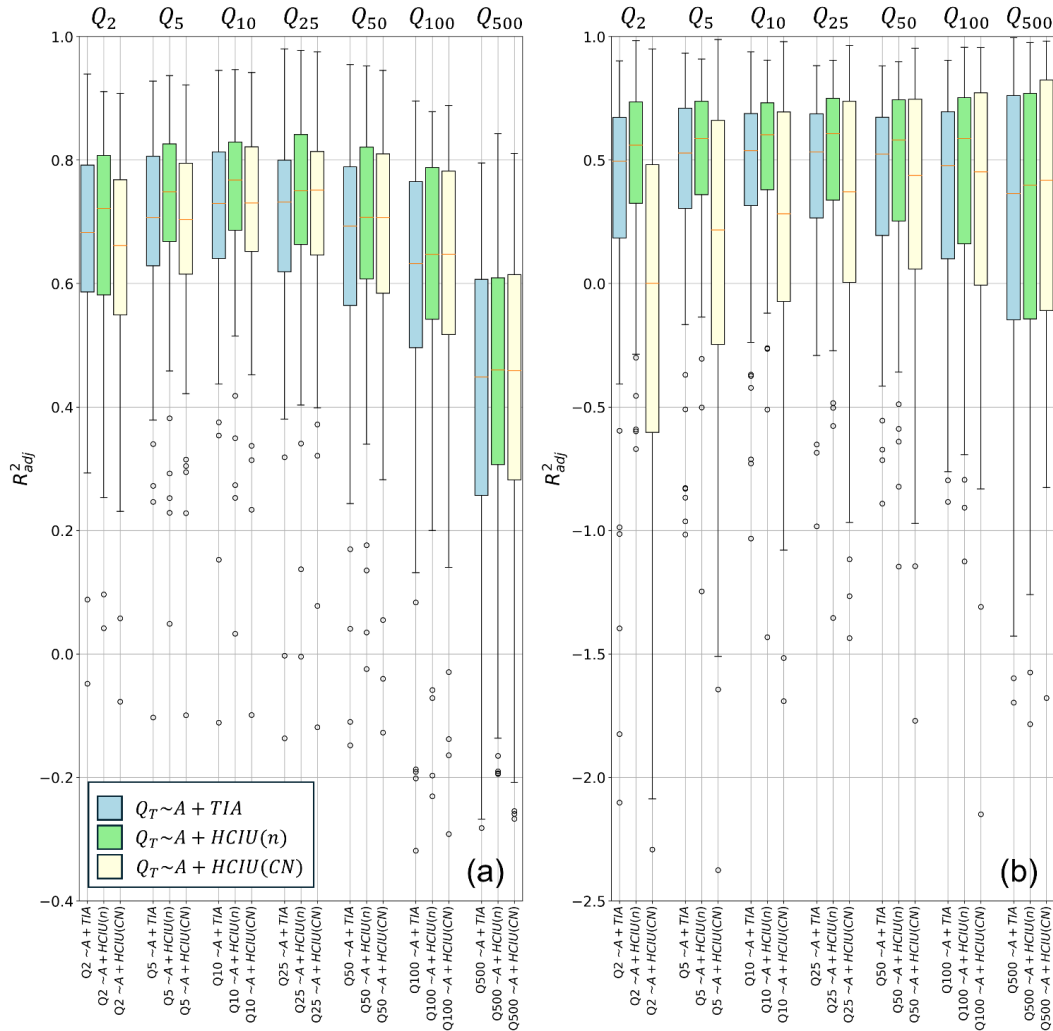
Figure 8. Boxplots of test errors for 1) the benchmark $Q_T \sim A + TIA$, 2) $Q_T \sim A + HCIU(n)$, and 3) $Q_T \sim A + HCIU(CN)$ models, when they are fitted and blind-tested on distinct basin subsets, for the a) EPAE and b) MO homogenous regions, respectively (see this same plots for VA in Appendix D). For each boxplot, filled bars represent error values between the first and the third quartiles, the upper (lower) whisker extends from the third (first) quartile by adding (subtracting) 1.5 times the interquartile range, and any outliers beyond the whiskers are marked as circles.

530   The boxplots of errors in Fig. 8 confirm that $HCIU(n)$ is the more robust urbanization metric for peak flow regression equations. For all flood quantiles, $HCIU(n)$ improves model performance (as compared to the $Q_T \sim A + TIA$ benchmark) both in average terms (as indicated by the systematically higher medians, as well as the higher location of the boxplots), as well as with respect to the error spread, which is narrower for all EPAE (Fig. 8a) and MO (Fig. 8b) quantiles, with the only exception of Q_2 for EPAE (Fig. 8a).

535   On the other hand, $HCIU(CN)$ exhibits again a more heterogeneous performance. In the EPAE case study (Fig. 8a), error boxplots associated with the $Q_T \sim A + HCIU(CN)$ are marginally better than those of the benchmark $Q_T \sim A + TIA$, but slightly worse for the two smallest quantiles (in agreement with what was observed in Fig. 7). A different picture is obtained for the

MO case (Fig. 8b), where $HCIU(CN)$ significantly underperforms the $Q_T \sim A + TIA$ benchmark, for most quantiles, indicating that $HCIU(CN)$ is not a robust urbanization metric for the MO region.

540   The same boxplots for VA, moved to Appendix D since they do not add any relevant additional information, indicate comparable results as those already observed when testing the new urbanization metric (both with the n- and CN-based weighting approaches) on the full dataset (Fig. 7c). Specifically, both $HCIU(n)$ and $HCIU(CN)$ lead to improvements in model performance, as their related error boxplots are shifted upward, as compared to the benchmark.

5 Discussion

545   Our results indicate that the proposed conceptual framework for deriving hydrologic-connectivity-based urbanization metrics does produce lumped basin descriptors that successfully encapsulate information about the flood-enhancing impacts of urban sectors with different land-development intensities (and thus, with different imperviousness levels), considering their spatial arrangement, but is also sensitive to the spectrum of mitigation effects afforded by undeveloped (pervious) patches, depending on their relative location within the watershed. This is obtained by differentially weighing the effects of different
550   LULC types through widely used and accepted conceptual criteria such as Manning's surface roughness coefficients and Curve Number values, hence capturing heterogeneity in the capacity of LULC patches to both generate and retain/detain runoff.

The resulting numerical value of $HCIU$ for a single watershed represents a measure of the proportion of hydrologic connectivity arising from the specific mosaic of land-cover patches in that watershed, relative to the maximum theoretical connectivity of that basin if its surface were completely paved. While this definition may not be as straightforward as that for
555   TIA, which is simply a proportion of impervious areas, it results in a conceptually more comprehensive, and hydrologically driven representation of the distributed impacts of urbanization on surface runoff dynamics, in a lumped basin descriptor. Like TIA, $HCIU$ can be used to characterize and compare different basins, either to simply determine which basin is more impacted by land development, or else to develop regional models. $HCIU$ can also be utilized for planning, to compare the expected hydrologic effects of different scenarios for land-development in a given watershed.

560   We suggest that $HCIU$ should also increase our explanatory power when predicting other event-related variables such as lag times and times of concentration. The $HCIU$ approach could also be further tested against TIA for predicting other hydrologic variables that are affected by land-development, such as water quality indicators.

In the next subsection, we discuss in more detail the possible reasons for the poor performance of the CN-based $HCIU$. We then highlight advantages and disadvantages of the proposed methodology and point out challenges and possible future
565   research directions to deploy the connectivity-based analysis framework to a range of different hydrologic applications.

5.1 Considerations on the low performance of $HCIU(CN)$

As noted in Section 4.1, the CN-based formulation of the normalized connectivity index and the resulting $HCIU(CN)$ (obtained as the weighted average of the former) are more complex than the n-based formulation, as they attempt to account for the combined effects of different coexisting land-use/land-cover and soil types. Because of this, the choice of the CN-based
570   weighting coefficients as well as the interpretation of the resulting raster maps of normalized connectivity require particular attention.

For our analysis, we adapted CN values associated with different land-use/land-cover types and hydrologic soil groups from the work by Wu et al. (2024), based on hydrologic modeling. According to their classification, urban cells with varying degrees of land development may be assigned CN values over a wide range, depending on the associated soil characteristics.
575   In some cases, moderately urbanized cells may have weights W not too dissimilar from those of some cells with natural land-cover types, but low soil infiltrability, meaning that both types of cells are expected to generate similar amounts of runoff.

However, it is clear that undeveloped patches would still mitigate hydrologic impacts better than urban areas, mostly through enhanced detention due to their higher roughness, delaying runoff contributions.

Interpretations for the overall low performance of $HCIU(CN)$ may hence include the variability in stormwater hydrology dynamics due to storm intensity and soil moisture conditions. Depending on these aspects, dominant control mechanisms on hydrologic connectivity and disconnection, such as soil infiltrability, rainfall interception by vegetation, and surface roughness, as well as their interplay, may significantly change (Saffarpour et al., 2016; Zölch et al., 2017). For instance, the potential for generating runoff in moderately urbanized cells may be mainly governed by the type of soil, when regular events are considered – like in the case of the validation of the CN classification proposed by Wu et al. (2024). On the other hand, when the scope of the analysis focuses on more extreme events (as in our case, with peak flow equations), the effects of land development may become preponderant (e.g., by decreasing response lag-times), since soils are more likely to reach saturated conditions. All of this in turn suggests the need to suitably adjust the CN values of urbanized cells to better differentiate them from pervious pixels, even when the latter display low infiltrability.

Another likely explanation is that CN also depends on antecedent soil moisture conditions (ASMCs), with different sets of values associated to distinct ASMC categories (i.e., dry, average, and wet; Wu et al., 2024). In our work, we considered the average scenario. However, because of the interactions between event intensity and soil moisture conditions, different sets of CN values, associated with different ASMCs, should probably be considered instead, depending on the predicted event's return period. In the case of small, more frequent events (where we found the worst performances for EPAE and MO; Fig. 7a and 7b), $HCIU(CN)$ might benefit from using lower CN values, to reflect drier soil conditions. On the other hand, for greater return-period events, soils are saturated faster, and higher CN values, related to wet ASMCs, might improve the predictive power of $HCIU(CN)$.

In summary, based on the overall low performance observed with $HCIU(CN)$, the adopted weighting approach based on average-ASMCs Curve Numbers may not be the best for our proposed methodological framework, at least when the analysis aims at predicting extreme peak flows. A poor tuning of the CN-based weighting coefficients, which do not clearly distinguish undeveloped patches with low infiltrability from developed areas with highly permeable soils, may also explain why the $HCIU(CN)$ seems less robust, compared to the simpler n-based version. Further research is needed to study the sensitivity of $HCIU$ to different CN-based weighting approaches and fine tune the coefficients to maximize its predictive power.

5.2 Advantages and limitations of the proposed approach and future research directions

The proposed conceptual framework builds on and takes advantage of our qualitative understanding of some of the varied and complex dynamics affecting a basin's hydrologic response. The main strength of the proposed $HCIU$ is that, in contrast with the traditional percentage of total impervious area or other metrics that index the impervious fraction of a basin, it takes into account the location and spatial arrangement of all types of LULC patches, in relation with basin topography, the stream network, and the outlet, in a continuum from the highly developed (which tend to generate more runoff, faster) to the undisturbed, forested patches (with the strongest mitigating effects on hydrologic response). This represents an advantage over other advanced urbanization metrics in the literature. For instance, while the methodologies adopted by Yang et al. (2011) and Beck et al. (2016) both frame the hydrologic interconnections across some main LULC categories simply based on geometric aspects such as the density, spatial adjacency, and granularity of distinct LULC patches, $HCIU$ captures the connectivity across a spectrum of surface patches as driven by basin topography. Or, in contrast with the two metrics proposed by Zhang and Shuster (2014), that also consider the effects of basin relief but adopt a binary, pervious-or-impervious LULC representation, $HCIU$ considers the continuous heterogeneity of hydrologic characteristics in the mosaic of LULC patches over a watershed.

This is achieved by alternatively using Manning's surface roughness coefficients or Curve Numbers, which are both well-established conceptualizations that quantify different LULC types' abilities to either facilitate the generation and transmission of runoff, or else retain, detain, or dampen water volumes, dependent on their surface roughness, extent (and type) of vegetated

areas, as well as infiltrability. Highly impervious patches with smooth surfaces and limited losses represent one extreme in the
620   continuous spectrum of LULC potentials for generating runoff, resulting in large peak flows; in the other are forested areas
and other LULC types with natural soils, presence of litter, and high vegetation densities, because of their ability to diminish
runoff volumes and travel speeds through interception (in the canopy and litter), temporary canopy storage, high surface
roughness, and variable infiltration capacity.

Besides its comprehensive formulation, that conceptually considers the synergistic effects of both topography and LULC,
625   another advantage of $HCIU$ is that it can be virtually derived for any basin in the U.S. or the world, from widely available data,
i.e., the DEM and LULC (or CN) maps. As a result, the proposed urbanization metric may easily find systematic application
in peak flow prediction models and, depending upon preliminary testing, also in a range of other water resources management
fields that require quantifying the level of urbanization in a basin, such as water quality assessments and stormwater
infrastructure design. We considered two alternative approaches to weigh the effects of different LULC types (and HSGs, in
630   the case of CN-based weights) on hydrologic connectivity. However, modelers may also try other weighting criteria, depending
on their specific needs. To foster the dissemination of our new metric, a link to a Python program to calculate the $HCIU$ of any
basin is provided in the Code Availability Statement (https://github.com/dllaira/HCIU-urbanization-metric).

A further advantage of the proposed approach is that it yields simple and easy-to-interpret, yet conceptually comprehensive
assessments of the hydrologic impacts of urbanization across different basins. It can also be used to compare different land-
635   development scenarios for the same watershed, aiding stakeholders in making urban planning decisions, or evaluating possible
future LULC changes due to, e.g., the distributed implementation of candidate stormwater control measures.

A current limitation of $HCIU$ is that it only frames connectivity patterns driven by basin relief (topography), even though
the potential presence of stormwater drainage infrastructure would be another important source of connectivity in any
urbanizing basin. In principle, the proposed methodology allows for considering the effects of stormwater infrastructure as
640   well; this would be achieved by first identifying pixels that are connected to each other and the stream network through
stormwater network links, and then computing the connectivity index in a way such that connectivity patterns due to the
drainage infrastructure override those from topography, whenever applicable. As we have found, however, information about
stormwater drainage networks is not easily available, which may impede considering this additional source of connectivity,
particularly in the case of multi-basin studies. Depending on data availability, an expanded version of $HCIU$ that also accounts
645   for the effects of stormwater drainage infrastructure as an additional source of connectivity should be another topic for future
research.

6 Conclusion

We proposed and tested a new, hydrologic-connectivity-based index of urbanization $HCIU$ that can be obtained in a GIS
framework from the digital elevation model and land-use/land-cover (or Curve Number) map of a basin. We showed that,
650   compared to the traditional fraction of total impervious area (TIA), $HCIU$ helps capture more information about the impacts
of land development on hydrologic response. TIA only indexes the proportion of impervious patches in a basin, while our new
metric also incorporates the emerging effects of the spatial arrangement of the different types of patches found in a watershed,
with their spectrum of surface characteristics, framed in terms of hydrologic connectivity.

The methodology builds on the well-established connectivity index, which has already found wide application in several
655   hydrologic and geomorphic problems. Our specific interpretation of the connectivity index, in the framework of our approach,
considers it as a distributed, directional property arising from the (potential) runoff interactions between urbanized sectors
(with possible local differences in land-development intensity) and the undeveloped, typically more pervious patches in a
watershed, driven by topographically induced pathways. We considered two alternative, widely used conceptual descriptors
for quantifying the potential for runoff generation of different land-use/land-cover types, i.e., Manning's surface roughness

660 coefficients and Curve Numbers. Depending on these metrics, the contributions on hydrologic connectivity of basin pixels with distinct surface characteristics are weighted differently. We found that weighting factors specified as a function of Manning's surface roughness coefficients result in more robust $HCIU$ metrics, as compared to Curve-Number-based weighting methods, when explaining urban peak flows. However, we do not exclude that a fine tuning of the latter might improve model performance.

665 Irrespective of the weighting criterion, the procedure for obtaining a lumped metric for the effects of urbanization on hydrologic response, starting from a connectivity map of the basin of interest, involves the following steps: first, we define a normalized connectivity map, with respect to the maximum connectivity scenario associated with a virtual, fully developed copy of the original watershed; then, we calculate $HCIU$ as a weighted average of the normalized connectivities of all basin pixels that are not part of the stream network, depending on the distance from their pour point to the watershed outlet, following 670 the stream network.

We have shown that our new urbanization metric improves the predictive power of existing peak-flow regional equations, for three comprehensive case studies. Further research is required to test $HCIU$'s explanatory power for other hydrologic-response (i.e., flood-related) variables, such as lag-time and time of concentration, as well as other hydrologic variables of interest that have traditionally displayed correlation with TIA, such as water quality indicators.

675 Besides its direct application as a metric of urbanization effects on basin response, $HCIU$'s sensitivity to the spatial arrangement of more developed and less developed (or undeveloped) sectors may provide a novel framework to facilitate comparisons of the hydrologic impacts caused by basin changes (e.g., due to urbanization or the introduction of stormwater runoff control measures), offering a valuable tool to stakeholders for informed urban-planning decisions. More research is needed to study the benefits and the range of applicability of the hydrologic connectivity-based index of urbanization.

680 **Appendix A**

Table A1. Case study basins. Area A, fraction of total impervious area TIA, and flood quantiles Q_2 to Q_{500} were retrieved from Southard (2010), Austin (2014), and Feaster et al. (2014), for the MO, VA, and EPAE case study, respectively; we calculated $HCIU(n)$ and $HCIU(CN)$ following the methodology proposed in this work.

	Gauge ID	A (km²)	TIA (%)	Case Study	Q_2 (m³/s)	Q_5 (m³/s)	Q_{10} (m³/s)	Q_{25} (m³/s)	Q_{50} (m³/s)	Q_{100} (m³/s)	Q_{500} (m³/s)	$HCIU(n)$	$HCIU(CN)$
1	01613900	41.3	10.59	VA	24.3	46.5	64.6	90.7	112.4	135.9	197.7	0.177	0.601
2	01615000	150.6	18.78	VA	67.3	125.1	174.7	251.3	319.1	397.0	622.4	0.468	0.645
3	01616000	44.0	55.88	VA	15.3	26.4	35.3	48.3	59.2	71.1	103.5	0.669	0.689
4	01621450	1.7	15.41	VA	1.3	2.4	3.6	5.7	7.9	10.7	20.7	0.514	0.693
5	01623000	1.7	14.05	VA	0.3	2.0	6.9	27.3	70.3	170.3	1133.8	0.464	0.643
6	01623500	10.0	18.99	VA	1.1	4.4	9.8	25.1	48.0	88.6	334.1	0.487	0.689
7	01624800	189.1	15.15	VA	71.5	121.9	162.2	221.2	271.2	326.2	477.4	0.480	0.663
8	01625000	965.4	13.51	VA	165.0	318.8	451.4	655.3	834.8	1038.9	1622.0	0.439	0.648
9	01626000	328.7	11.22	VA	76.1	165.0	255.5	417.4	581.3	790.6	1514.1	0.294	0.620
10	01626500	345.7	13.66	VA	92.9	199.3	299.6	466.1	622.4	809.3	1387.0	0.319	0.625
11	01626850	382.7	15.6	VA	113.5	239.5	361.6	571.2	774.7	1025.4	1843.1	0.319	0.627
12	01627500	548.2	14.84	VA	152.9	318.0	464.7	694.6	899.6	1133.8	1807.2	0.314	0.628
13	01628500	2795.4	11.65	VA	466.9	902.2	1303.1	1964.3	2586.7	3335.7	5697.3	0.370	0.633
14	01629500	3554.2	10.97	VA	552.2	1078.0	1575.0	2414.0	3222.5	4213.5	7438.8	0.342	0.628
15	01631000	4232.8	10.55	VA	590.4	1153.3	1675.2	2539.5	3355.5	4341.0	7455.8	0.320	0.626
16	01636210	36.3	10.71	VA	21.0	34.9	46.6	64.4	80.1	98.1	150.4	0.178	0.607
17	0163626650	29.1	15.52	VA	15.9	20.1	22.8	26.2	28.7	31.1	37.0	0.188	0.603

18	01638350	81.9	10.48	VA	48.9	118.7	194.3	336.1	485.4	680.7	1148.8	0.465	0.617
19	01643805	98.7	11.39	VA	128.5	296.5	469.2	778.4	1089.9	1484.7	2827.7	0.460	0.608
20	01644280	197.2	38.7	VA	148.0	186.2	212.2	245.9	271.8	298.2	363.3	0.571	0.644
21	01644290	0.2	91.4	VA	0.2	0.8	1.9	5.0	9.7	18.2	71.0	0.933	0.827
22	01644291	0.2	91.43	VA	2.9	4.7	6.2	8.6	10.8	13.4	21.3	0.948	0.869
23	01644295	0.9	75.03	VA	2.3	4.8	7.2	11.3	15.2	20.1	35.9	0.664	0.712
24	01644300	8.8	81.35	VA	10.6	14.7	17.8	22.0	25.5	29.2	39.0	0.768	0.724
25	01645700	11.3	47.91	VA	13.8	21.1	26.4	33.7	39.6	45.8	61.7	0.464	0.647
26	01645750	4.1	24.68	VA	2.9	5.0	6.7	9.6	12.2	15.3	25.0	0.239	0.595
27	01645784	2.0	62.38	VA	11.9	17.6	21.7	27.3	31.7	36.2	47.7	0.574	0.635
28	01645900	13.1	50.81	VA	10.3	16.8	22.2	30.4	37.6	46.0	70.4	0.559	0.642
29	01645975	8.3	29.52	VA	34.5	37.4	39.2	41.5	43.2	44.8	48.6	0.267	0.615
30	01646000	149.8	35.77	VA	50.1	95.7	143.7	234.0	330.7	460.7	960.2	0.399	0.615
31	01646200	12.1	61.73	VA	31.3	62.0	91.4	141.6	190.4	250.9	450.5	0.557	0.660
32	01646600	7.5	74.53	VA	17.6	26.4	32.9	42.0	49.4	57.3	78.1	0.728	0.653
33	01646700	21.4	67.85	VA	35.6	59.9	80.7	112.8	141.5	174.8	273.7	0.627	0.634
34	01646750	1.1	90.74	VA	8.1	14.1	19.3	27.6	35.1	43.9	70.5	0.729	0.661
35	01646800	6.0	64.33	VA	27.1	44.9	60.7	85.9	109.3	137.2	224.3	0.630	0.626
36	01652400	2.4	91	VA	19.3	25.7	30.4	36.8	41.9	47.4	61.7	0.781	0.688
37	01652430	2.4	91.8	VA	18.8	29.5	38.6	52.6	65.2	79.9	124.0	0.831	0.694
38	01652470	3.4	93.64	VA	21.1	39.4	56.3	84.5	111.5	144.3	250.1	0.849	0.736
39	01652500	32.6	86.5	VA	84.3	156.3	217.6	311.5	394.2	488.2	758.0	0.776	0.699
40	01652600	7.1	71.83	VA	15.5	32.5	49.2	78.0	106.3	141.4	257.9	0.759	0.677
41	01652610	18.4	63.05	VA	19.9	34.4	47.9	70.3	91.8	118.2	204.8	0.563	0.638
42	01652620	4.9	67.64	VA	19.0	31.4	41.5	56.2	68.7	82.6	121.3	0.670	0.645
43	01652645	1.3	70.99	VA	8.4	8.9	9.2	9.5	9.7	10.0	10.4	0.658	0.669
44	01652650	12.0	71.48	VA	29.4	56.8	82.9	127.4	170.6	224.0	400.4	0.680	0.663
45	01652710	5.4	63.68	VA	15.4	24.7	31.8	42.1	50.6	60.0	85.2	0.522	0.623
46	01652810	5.9	64.51	VA	10.3	15.8	20.4	27.4	33.5	40.6	61.5	0.631	0.643
47	01652910	34.9	73.91	VA	59.7	104.9	142.2	198.2	246.7	301.3	455.1	0.669	0.688
48	01653000	87.7	70.21	VA	118.1	197.5	260.8	353.1	431.3	517.3	753.2	0.660	0.684
49	01653210	6.7	78.74	VA	16.2	23.8	29.6	37.9	44.9	52.5	73.3	0.736	0.647
50	01653447	2.0	81.53	VA	6.1	8.5	10.3	12.8	14.8	17.0	22.6	0.773	0.701
51	01653900	17.8	73.88	VA	36.0	74.3	114.4	189.2	268.1	372.9	762.0	0.714	0.676
52	01653950	3.1	71.38	VA	27.4	43.8	56.8	75.8	91.9	109.6	158.9	0.698	0.660
53	01654000	61.8	62.22	VA	66.8	122.3	170.0	244.0	310.1	386.0	608.0	0.591	0.658
54	01654500	9.6	59.32	VA	12.1	28.0	46.3	82.9	124.3	182.1	417.1	0.513	0.622
55	01655000	96.0	61.81	VA	40.1	59.8	75.8	99.9	120.9	144.8	213.9	0.570	0.652
56	01655310	9.9	64.03	VA	12.5	26.4	41.8	72.0	105.4	151.4	335.3	0.623	0.646
57	01655350	39.3	64.87	VA	24.7	40.6	55.4	80.2	104.2	133.9	232.7	0.561	0.643
58	01655370	9.4	68.32	VA	14.1	26.8	38.3	57.1	74.6	95.5	160.7	0.600	0.638
59	01655380	16.3	30.47	VA	12.9	24.6	35.8	54.8	73.3	96.2	172.4	0.378	0.628
60	01655390	81.0	54.24	VA	44.1	77.5	109.1	163.0	215.7	281.5	503.2	0.480	0.637
61	01656800	20.1	51.67	VA	9.8	11.2	12.0	13.0	13.7	14.4	16.1	0.540	0.612
62	01656960	128.8	52.27	VA	88.3	169.9	240.1	348.3	443.7	552.5	863.1	0.576	0.647
63	01657000	378.1	29.1	VA	193.3	354.0	510.3	784.1	1058.2	1406.5	2617.9	0.481	0.625
64	01657415	478.4	29.55	VA	304.1	564.4	831.4	1322.7	1838.0	2520.5	5065.9	0.455	0.633
65	01657500	1476.7	15.85	VA	312.1	458.4	566.3	715.3	835.3	963.6	1297.5	0.387	0.618

66	01657655	10.2	45.08	VA	15.8	27.3	37.3	53.0	67.4	84.2	135.4	0.430	0.616
67	01657800	11.7	41.39	VA	14.7	21.5	27.0	35.2	42.2	50.2	72.8	0.578	0.627
68	01667600	1.7	12.35	VA	2.2	3.0	3.5	4.3	4.8	5.4	6.9	0.423	0.594
69	01673500	14.9	31.5	VA	3.1	5.6	7.9	11.9	15.8	20.6	36.6	0.414	0.603
70	01673550	66.1	14.95	VA	10.7	24.3	41.1	77.5	121.8	188.5	497.2	0.319	0.603
71	02019400	75.9	13.09	VA	60.7	110.3	154.2	224.4	288.8	364.7	596.4	0.432	0.677
72	02027700	1.2	13.56	VA	1.0	2.0	3.1	5.0	6.9	9.3	17.9	0.176	0.571
73	02030800	7.0	17.31	VA	6.9	11.3	14.8	20.0	24.4	29.3	42.7	0.143	0.608
74	02031000	246.7	11.54	VA	130.3	252.2	352.5	500.1	624.1	759.7	1121.9	0.263	0.604
75	02033500	1303.5	12.41	VA	253.3	346.0	417.7	520.5	606.8	702.0	963.6	0.287	0.604
76	02034000	1716.6	11.83	VA	445.4	821.5	1147.1	1656.3	2112.7	2640.3	4196.6	0.287	0.600
77	02034050	4.1	13.74	VA	5.6	18.0	36.2	81.6	143.3	244.0	773.6	0.331	0.586
78	02037800	47.0	66.61	VA	13.5	29.4	47.1	82.1	121.1	175.4	393.9	0.567	0.629
79	02038000	85.7	58.19	VA	21.9	52.4	87.6	158.3	238.0	349.4	799.1	0.496	0.621
80	02038500	138.2	59.25	VA	30.8	63.6	98.3	163.7	233.5	327.1	680.5	0.530	0.629
81	02042000	363.0	16.99	VA	56.3	131.8	223.1	417.1	647.9	987.4	2494.4	0.317	0.589
82	02042287	161.0	23.7	VA	45.4	86.5	125.7	192.6	258.0	339.2	610.2	0.413	0.616
83	02042426	97.0	66.86	VA	55.7	64.4	70.2	77.6	83.1	88.7	102.1	0.659	0.669
84	02042500	651.3	24.49	VA	45.7	86.0	124.9	192.2	258.8	342.6	627.8	0.395	0.614
85	02042780	6.4	14.22	VA	2.6	3.6	4.5	5.8	7.0	8.3	12.2	0.306	0.557
86	02044400	4.2	22.16	VA	5.5	16.1	30.6	64.7	108.8	178.1	517.9	0.392	0.573
87	02055000	994.3	18.65	VA	216.1	363.3	472.6	621.3	738.8	860.8	1165.8	0.286	0.614
88	02055100	30.3	14.73	VA	22.0	49.8	77.6	126.1	173.8	233.2	428.4	0.431	0.679
89	02056000	1319.5	23.56	VA	311.2	496.7	640.2	845.3	1015.2	1200.6	1698.7	0.345	0.627
90	02056650	144.5	18.67	VA	75.7	160.6	240.7	373.5	498.1	647.3	1110.6	0.226	0.596
91	02057500	2634.0	15.21	VA	451.4	735.7	964.8	1303.7	1594.5	1919.9	2834.5	0.341	0.622
92	02057700	2.0	71.86	VA	4.0	5.4	6.4	7.8	8.8	9.9	12.7	0.706	0.692
93	02059000	3673.5	12.18	VA	587.6	908.1	1152.8	1499.9	1786.2	2096.9	2928.0	0.327	0.612
94	02059450	28.4	10.81	VA	12.7	24.6	35.9	55.5	74.8	98.9	179.7	0.208	0.607
95	02060500	4615.3	10.91	VA	844.7	1294.1	1640.1	2134.0	2544.6	2993.1	4205.1	0.323	0.607
96	02061150	4.0	14.37	VA	4.0	10.8	19.1	36.3	56.0	84.1	199.2	0.374	0.623
97	02062500	6225.6	10.22	VA	887.2	1383.0	1792.2	2413.4	2959.1	3584.9	5414.2	0.245	0.605
98	02076400	5.2	19.11	VA	5.1	8.2	10.7	14.6	18.1	22.1	34.1	0.415	0.612
99	02076500	23.8	15.84	VA	14.1	26.4	36.8	52.5	66.2	81.5	124.6	0.411	0.592
100	02086849	56.7	20.3	EPAE	56.1	67.7	74.2	81.3	86.1	90.3	99.4	0.638	0.637
101	0208726005	196.8	16.7	EPAE	64.3	111.3	146.7	195.1	233.3	273.0	371.0	0.575	0.626
102	02087324	313.4	16.5	EPAE	97.4	154.3	206.4	294.5	376.6	481.4	818.4	0.629	0.631
103	0208732885	17.7	29.5	EPAE	26.0	47.9	67.1	98.0	126.3	159.7	261.9	0.792	0.692
104	02087359	77.2	21.3	EPAE	40.8	75.0	109.6	172.7	237.6	322.8	634.3	0.716	0.660
105	02087580	54.4	15.3	EPAE	52.1	78.2	101.7	139.3	174.7	217.8	354.0	0.674	0.642
106	0209399200	41.2	22.5	EPAE	31.4	57.5	77.6	106.2	129.4	154.3	217.2	0.701	0.656
107	02094659	19.0	41.2	EPAE	52.7	76.5	92.3	113.0	128.6	144.1	181.5	0.853	0.721
108	02094770	39.9	39.5	EPAE	47.3	63.4	73.9	87.5	97.4	107.3	131.1	0.839	0.718
109	02095000	88.1	35.5	EPAE	79.6	90.6	97.4	105.3	110.7	116.1	127.7	0.778	0.704
110	02095271	36.8	32.7	EPAE	58.0	78.4	90.9	105.3	115.2	124.6	144.7	0.844	0.695
111	02095500	96.1	28.8	EPAE	80.7	127.1	161.4	208.1	244.9	283.2	382.3	0.735	0.680
112	0209553650	229.2	27	EPAE	143.3	166.2	178.7	192.3	201.0	209.5	225.4	0.669	0.674
113	0209741955	54.6	14.4	EPAE	143.3	166.2	178.7	192.3	201.0	209.5	225.4	0.571	0.621

114	02115845	13.4	20	EPAE	45.9	56.9	64.0	72.2	78.4	84.4	98.3	0.850	0.699
115	0212414900	89.6	19.1	EPAE	85.0	141.6	194.0	281.8	368.1	470.1	818.4	0.660	0.651
116	0214266000	68.1	14.8	EPAE	27.7	50.1	71.6	108.7	145.0	190.6	345.5	0.576	0.633
117	02142900	42.5	21	EPAE	43.6	65.1	81.3	103.9	122.0	141.9	193.7	0.641	0.656
118	0214291555	81.6	17.4	EPAE	56.4	87.8	109.6	138.2	159.7	181.2	232.8	0.616	0.641
119	0214295600	26.9	20.4	EPAE	33.1	53.2	67.7	86.9	101.7	117.2	154.9	0.692	0.649
120	02145940	9.1	25.5	EPAE	24.7	28.6	30.9	33.1	34.8	36.2	39.1	0.812	0.655
121	02146211	15.5	26	EPAE	25.3	39.1	52.1	74.5	97.1	125.4	224.0	0.706	0.683
122	0214627970	23.5	32	EPAE	70.5	105.3	128.0	156.0	176.1	196.2	240.4	0.801	0.710
123	02146300	79.5	34.2	EPAE	116.4	167.1	206.1	261.4	305.8	356.8	492.7	0.793	0.712
124	02146315	14.8	36.8	EPAE	48.4	71.6	87.2	106.5	120.6	134.2	165.9	0.820	0.710
125	02146348	23.7	24.1	EPAE	22.4	33.4	40.5	49.0	54.7	60.3	71.9	0.541	0.664
126	02146381	169.1	32.4	EPAE	99.4	146.1	184.9	243.8	297.3	356.8	532.4	0.733	0.696
127	02146409	30.6	47.9	EPAE	94.0	120.6	133.9	147.5	155.7	162.5	174.7	0.869	0.764
128	0214642825	13.5	24.6	EPAE	41.9	59.7	73.9	94.6	112.1	132.0	188.0	0.800	0.662
129	0214645022	49.2	25	EPAE	75.3	111.6	138.8	176.1	206.4	239.3	325.6	0.806	0.670
130	02146470	6.8	32.8	EPAE	32.0	48.1	59.2	73.3	84.1	95.1	120.9	0.851	0.681
131	02146500	106.2	22	EPAE	110.2	151.5	178.7	213.2	238.7	264.2	325.6	0.828	0.698
132	02146507	110.3	32	EPAE	192.8	266.7	317.1	385.1	438.9	492.7	628.6	0.826	0.697
133	02146530	127.4	32	EPAE	137.3	194.0	236.7	294.5	342.6	393.6	529.5	0.823	0.696
134	0214655255	19.0	18.2	EPAE	33.7	77.0	114.7	171.0	217.8	268.4	399.3	0.725	0.650
135	02146562	14.8	26.4	EPAE	25.7	54.4	82.1	129.1	174.7	229.6	407.8	0.796	0.674
136	02146600	100.0	20.2	EPAE	105.3	145.3	170.8	202.2	224.8	247.8	300.2	0.700	0.652
137	02146700	18.0	21.3	EPAE	48.1	72.2	88.3	109.0	124.6	140.2	176.7	0.798	0.642
138	02146750	239.3	19.5	EPAE	145.0	201.3	235.0	274.1	300.2	325.6	376.6	0.725	0.648
139	0214678175	17.9	31.4	EPAE	27.0	40.2	50.1	64.0	75.3	87.8	120.1	0.704	0.689
140	02159785	1.0	19.3	EPAE	4.1	5.9	6.9	8.1	8.9	9.7	11.4	0.721	0.644
141	02160325	23.4	22.3	EPAE	21.3	34.3	49.8	82.4	121.2	178.7	441.7	0.704	0.658
142	02164000	125.9	18.8	EPAE	68.0	98.5	120.6	150.4	173.9	198.5	261.9	0.645	0.655
143	02164011	7.8	34.9	EPAE	26.7	33.1	36.5	40.2	42.8	44.7	48.7	0.832	0.696
144	02168845	1.0	26.6	EPAE	4.4	5.4	6.1	7.1	7.8	8.6	10.4	0.778	0.657
145	02203800	107.5	30.9	EPAE	107.6	159.7	189.2	221.7	242.7	261.4	297.3	0.680	0.679
146	02203835	8.9	16.8	EPAE	20.2	28.3	34.5	43.3	50.4	58.0	78.4	0.648	0.610
147	02203845	2.5	24.7	EPAE	12.1	16.7	19.0	21.2	22.5	23.5	25.2	0.721	0.638
148	02203884	4.9	27.7	EPAE	19.0	26.3	31.1	36.8	41.3	45.6	55.8	0.678	0.645
149	02203900	256.4	23.6	EPAE	148.9	215.2	256.6	305.8	339.8	371.0	438.9	0.645	0.650
150	02204070	471.4	20.2	EPAE	186.3	266.7	325.6	402.1	464.4	526.7	690.9	0.596	0.635
151	02205000	3.3	22.4	EPAE	8.5	18.1	26.2	37.9	47.6	58.0	84.4	0.720	0.655
152	02205230	0.9	15.4	EPAE	4.0	5.6	6.5	7.7	8.5	9.3	11.0	0.590	0.616
153	02205500	6.3	27.1	EPAE	15.3	31.7	48.7	80.7	114.7	159.7	328.5	0.685	0.652
154	02205596	18.7	22	EPAE	20.8	31.1	37.9	46.4	52.7	58.6	72.5	0.681	0.652
155	02206105	0.4	24.9	EPAE	2.4	3.6	4.4	5.6	6.5	7.4	9.6	0.704	0.613
156	02206136	0.9	23.8	EPAE	3.7	4.6	5.3	6.0	6.5	7.1	8.3	0.620	0.614
157	02206500	347.1	22.1	EPAE	102.8	161.7	207.6	271.6	325.6	382.3	535.2	0.656	0.659
158	02207000	14.3	14.3	EPAE	24.1	37.7	46.7	58.0	66.0	73.9	91.5	0.581	0.614
159	02207500	979.0	12.5	EPAE	156.0	270.4	393.6	625.8	877.8	1223.3	2593.8	0.549	0.625
160	02208050	25.8	22.4	EPAE	19.7	32.6	43.3	59.7	74.2	91.2	140.2	0.657	0.656
161	02217505	3.7	29.1	EPAE	14.3	19.0	22.5	27.2	31.1	35.4	46.7	0.815	0.673

162	02218565	14.7	16.4	EPAE	14.0	23.9	30.9	40.2	47.3	54.4	70.8	0.600	0.636
163	02334885	121.7	17.8	EPAE	50.4	86.9	115.5	155.7	188.3	224.0	317.1	0.570	0.642
164	02335347	0.5	32.1	EPAE	4.2	5.9	6.9	8.0	8.7	9.4	10.8	0.819	0.705
165	02335700	186.5	14.5	EPAE	57.8	100.5	132.2	175.0	208.4	243.2	328.5	0.555	0.634
166	02335870	79.5	20.3	EPAE	105.9	162.3	199.9	247.8	282.6	317.1	396.4	0.632	0.633
167	02336080	49.5	33.1	EPAE	61.7	68.0	72.5	78.4	83.0	87.8	100.0	0.684	0.684
168	02336102	6.0	22	EPAE	20.5	25.6	28.6	32.0	34.3	36.5	41.3	0.665	0.622
169	02336238	2.4	20.9	EPAE	16.6	20.9	23.9	27.9	30.9	34.0	41.9	0.740	0.629
170	02336300	224.8	31	EPAE	182.9	231.3	261.9	300.2	328.5	354.0	419.1	0.711	0.679
171	02336360	68.9	27.9	EPAE	69.1	88.9	101.9	117.8	129.7	141.6	169.1	0.674	0.662
172	02336635	81.6	19.9	EPAE	86.1	150.4	203.3	281.2	348.3	424.8	640.0	0.617	0.636
173	02336700	1.8	17.2	EPAE	8.5	10.8	12.2	13.8	15.0	16.1	18.5	0.681	0.612
174	02336705	22.8	19.6	EPAE	76.2	98.8	113.0	130.5	143.0	155.7	183.8	0.624	0.620
175	02341548	4.1	21	EPAE	11.6	16.3	19.3	23.1	26.0	28.9	35.7	0.718	0.666
176	02392975	87.0	24.2	EPAE	52.1	85.5	116.1	166.8	215.2	274.1	467.2	0.649	0.665
177	02395990	0.9	13.2	EPAE	3.1	4.6	5.5	6.6	7.3	7.9	9.3	0.734	0.615
178	02396550	0.6	25.1	EPAE	4.0	4.8	5.4	5.9	6.3	6.7	7.4	0.877	0.678
179	03165200	2.8	33.69	VA	2.6	4.9	6.7	9.4	11.8	14.3	21.2	0.492	0.609
180	03167300	1.7	10.01	VA	1.8	3.2	4.3	6.0	7.4	8.9	13.0	0.414	0.607
181	03167700	11.6	20.1	VA	9.1	14.3	18.4	24.5	29.7	35.5	51.7	0.456	0.605
182	03177700	103.0	26.83	VA	19.9	26.6	31.1	36.8	41.2	45.6	56.4	0.441	0.649
183	03177710	114.7	25.75	VA	21.0	29.1	34.6	41.5	46.7	52.0	64.4	0.364	0.610
184	03474700	21.2	16	VA	6.7	12.6	18.1	27.4	36.4	47.6	84.6	0.437	0.683
185	03474800	20.3	10.15	VA	9.6	21.2	31.2	46.3	59.0	72.9	109.8	0.419	0.693
186	03475600	8.9	20.51	VA	1.2	1.5	1.8	2.2	2.5	2.8	3.7	0.557	0.715
187	03475700	7.2	10.06	VA	3.8	6.4	8.4	11.0	13.2	15.4	20.9	0.522	0.714
188	03478400	69.8	14.42	VA	12.5	18.7	23.3	29.7	34.9	40.5	55.1	0.481	0.702
189	03524500	225.7	15.03	VA	78.6	125.4	166.4	232.1	292.8	365.3	591.8	0.288	0.623
190	03525800	1.8	16.53	VA	2.6	3.6	4.2	5.1	5.8	6.5	8.2	0.397	0.605
191	03530000	103.0	12.06	VA	65.0	91.5	109.3	131.8	148.6	165.4	205.3	0.255	0.599
192	06893300	68.6	36.3	MO	120.1	177.3	219.5	277.5	322.8	373.8	504.0	0.807	0.716
193	06893500	476.6	16.8	MO	286.0	447.4	574.8	761.7	920.3	1095.9	1588.6	0.640	0.691
194	06893560	40.4	32.7	MO	89.2	165.7	238.7	362.5	487.0	640.0	1152.5	0.844	0.708
195	06893562	46.9	33.1	MO	122.3	192.3	261.4	382.3	506.9	665.4	1237.4	0.844	0.711
196	06893600	12.9	31.2	MO	42.2	62.6	75.0	89.5	99.1	107.9	125.7	0.834	0.690
197	06894000	489.5	14.1	MO	140.7	245.8	334.1	475.7	597.5	741.9	1163.8	0.581	0.671
198	06910200	3.0	8.48	MO	9.4	15.4	19.5	24.8	28.6	32.6	41.3	0.477	0.638
199	06910230	182.1	5.15	MO	122.0	189.4	238.4	305.8	356.8	410.6	546.5	0.452	0.639
200	06910430	1.3	2.33	MO	2.6	5.5	8.4	13.6	18.9	25.7	49.0	0.672	0.625
201	06923000	2.0	14	MO	5.4	8.7	11.2	14.8	17.8	20.9	29.4	0.813	0.702
202	06929000	2.8	11.5	MO	5.6	11.8	17.3	25.9	33.4	41.9	66.3	0.526	0.669
203	06935800	2.0	25.2	MO	11.4	18.3	22.9	28.6	32.6	36.5	45.0	0.790	0.669
204	06935850	16.8	29.5	MO	39.4	54.1	64.6	78.4	89.2	100.5	129.1	0.744	0.664
205	06935890	57.5	26	MO	71.1	120.3	160.6	220.0	271.3	328.5	487.0	0.695	0.661
206	06935955	30.3	39.8	MO	62.3	91.2	110.7	135.4	153.8	172.2	215.5	0.847	0.734
207	06935980	8.8	42.3	MO	49.6	74.5	90.6	109.9	123.7	136.8	165.4	0.874	0.747
208	06936475	106.2	40	MO	149.5	205.9	239.6	278.6	305.8	331.3	382.3	0.826	0.625
209	07005000	61.6	32.8	MO	167.1	237.6	288.8	354.0	407.8	461.6	600.3	0.806	0.700

210	07010022	22.6	43.5	MO	92.3	116.4	130.8	147.5	159.1	170.2	194.0	0.876	0.737
211	07010030	5.0	26.5	MO	22.1	34.3	43.3	55.5	65.1	75.3	101.4	0.784	0.655
212	07010035	3.8	27.3	MO	18.1	30.6	38.8	48.7	55.2	61.4	74.2	0.757	0.669
213	07010086	94.0	31.6	MO	123.2	168.8	204.2	255.7	300.2	348.3	481.4	0.846	0.689
214	07010090	9.1	35.5	MO	35.7	46.4	52.4	58.0	61.7	64.6	70.2	0.808	0.699
215	07010180	47.1	37.2	MO	94.6	120.1	137.9	160.8	179.0	197.4	243.2	0.842	0.696
216	07010208	5.8	37.7	MO	30.0	44.2	53.8	66.3	75.9	85.2	108.2	0.858	0.714
217	07019317	20.4	39.4	MO	114.1	165.4	201.9	251.5	288.8	331.3	436.1	0.847	0.700
218	07048490	3.3	35.7	MO	18.1	25.8	31.4	39.4	45.6	52.4	69.9	0.813	0.695
219	07052000	50.5	46	MO	77.9	124.0	162.5	221.4	274.1	334.1	512.5	0.834	0.755
220	07052100	91.4	35.6	MO	69.4	111.9	150.1	212.9	271.8	342.6	572.0	0.736	0.725
221	07052160	151.3	17.8	MO	76.5	119.5	155.2	209.5	257.1	311.5	470.1	0.699	0.706
222	07063200	0.7	7.94	MO	3.5	5.9	7.6	9.6	11.1	12.5	15.6	0.685	0.678
223	07186600	109.6	13	MO	56.1	82.4	99.4	120.6	135.9	150.6	184.1	0.589	0.677
224	07195000	335.9	8.67	MO	156.3	297.3	407.8	560.7	682.4	812.7	1135.5	0.559	0.652
225	07195865	50.5	8.35	MO	48.1	81.3	107.0	143.3	173.0	205.3	288.8	0.541	0.631

685 **Appendix B**

Table B1. Manning's roughness coefficients associated to the different NLCD land-use/land-cover types (adapted from Liu & De Smedt, 2004; Hooke et al., 2021).

Land-use/Land-cover	n
Developed, Open Space	0.12
Developed, Low Intensity	0.1
Developed, Medium Intensity	0.07
Developed, High Intensity	0.02
Barren Land	0.1
Deciduous Needleleaf Forest	0.4
Evergreen Needleleaf Forest	0.4
Mixed Forest	0.55
Evergreen Broadleaf Forest	0.6
Deciduous Broadleaf Forest	0.8
Shrubs/Scrubs	0.4
Herbaceous	0.3
Hay/Pasture	0.3
Cultivated Crops	0.35
Woody Wetlands	0.5
Emergent Herbaceous Wetlands	0.5

Appendix C

690 **Table C1. Curve Numbers associated to NLCD land-use/land-cover types and hydrologic soil groups (adapted from Wu et al., 2024).**

Land-use/Land-cover	Hydrologic Soil Group			
	A	B	C	D
Developed, Open Space	45	65	76	82

Developed, Low Intensity	60	74	82	86
Developed, Medium Intensity	77	85	90	92
Developed, High Intensity	92	94	96	96
Barren Land	77	86	91	94
Deciduous Needleleaf Forest	45	66	77	83
Evergreen Needleleaf Forest	30	55	70	77
Mixed Forest	36	60	73	79
Evergreen Broadleaf Forest	30	55	70	77
Deciduous Broadleaf Forest	45	66	77	83
Shrubs/Scrubs	33	42	55	62
Herbaceous	30	58	71	78
Hay/Pasture	49	69	79	84
Cultivated Crops	62	75	83	87
Woody Wetlands	78	78	78	78
Emergent Herbaceous Wetlands	85	85	85	85

Appendix D
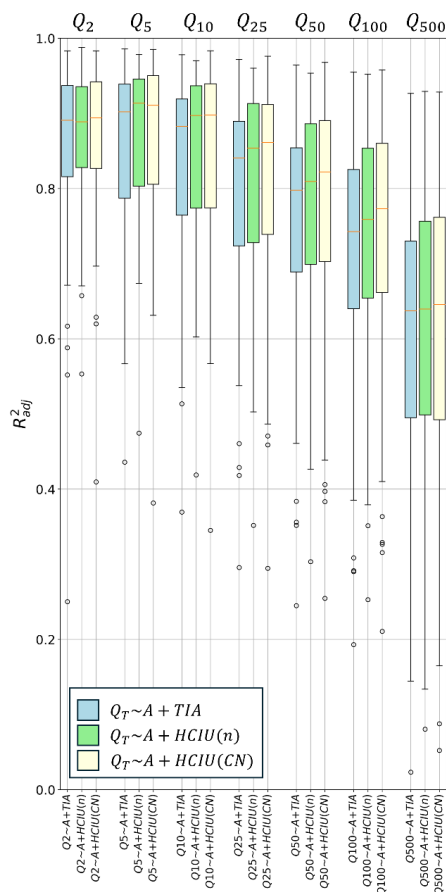
Figure D1. Boxplots of test errors for 1) the benchmark $Q_T \sim A + TIA$, 2) $Q_T \sim A + HCIU(n)$, and 3) $Q_T \sim A + HCIU(CN)$ models, when they are fitted and blind-tested on distinct basin subsets, for the VA homogenous region. For each boxplot, filled bars represent error values between the first and the third quartiles, the upper (lower) whisker extends from the third (first) quartile by adding (subtracting) 1.5 times the interquartile range, and any outliers beyond the whiskers are marked as circles.

Appendix E

Table E1. Outlet coordinates, referred to the World Geodetic System (WGS84).

	Gauge ID	Case Study	Longitude	Latitude
1	01613900	VA	-78.288059	39.214548
2	01615000	VA	-78.078333	39.174722
3	01616000	VA	-78.085833	39.177882
4	01621450	VA	-78.917806	38.391793
5	01623000	VA	-79.126142	38.166797
6	01623500	VA	-79.117809	38.183463
7	01624800	VA	-78.994471	38.128467
8	01625000	VA	-78.861970	38.261796
9	01626000	VA	-78.908079	38.057636
10	01626500	VA	-78.896968	38.061247
11	01626850	VA	-78.876968	38.088746
12	01627500	VA	-78.836692	38.218742
13	01628500	VA	-78.754746	38.322628
14	01629500	VA	-78.534733	38.646231
15	01631000	VA	-78.210834	38.914001
16	01636210	VA	-78.185833	38.905667
17	0163626650	VA	-78.128056	38.934167
18	01638350	VA	-77.615444	39.191111
19	01643805	VA	-77.683944	39.072306
20	01644280	VA	-77.432389	39.046417
21	01644290	VA	-77.371375	38.949277
22	01644291	VA	-77.373041	38.949833
23	01644295	VA	-77.367486	38.952888
24	01644300	VA	-77.371097	38.966777
25	01645700	VA	-77.338041	38.874834
26	01645750	VA	-77.353041	38.897889
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29	01645975	VA	-77.246648	38.971221
30	01646000	VA	-77.245814	38.975943
31	01646200	VA	-77.205536	38.958999
32	01646600	VA	-77.184425	38.911500
33	01646700	VA	-77.139146	38.936222
34	01646750	VA	-77.137757	38.905111
35	01646800	VA	-77.144979	38.922889
36	01652400	VA	-77.126646	38.858723
37	01652430	VA	-77.102201	38.861779
38	01652470	VA	-77.104145	38.842613
39	01652500	VA	-77.085861	38.843333
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41	01652610	VA	-77.174147	38.846501
42	01652620	VA	-77.178869	38.879556
43	01652645	VA	-77.170814	38.865112
44	01652650	VA	-77.165536	38.860390
45	01652710	VA	-77.186926	38.801502
46	01652810	VA	-77.151369	38.810113

47	01652910	VA	-77.127757	38.803169
48	01653000	VA	-77.105590	38.804447
49	01653210	VA	-77.083589	38.793169
50	01653447	VA	-77.064700	38.788725
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53	01654000	VA	-77.228316	38.812891
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55	01655000	VA	-77.202204	38.754281
56	01655310	VA	-77.288318	38.801780
57	01655350	VA	-77.226650	38.757336
58	01655370	VA	-77.233872	38.750392
59	01655380	VA	-77.252484	38.736503
60	01655390	VA	-77.214149	38.704004
61	01656800	VA	-77.466656	38.908445
62	01656960	VA	-77.465544	38.821225
63	01657000	VA	-77.457489	38.797892
64	01657415	VA	-77.414154	38.766504
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66	01657655	VA	-77.289984	38.680116
67	01657800	VA	-77.226371	38.680116
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70	01673550	VA	-77.257755	37.662643
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76	02034000	VA	-78.265837	37.857919
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81	02042000	VA	-77.494153	37.315428
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83	02042426	VA	-77.424149	37.613201
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85	02042780	VA	-76.766904	37.314036
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93	02059000	VA	-79.473083	37.012923
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97	02062500	VA	-78.945722	37.039444
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163	02334885	EPAE	-84.088839	34.032626
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195	06893562	MO	-94.578711	39.038983
196	06893600	MO	-94.451000	39.076900

197	06894000	MO	-94.300753	39.100543
198	06910200	MO	-92.323627	39.002679
199	06910230	MO	-92.340000	38.927900
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203	06935800	MO	-90.583937	38.618272
204	06935850	MO	-90.526652	38.646307
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206	06935955	MO	-90.447450	38.728081
207	06935980	MO	-90.432829	38.764208
208	06936475	MO	-90.251215	38.818156
209	07005000	MO	-90.226277	38.736631
210	07010022	MO	-90.323740	38.668242
211	07010030	MO	-90.314768	38.676892
212	07010035	MO	-90.302848	38.682617
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215	07010180	MO	-90.299632	38.526898
216	07010208	MO	-90.292979	38.490848
217	07019317	MO	-90.341065	38.483307
218	07048490	MO	-94.162300	36.048400
219	07052000	MO	-93.331146	37.186689
220	07052100	MO	-93.370200	37.168500
221	07052160	MO	-93.404186	37.117840
222	07063200	MO	-90.430922	36.784024
223	07186600	MO	-94.582200	37.121100
224	07195000	MO	-94.288400	36.222000
225	07195865	MO	-94.605200	36.201800

700 **Code and data availability**

An open-source, Python-based version of the code used in this paper is available from https://github.com/dllaira/HCIU-urbanization-metric. Basin boundaries for the MO and EPAE cases studies were obtained from https://streamstats.usgs.gov/ss/?BP=submitBatch (U.S. Geological Survey, 2019), using the outlet coordinates given in Appendix E, while those for the VA case study from https://www.sciencebase.gov/catalog/item/631405e3d34e36012efa34bf

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710 headwater locations were retrieved from https://www.usgs.gov/national-hydrography/nhdplus-high-resolution (Moore et al., 2019).

Author contributions

CM proposed the idea to derive a new urbanization metric that is sensitive to the spatial arrangement of surface patches with different characteristics. FD suggested considering hydrologic connectivity as the basis for deriving a descriptor with this

715 property and formulated the definition of *HCIU*. FD prepared the case studies and software used in this work, and wrote the manuscript, which was revised and edited by CM. CM supervised and secured the funding to support this work.

Competing interests

The authors declare that they have no conflict of interest.

Acknowledgements

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