

**INFORMATION TRANSFER FOR HYDROLOGIC PREDICTION IN
UNGAUGED RIVER BASINS**

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Presented to
The Academic Faculty

By

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**INFORMATION TRANSFER FOR HYDROLOGIC PREDICTION IN
UNGAUGED RIVER BASINS**

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To my parents, Dileep and Neela

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SUMMARY

Long-term measurements of river streamflow are essential for numerous applications in water resources. However, in many parts of the world, developed as well as developing, rivers are not gauged for continuous monitoring. Streamflow prediction at such “ungauged” river catchments requires information transfer from gauged catchments that are perceived to be hydrologically similar to them. Achieving good predictability at ungauged catchments requires an in-depth understanding of the physical and climatic controls on hydrologic similarity among catchments. This dissertation attempts to gain a better understanding of these controls through three independent research studies that use data from catchments across the continental United States.

In the first study, I explore whether streamflow similarity among nearby catchments is preserved across flow conditions. Catchments located across four river basins in the northeast United States are analyzed to quantify the spatio-temporal variability in streamflows across flow percentiles. Results show that similarity in catchment stream response is dynamic and highly dependent on flow conditions. Specifically, within each of the four basins, the coefficient of variation is high at low flow percentiles and gradually reduces for higher flow percentiles. Greater similarity in streamflows is observed during the winter and spring (wet) seasons compared to the summer and fall (dry) seasons. This study concludes that high variability at low flows is controlled by the dominance of high evaporative demand, whereas low variability at high flows is controlled by the dominance of precipitation input relative to evapotranspiration.

In the second study, I examine whether streamflow similarity among catchments exists across a wide range of climatic and geographic regions. Data from 756 catchments across the United States is used and daily streamflow at each catchment is simulated using distance-based streamflow interpolation from neighboring catchments. With this approach, high predictability at a catchment indicates that catchments in its vicinity have similar streamflows. Results show that high predictability catchments are mainly confined to the Appalachian Mountains, the Rocky Mountains, and Cascade Mountains in the Pacific Northwest. Low predictability catchments are located mostly in the drier regions of US to the west of Mississippi river. Results suggest that high streamflow similarity among nearby catchments (and therefore, good predictability at ungauged catchments) is more likely in humid runoff-dominated regions than in dry evapotranspiration-dominated regions. I further find that having higher density and/or closer distance of gauged catchments near an ungauged catchment does not necessarily guarantee good predictability at an ungauged catchment.

In the third study, my goal is to identify what constitutes the essential information that must be transferred from gauged to ungauged catchments in order to achieve good model predictability. A simple daily time-step rainfall-runoff model is developed and implemented over 756 catchments located across the United States. For characterization of hydrologic similarity between the gauged and ungauged catchments, the methods based on physical proximity and spatial proximity measures are compared. Results show that the rainfall-runoff model simulates well at catchments in humid low-energy environments, most of which are located in the eastern part of the US, the Rocky Mountains, and along the west coast (to the west of Cascade Mountains). Within these

regions, transfer of the parameter characterizing hydrograph recession provides reliable streamflow predictions at ungauged catchments, with a loss in prediction efficiency of less than 10% in most catchments. Results further show that transferring model parameters from gauged catchments based on spatial proximity measures provides better streamflow predictability at ungauged catchments than that based on physical proximity measures.

The results presented in this dissertation show that climate exerts a strong control on hydrologic similarity among catchments. This has ramifications for determining the regions in which hydrologic information can be reliably transferred from gauged catchments to make predictions at ungauged catchments. The results further suggest that an understanding of the interaction between climate and topography is essential for quantifying the spatial variability in catchment hydrologic behavior at a regional scale.

1. INTRODUCTION

1.1 Research Motivation

The commonly used tools for quantitative decision making in water resources planning and management are essentially data driven, i.e., they are estimated from past streamflow measurements [Beven, 2001; Wagener *et al.*, 2007]. Such tools include: flow duration curves, flood frequency curves, streamflow quantiles, mean annual flood, and unit hydrographs. Moreover, the accuracy of these quantitative tools is highly dependent on the record length of streamflow measurements that they are derived from. For instance, an estimate of a 100-year flood is more robust if it is derived from the past 30 years of data than from the past 5 years of data. Streamflow measurements are also important for characterizing the hydrologic behavior of river basins within modeling frameworks, so that future assessments of hydrologic behavior in response to climate and/or land-use change can be obtained. However, in many parts of the world, developed as well as developing, rivers are not gauged for long-term continuous monitoring. This lack of data limits the ability of decision-makers to assess the risks and vulnerabilities of water resources under potential future climate and land-use scenarios and can affect the quality of life of the human population.

Hydrologists have become increasingly aware of the challenges involved in making predictions in ungauged basins. The International Association of Hydrological Sciences (IAHS) has launched a long-term research initiative by declaring the years 2003 – 2012 as the IAHS Decade on Predictions in Ungauged Basins (PUB), which is commonly referred to in hydrology community as the PUB initiative [Sivapalan *et al.*,

2003]. The aim of this initiative is to increase the awareness about the inadequacies of the current state of science in addressing the PUB problem, and promoting coordinated science strategies that focus on the estimation and reduction of prediction uncertainty in hydrologic systems [Wagner *et al.*, 2004]. The prediction sought after involves any hydrologic information, such as, flood frequency, annual yield, or daily streamflow values, which can help the decision makers in obtaining a quantitative characterization of the system behavior at the ungauged location. An important aspect of these strategies also involves improved characterization of the environmental factors controlling spatial and temporal variability of landscape hydrologic response at regional scales.

1.2 Scope of the Study

Transferring hydrologic information from gauged to ungauged catchments is a widely used approach for predicting at ungauged catchments [Blöschl and Sivapalan, 1995; Merz and Blöschl, 2004; Oudin *et al.*, 2008]. The transfer of information is favored among catchments that are perceived to be similar in terms of hydrologic response. In this regard, the aim of this dissertation is: (1) to determine the physical and hydro-climatic conditions at which streamflow similarity among catchments is more likely to be manifested, and (2) to identify the type of information whose transfer among hydrologically similar catchments is essential for characterization of hydrologic behavior at daily time-scale at an ungauged site. The following research questions are to be addressed in this study:

- At which flow conditions (e.g., low flow, high flow) are the nearby catchments within a region more likely to have similar streamflows?

- In which environment (e.g., humid, arid, plain, mountainous) is streamflow similarity among nearby catchments more likely?
- Within a hydrologic modeling framework, what type of information (e.g., recession, subsurface flow, hydraulic conductivity, etc.) must be transferred from gauged catchments to obtain acceptably high streamflow predictability at ungauged catchments?

1.3 Summary of the Research Tasks

To address the questions raised in section 1.2, the following research tasks have been conducted: 1) Quantify the spatio-temporal variability in streamflows among nearby catchments across the entire spectrum of flow conditions; 2) Quantify the environmental factors controlling streamflow similarity among nearby catchments, so that hydrologic information can be transferred from gauged catchments to predict at ungauged catchments; 3) Identify the appropriate hydrologic model components whose transfer among similar catchments is critical for obtaining good streamflow prediction at the ungauged catchments.

The above three tasks have been conducted in the form of three independent research studies. In this dissertation, these studies (Chapters 3, 4, and 5) have been presented in a research journal style format. Below are the brief descriptions of the three major research tasks and their main findings.

To quantify the spatio-temporal variability in streamflows among nearby catchments

Flow duration curves are analyzed for 25 gauged catchments located across four river basins in the northeast United States. The coefficient of variation of streamflow percentiles is used as a measure of variability among catchments across flow conditions. It is found that the similarity in catchment stream response is dynamic and highly dependent on flow conditions. Greater similarity in streamflows is observed during the winter and spring (wet) seasons compared to the summer and fall (dry) seasons. Results suggest that the spatial variability in streamflow at low flows is primarily controlled by the dominance of high evaporative demand during the warm period. On the other hand, spatial variability at high flows during the cold period is controlled mostly by the increased dominance of precipitation input over evapotranspiration.

To quantify the environmental factors controlling streamflow similarity and transferability of hydrologic information among nearby catchments

Data from 756 catchments within the continental US is used and daily streamflows at ungauged catchments are simulated using distance based interpolation of streamflows from neighboring catchments. The prediction efficiency at ungauged catchments is then compared against numerous physiographic and hydro-climatic properties to identify the conditions that favor high streamflow similarity within a region. It is found that distinct geographic regions exist in US where transfer of streamflow values from nearby catchments is useful for retrospective prediction of daily streamflow at ungauged catchments. Specifically, the high predictability catchments are predominantly located

along Appalachian Mountains in eastern US, Rocky Mountains, and Cascade Mountains in Pacific Northwest. Low predictability catchments are located in drier regions west of Mississippi river. Positive trends with respect to prediction efficiency are observed in four catchment properties: channel slope, runoff ratio, baseflow runoff ratio, and the slope of flow duration curve. Results suggest that high streamflow similarity among nearby catchments (and therefore, good predictability at ungauged catchments) is more likely in humid runoff-dominated regions than in dry evapotranspiration-dominated regions.

To identify the hydrologic model components whose transfer is critical for good prediction at ungauged catchments

A simple daily time-step hydrologic model is developed that calibrates for the hydrograph recession properties of a catchment. The model is implemented over 756 catchments located across the continental United States and transferability of its structure and parameters is tested for predicting at ungauged catchments. For characterization of hydrologic similarity between the gauged and ungauged catchments, methods based on physical proximity and spatial proximity measures are compared. It is found that transfer of the parameter characterizing hydrograph recession provides reliable streamflow predictions at ungauged catchments, with a loss in prediction efficiency of less than 10% in most catchments. Results further show that borrowing model parameters from gauged catchments based on spatial proximity measures provides better streamflow predictability at ungauged catchments than that based on physical proximity measures.

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2. BACKGROUND AND LITERATURE REVIEW

2.1 Hydrologic Models and their Limitations at Ungauged Catchments

Prediction of streamflows at drainage basins (or catchments) is typically done through the use of hydrologic models. A hydrologic model essentially characterizes the transformation of the input signal (rainfall) into the output signal (streamflow)[*Beven, 2001*]. Two broad categories of hydrologic models are: the process-based and the statistically based models. In process-based models, different hydrological process components (infiltration, evapotranspiration, surface runoff, subsurface runoff) are explicitly represented, and the dynamic interaction between these components is expected to produce the streamflow at the catchment outlet [*Farmer et al., 2003; Sivapalan, 2005*]. The number of components within these models and their complexities are based on some a priori conceptualization of the internal functioning of a catchment. Some of the widely used process-based hydrologic models are: TOPMODEL [*Beven and Kirkby, 1979*], SWAT [*Arnold et al., 1998*], VIC [*Liang et al., 1994*], HBV [*Bergström, 1995*]. On the other hand, hydrologic models that use the statistical concepts of artificial neural networks (ANN), regression, or auto-regressive moving average (ARMA, ARMAX) also provide good forecasting capability, but do not provide any understanding about the hydrologic functioning of catchments as the internal components in these models are not physically realistic [*Hsu et al., 1995; Sudheer et al., 2002; Toth et al., 2000*].

Ideally, hydrologic models should be readily applicable at ungauged catchments since they only require climate data (e.g., rainfall, temperature, etc.) as inputs. However, prior to applying the models for streamflow predictions, a major task in all the hydrologic

models involves calibration of model parameters. Hydrologic models contain parameters in their process representations whose values can only be obtained through calibration with historic streamflow data at a given catchment [*Hay and McCabe, 2002; Martinez and Gupta, 2010; Merz and Blöschl, 2004*]. Unfortunately, it is not possible to obtain some parameters of models by either measurement or a priori estimation. The problem of obtaining measurable parameters exists because the processes represented in models are based on small scale physical understanding of fluid flow, whereas tremendous heterogeneity exists in soil properties, topography and land-use that is virtually impossible to characterize at the scale of a catchment [*Beven, 2001; Wagener and Wheeler, 2006*]. Studies that have attempted to link calibrated model parameters to measurable physical attributes of catchments have found weak relationships at best [*Kokkonen et al., 2003; Merz and Blöschl, 2004; Refsgaard and Knudsen, 1996; Seibert, 1999*]. Moreover, recent studies have also found that the values of model parameters can vary depending on the historical period used for calibration [*Merz et al., 2011*]. The need for calibrating hydrologic models is perhaps the biggest obstacle for predicting streamflow at ungauged catchments at finer time-scales since they do not have the historic data with which the models can be calibrated.

The second issue with direct implementation of hydrologic models at ungauged catchments is the uncertainty in determining whether the chosen model structure adequately represents the hydrologic processes at the ungauged catchment of interest. Studies have shown that simulation efficiency of hydrologic models varies according to the climate and topography of the landscape. For instance, *Abdulla and Lettenmaier [1997]* implemented the VIC-2L model at 34 catchments within the Arkansas-Red river

basin in US and found that the model performance was good in humid and semi-humid catchments, but inferior in semi-arid catchments. *Hay and McCabe* [2002] simulated monthly streamflows at 44 catchments within the United States using a simple water balance model and found that the calibrated model provided better streamflow estimates in the humid eastern regions of the US than in the drier regions of central US. *Oudin et al.* [2008] used two hydrologic models (TOPMO and GR4J) at 913 catchments in France and found that both the calibrated models performed well in western France but had lesser predictability in southern parts of the country. They noted that “...southern catchments are generally difficult to model since intense and spatially variable rainfall events make the streamflows vary strongly in time and amplitude”. While the climate and topography of a catchment provide significant clues regarding the expected predictability with any particular model, calibrating the model with past streamflow data is the most certain way to determine it.

2.2 Information Transfer to Ungauged Catchments

Due to the difficulty in direct implementation of hydrologic models at ungauged catchments, alternative strategies for prediction become necessary. Prediction of streamflows at ungauged catchments is typically performed through the transfer of hydrologic information (e.g., model parameters, hydrologic indices, streamflow values) from gauged to ungauged catchments. This procedure is commonly referred to as regionalization [*Merz and Blöschl*, 2004; *Oudin et al.*, 2010]. Regionalization enables extrapolation of the process understanding gained through measurements at a particular location over a larger areal extent [*Blöschl and Sivapalan*, 1995].

Transfer of hydrologic model parameters from gauged to ungauged catchments is perhaps the most common procedure [Merz and Blöschl, 2004]. Hydrologic models that have been used extensively for this purpose include: HBV [Göttinger and Bárdossy, 2007; Merz and Blöschl, 2004; Seibert, 1999], IHACRES [Kokkonen et al., 2003; Schreider et al., 1996], PDM [Kay et al., 2007; Lamb and Kay, 2004]. Alternatively, model-independent methods have been developed that incorporate the spatial variability of streamflow within a region [Archfield and Vogel, 2010; Skøien and Blöschl, 2007; Smakhtin, 1999]. These model-independent methods have the advantage that they can circumvent the deficiencies associated with any particular hydrologic model structure. Smakhtin et al. [1997] developed regionalized flow duration curves for catchments in South Africa and estimated streamflows at ungauged catchments through transfer of daily streamflow data from nearby gauged catchments using the interpolation technique described in Hughes and Smakhtin [1996]. Archfield and Vogel [2010] developed the map-correlation method to identify the donor gauged catchment that is likely to have high correlation to the ungauged catchment for direct transfer of daily streamflow time series. Skøien and Blöschl [2007] used the concept of topological kriging, or top-kriging [Skøien et al., 2006], on 376 catchments in Austria to predict hourly and daily streamflow in ungauged catchments. They used the topological distances between the gauged and ungauged catchments in a kriging framework, and performed a distance-based interpolation of streamflow to simulate at the ungauged catchments.

In order to successfully transfer the hydrologic information among catchments, it is important to ensure that the donor (gauged) and receiver (ungauged) catchments are similar to each other in terms of hydrologic behavior. Unfortunately, a universally

accepted metric of hydrologic similarity among catchments does not exist yet [McDonnell *et al.*, 2007; Wagener *et al.*, 2007]. Two popular approaches can be found in the literature to ascribe similarity among catchments: physical proximity approach and spatial proximity approach [Merz and Blöschl, 2004; Oudin *et al.*, 2008; Parajka *et al.*, 2005]. The physical proximity approach assumes that similarity in physical attributes (slope, soils, aspect, etc.) among catchments is indicative of hydrologic similarity and governs the information transfer to ungauged catchments. Acreman and Sinclair [1986] grouped 186 catchments in Scotland into five homogeneity regions based on six basin characteristics, viz., drainage area, stream frequency, channel slope, mean annual rainfall, fraction of basin covered by lakes and soil type index. Wiltshire [1986] grouped 376 British catchments into five homogeneous regions based on catchment attributes such as basin area, average annual rainfall and urban fraction. Burn and Goel [2000] grouped catchments in central India for flood frequency estimation using attributes such as catchment area, stream length and main channel slope. Wolock *et al.* [2004] used the hydrologic landscapes concept of Winter [2001] to group 43,931 catchments in United States into 20 regions based on identification of similarities in topography (% slope), soil (% sand) and climate (annual rainfall, potential evapotranspiration). On the other hand, the spatial proximity approach assumes that catchments that are located close to each other are more likely to have similar climatic patterns and landscape evolution. Therefore, the geographic distance among catchments alone provides a reliable estimate of catchment similarity [Merz and Blöschl, 2004; Mosley, 1981; Vandewiele and Elias, 1995; Vandewiele *et al.*, 1991].

2.3 Gaps in our Current Understanding

The notion of hydrologic similarity itself is not fully understood yet. While ascribing catchment similarity based on physical attributes is intuitive, studies have consistently shown that physical proximity among catchments does not necessarily translate into similarity in hydrologic behavior [Burn and Boorman, 1993; Kokkonen *et al.*, 2003; Post and Jakeman, 1996; Seibert, 1999]. On the other hand, spatial proximity among catchments alone has proven to be more effective for predicting at ungauged catchments. Merz and Blöschl [2004] compared eight parameter transfer methods using the HBV model for 308 catchments in Austria and concluded that methods based on spatial proximity alone performed better than those based on catchment attributes. Oudin *et al.* [2008] compared three different regionalization approaches to simulate streamflows in 913 French catchments and found that the spatial proximity approach outperformed the other approaches. Zhang and Chiew [2009] obtained similar results using the hydrologic data from 210 catchments in Australia.

Even when we consider catchments that are located in close proximity to each other, there are two main aspects of hydrologic similarity that are not completely understood. First, we do not know whether similarity among those catchments is preserved across flow conditions. For instance, it is possible that streamflow similarity among catchments depends on hydrologic controls that are sensitive to seasonal fluctuations in flow regimes. In such a case, one might expect the similarity among catchments to have a dynamic form and vary with flow conditions. Second, it is also not known whether streamflow similarity among nearby catchments is manifested everywhere. In other words, do catchments in close proximity have similar streamflow

response regardless of their location in either New Mexico (arid region) or Vermont (humid region)? If streamflow similarity exists only in regions that meet certain physiographic and/or climatic conditions, it is important to know these conditions that favor streamflow similarity within a region.

Transfer of model parameters from gauged catchments is essential for implementing hydrologic models at ungauged catchments. However, many models have a tendency towards over-parameterization [*Beven and Freer, 2001*]. This is a major concern since over-parameterization affects how efficiently the core hydrologic information is transferred to ungauged catchments. Large disparity exists in the number of calibration parameters in commonly used models; from as low as 4 parameters (GR4J, *Oudin et al., [2008]*) up to 11 parameters (HBV, *Parajka et al., [2005]*). Having large number of calibration parameters in a model increases the likelihood that: (1) there will be internal dependencies among the parameters, and (2) some parameters might represent the idiosyncratic behavior of each individual catchment [*Wagener and Wheater, 2006*]. A common solution to overcome this problem is to transfer the entire set of calibrated parameters from gauged to ungauged catchments. Although this solution serves the practical purpose of simulating at an ungauged catchment, it does not improve our understanding as to which process representations can be roughly approximated at an ungauged catchment, and which ones genuinely require additional information from the donor gauged catchments. Therefore, there is a need to identify what constitutes the critical information that must be transferred among hydrologically similar catchments to achieve good model predictability at ungauged sites.

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3. HYDROLOGIC SIMILARITY AMONG CATCHMENTS UNDER VARIABLE FLOW CONDITIONS

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3.1 Abstract

An assessment of regional similarity in catchment stream response is often needed for accurate predictions in ungauged catchments. However, it is not clear whether similarity among catchments is preserved at all flow conditions. We address this question through the analysis of flow duration curves for 25 gauged catchments located across four river basins in the northeast United States. The coefficient of variation of streamflow percentiles is used as a measure of variability among catchments across flow conditions. Results show that similarity in catchment stream response is dynamic and highly dependent on flow conditions. Specifically, within each of the four basins, the coefficient of variation is high at low flow percentiles and gradually reduces for higher flow percentiles. Analysis of the inter-annual variation in streamflow percentiles shows a similar reduction in variability from low flow to high flow percentiles. Greater similarity in streamflows is observed during the winter and spring (wet) seasons compared to the summer and fall (dry) seasons. Results suggest that the spatial variability in streamflow at low flows is primarily controlled by the dominance of high evaporative demand during the warm period. On the other hand, spatial variability at high flows during the cold

period is controlled mostly by the increased dominance of precipitation input over evapotranspiration. By evaluating variability over the entire range of streamflow percentiles, this work explores the nature of hydrologic similarity from an inter-seasonal perspective.

3.2 Introduction

A number of problems in hydrology require estimation of regional similarity in catchment stream response. These include: regional flood frequency analysis [*Acreman and Sinclair, 1986; Burn, 1997; R. Merz and Blöschl, 2005*], parameter regionalization for lumped hydrologic models [*Burn and Boorman, 1993; Ralf Merz and Blöschl, 2004*], regional low flow predictions [*Laaha and Blöschl, 2006; Nathan and McMahon, 1990*], and water quality assessment [*Wolock et al., 2004*]. A common goal in many of these studies involves the transfer of hydrologic information, such as flood quantiles [*Burn and Goel, 2000*], model parameters [*Oudin et al., 2008; Zhang and Chiew, 2009*], etc., from gauged to ungauged catchments. Unfortunately, a universally accepted metric of hydrologic similarity among catchments does not exist yet [*McDonnell et al., 2007; Wagener et al., 2007*].

Several approaches for quantification of catchment hydrologic similarity have been documented in the hydrology literature. One widely used approach involves the use of similarity in catchment physiographic characteristics. *Acreman and Sinclair [1986]* grouped 186 catchments in Scotland into five homogeneity regions based on six basin characteristics, viz., drainage area, stream frequency, channel slope, mean annual rainfall,

fraction of basin covered by lakes and soil type index. *Wiltshire* [1986] grouped 376 British catchments into five homogeneous regions based on catchment attributes such as basin area, average annual rainfall and urban fraction. *Burn and Goel* [2000] grouped catchments in central India for flood frequency estimation using attributes such as catchment area, stream length and main channel slope. *Wolock et al.* [2004] used the hydrologic landscapes concept of *Winter* [2001] to group 43,931 catchments in United States into 20 regions based on identification of similarities in topography (% slope), soil (% sand) and climate (annual rainfall, potential evapotranspiration).

Another approach for characterizing regional similarity among catchments uses hydrologic information directly derived from streamflow data of gauged catchments. *Mosley* [1981] clustered 174 New Zealand catchments into hydrologically homogeneous regions based on similarities in specific mean annual flood and the coefficient of variation of instantaneous flood discharge. *Ogunkoya* [1988] used parameters such as runoff coefficient, flow variability index, annual runoff, etc. that were directly obtained from the daily streamflow data to group catchments in southwest Nigeria into five hydrologic regions. *Kachroo et al.* [2000] used the combined data of annual maximum flood and physiographic attribute information from 77 gauged catchments in Tanzania and partitioned the country into 12 homogeneous regions.

Regardless of the approach used, the controls on hydrologic similarity are still poorly understood. Moreover, it is also not clear whether similarity among two or more catchments is preserved across flow conditions. For instance, it is possible that streamflow similarity among catchments depends on hydrologic controls that are sensitive to seasonal fluctuations in flow regimes. In such a case, one might expect the

similarity among catchments to have a dynamic form and vary with flow conditions. In this study, we explore the controls on hydrologic similarity by considering four river basins in the northeast United States, and use the data from multiple gauged catchments within each basin. The criteria for selecting catchments within each basin are similarity in the long-term annual rainfall and runoff. We use long-term daily streamflow records from 25 gauged catchments located within these four river basins and analyze the spatial and inter-annual variability in their streamflow percentiles. Our *a priori* assumption is that since catchments within each basin are in close proximity and also similar in annual rainfall and runoff, their stream response is likely to be similar across flow conditions. The questions addressed in this study are: (1) does the stream response similarity among catchments exist under all flow conditions, and if not, (2) under which conditions are the catchments likely to be similar in hydrologic response.

3.3 Data

We consider four river basins located in the northeast United States, viz., Allegheny, Upper Delaware, Lower Susquehanna, and Lower Chesapeake (**Figure 3.1**). Streams in the Upper Delaware, Lower Susquehanna, and Lower Chesapeake basins flow eastwards into the Atlantic Ocean, while those in the Allegheny basin flow westwards to join the Mississippi river and ultimately flow into the Gulf of Mexico. The Allegheny basin is located within the Allegheny plateau, and is underlain by sedimentary rocks that are fractured, faulted and folded at several locations. The channel bedrock consists of weathered rock material, Quaternary glacio-fluvial deposits, and alluvium [Anderson *et al.*, 2000]. Soils in areas of steep slopes are shallow and poorly drained, while the soils

on gentler slopes are deep, well drained and fertile. The Upper Delaware basin is located in the eastern part of the Allegheny plateau and the northern part of the Appalachian plateau. The existing topography of the river basin was formed by recent glaciations, and therefore, the parent material is composed of glacial till deposits in the uplands [Ayers *et al.*, 1994]. The Lower Susquehanna basin contains Precambrian to Triassic bedrocks that are structurally complex and lithologically diverse. The structural complexity across its landscape is the result of periods of uplift and collision of continental plates [Risser and Siwiec, 1996]. The Lower Chesapeake basin consists of Rappahannock River and its tributaries that drain into the Chesapeake Bay. This basin drains parts of the Blue Ridge and Piedmont physiographic provinces in northeastern Virginia. The sediment in this watershed is derived from the weathered felsic crystalline rocks in the Blue Ridge and Piedmont [Nelson, 1960].

The U. S. Geological Survey's Hydro-Climate Data Network (HCDN) [Slack *et al.*, 1993] is used as the database for catchment selection. The HCDN primarily consists of data for catchments that are not severely affected by human activity. While the streamflow records in HCDN span from 1874 to 1988, most catchments have consistent and continuous records from water year 1970 onwards. Within each basin, we examine all the gauged catchments that are part of the HCDN database. Daily streamflow for each catchment is obtained for the water years 1970 to 1988 (i.e., 1st October, 1969 to 30th September, 1988). Monthly precipitation data for each catchment is obtained from the hydro-climatic dataset developed by Vogel and Sankarasubramanian [2005]. Average annual rainfall (P_{ann}) and average annual discharge (Q_{ann}) are calculated for each catchment using the data spanning 19 years. The coefficient of variation (CV = Standard

deviation / Mean) of P_{ann} and Q_{ann} is then calculated for each basin. If the CV of either P_{ann} or Q_{ann} exceeds 0.1 in a basin, the outlier catchments with P_{ann} or Q_{ann} value farthest from the basin mean are eliminated and the CV values are recalculated. The criterion of $CV < 0.1$ ensures that, within each of the four basins, only those catchments are chosen that have homogeneity in their long-term annual rainfall and streamflow. We select 25 gauged catchments among our four basins with drainage areas varying from 65 km² to 4163 km² (see **Figure 3.1**). The average annual rainfall of the selected catchments for the water years 1970 - 1988 ranged from 1025 mm to 1230 mm. **Figure 3.2** shows the precipitation duration curves (percentile value vs. precipitation amount) of the 25 catchments. These curves are similar for catchments within each basin and suggest the existence of similarity in the precipitation input patterns. Estimates of monthly potential evapotranspiration (PET) for each catchment are obtained from the *Vogel and Sankarasubramanian* [2005] dataset, where they used the PET formulation introduced by *Hargreaves and Samani* [1982]. The baseflow and the baseflow index (BFI), i.e., baseflow / total flow, of catchments are calculated using the one parameter single-pass digital filter method of baseflow separation [*Arnold and Allen*, 1999; *Eckhardt*, 2008]. The physiographic and hydro-climatic information of the catchments is summarized in **Table 3.1**.

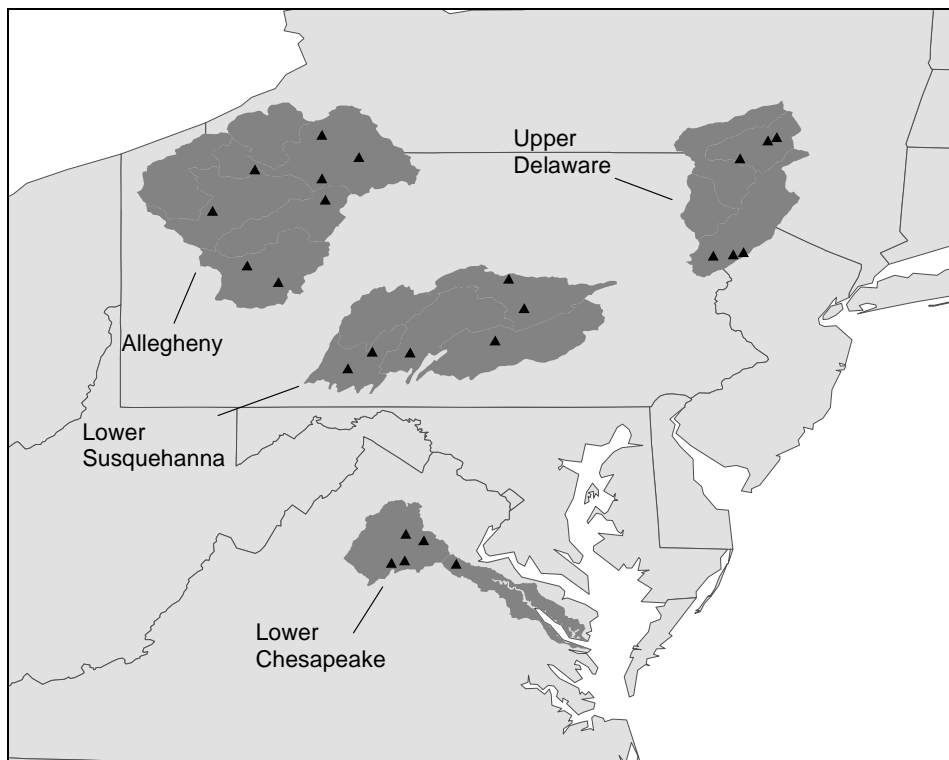


Figure 3.1: Four river basins and the 25 nested catchments in northeast United States.

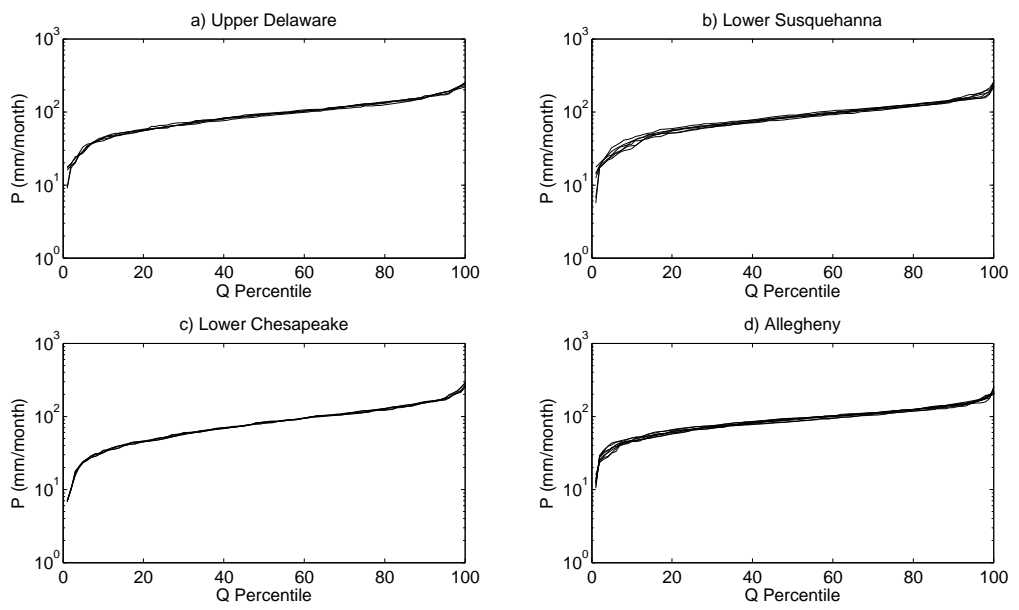


Figure 3.2: Precipitation Duration Curves of all the catchments within a) Upper Delaware, b) Lower Susquehanna, c) Lower Chesapeake, and d) Allegheny basin.

Table 3.1: Details of the 25 catchments within the four river basins.

River Basin	$CV(Q_{ann})$	$CV(P_{ann})$	USGS Stn No.	Area (km ²)	Slope (m/km)	BFI	Annual Q (mm)	Annual P (mm)
Upper Delaware	0.09	0.03	1420500	623.9	6.3	0.657	842.3	1118.4
			1413500	422.0	2.9	0.662	702.9	1172.9
			1414500	65.2	22.8	0.667	783.7	1162.0
			1439500	302.9	6.6	0.708	750.2	1150.1
			1440400	170.6	15.3	0.685	786.2	1227.9
			1440000	165.7	7.1	0.697	641.0	1152.3
Lower Susquehanna	0.09	0.05	1555000	779.3	3.6	0.710	579.7	1055.8
			1555500	419.4	2.1	0.617	542.1	1077.1
			1562000	1957.2	1.3	0.632	479.3	1200.8
			1560000	445.3	8.1	0.590	519.9	1194.8
			1564500	530.7	2.7	0.578	457.2	1154.6
			1568000	517.8	1.4	0.628	556.6	1099.4
Lower Chesapeake	0.08	0.02	1664000	1605.1	1.8	0.658	420.8	1047.4
			1667500	1222.0	2.8	0.669	442.9	1064.9
			1663500	743.0	5.6	0.668	459.9	1025.1
			1666500	463.4	6.6	0.670	489.4	1063.4
			1668000	4131.9	1.3	0.628	399.4	1075.4
Allegheny	0.07	0.04	3011020	4162.9	1.0	0.663	622.2	1087.6
			3010500	1423.9	2.1	0.653	633.6	1025.3
			3015500	831.0	1.4	0.603	688.7	1175.4
			3011800	120.1	6.7	0.661	595.5	1128.0
			3020500	776.7	1.6	0.615	672.1	1107.7
			3028000	163.1	7.9	0.656	738.9	1148.0
			3032500	1366.9	1.0	0.637	631.2	1130.5
			3034500	226.3	3.2	0.595	661.5	1160.0

3.4 Methods

3.4.1 Flow duration curve

We use the variability in streamflow percentiles of flow duration curves (FDC) [Searcy, 1959; Smakhtin, 2001; R. M. Vogel and Fennessey, 1994; Richard M. Vogel and Fennessey, 1995] to examine similarity among catchments under varying flow conditions. The FDC graphically illustrates the amount of time (expressed as a percentage) a specific streamflow value is equaled or exceeded in a catchment within a specified period of hydrologic record. Traditionally, FDC is constructed over an entire chosen period of hydrologic record [Searcy, 1959]. However, this makes the FDC sensitive to the period chosen, especially the exceptionally dry or wet years in the record, and might not reflect the typical hydrologic behavior of the catchment. To reduce the bias of a chosen period of record, Vogel and Fennessey [1994] suggested an alternate method for constructing FDC that is based on inter-annual calculations. Following Vogel and Fennessey [1994], considering the daily streamflow record of n years, the flow percentile values are calculated for each of the n years separately. The median of all n values for each flow percentile is then calculated and the median FDC is constructed. Through this procedure, the FDC is less sensitive to the exceptional years of flood or drought in the record, and we obtain the FDC for a typical (or median) year for the catchment. A detailed review of the physical interpretation and water resources applications of the FDC is provided in Vogel and Fennessey [1995].

3.4.2 Assessing variability in flow percentiles

The median FDCs of all 25 catchments are constructed with $n = 19$ years. Flow percentiles are obtained for all integer values ranging from 0 (minimum flow) to 100

(maximum flow). Within each basin, we obtain the CV value of each flow percentile from the median FDCs of all the catchments. The CV of flow percentiles is used as a measure of variability among catchments across flow conditions. Since the CV is a dimensionless metric, we consider it more suitable for comparing variability across a wide range of streamflow magnitudes. We further measure the inter-annual temporal variability of flow percentiles by calculating the CV of each individual percentile among all the 19 years of record. The inter-annual CV of the flow percentiles is measured individually for each of the 25 catchments.

3.5 Results

3.5.1 *Spatial and temporal variability in streamflow across flow percentiles*

Figure 3.3 shows the FDCs of all 25 catchments, grouped by their respective river basin. The FDCs are plotted as streamflow value vs. the streamflow percentile (i.e., the amount of time the streamflow is below that particular value). The high flow percentiles appear similar within all the four basins. The low flow percentiles appear more divergent from each other, especially in the Upper Delaware and Lower Susquehanna basins. **Figure 3.4** shows the CV of all streamflow percentiles for the four basins and quantifies the intra-basin variability in streamflow percentiles. In all the four basins, CV is high at low flow conditions and trends lower for high flow percentiles (except for extremely high flow). However, the pattern of variability reduction is different within each river basin. In the Upper Delaware and Allegheny basins, the CV drops fast at lower percentiles (< 20%), stays low at intermediate percentiles (approximately from 20% to 90%), and then increases again for extremely high flow

percentiles. In Lower Susquehanna basin, the CV reduces almost at a constant rate until about 95th percentile and then increases sharply near the highest flow percentiles. In the Lower Chesapeake basin, the CV drops rapidly from 0th percentile (minimum flow) to about 10th percentile, increases again until about 25th percentile and then continues its gradual decrease. The lowest CV values are observed in the range of 40th and 75th percentiles in the Lower Chesapeake basin.

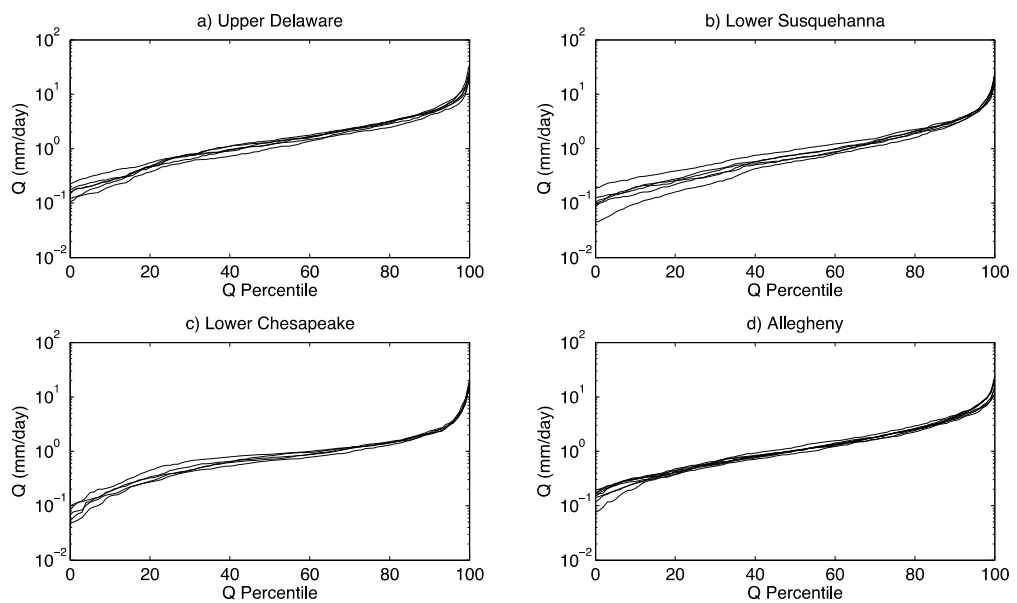


Figure 3.3: Flow Duration Curves of all the catchments within a) Upper Delaware, b) Lower Susquehanna, c) Lower Chesapeake, and d) Allegheny basin.

A sudden increase in the CV is observed at extremely high flow percentiles (> 90%) in the Upper Delaware, Lower Susquehanna and Allegheny basins (**Figure 3.4**). A sharp rise in CV, however, is not observed at high flow percentiles in the Lower Chesapeake basin, where there is a more gradual increase. In all the four basins, difference between the highest and the lowest CV values is significant (**Figure 3.4**). In the Upper Delaware, Lower Chesapeake and Allegheny basins, CV reduces from the highest value of about 0.3 to the lowest value near 0.1. In the Lower Susquehanna basin, the highest CV is about 0.45, while the lowest CV is approximately 0.05. **Figure 3.5** shows the inter-annual CVs of flow percentiles for each individual catchment. High CV is observed at the low flow and extremely high flow percentiles, whereas low CV is observed at intermediate flow percentiles for the majority of catchments. There are a few catchments, especially within the Lower Susquehanna basin, that are exceptions to this trend. In those catchments, the CV in the 20th - 60th percentile range is higher than the CV for below 20th percentile flows. Moreover, the relationships between inter-annual CVs and catchment properties such as drainage area and baseflow index (BFI) have considerable scatter and no significant trends are observed (Result not shown). Overall, the intra-basin differences in inter-annual variability of catchment stream response exist mostly at lower flow percentiles. The magnitudes of CVs are more similar at higher flow percentiles.

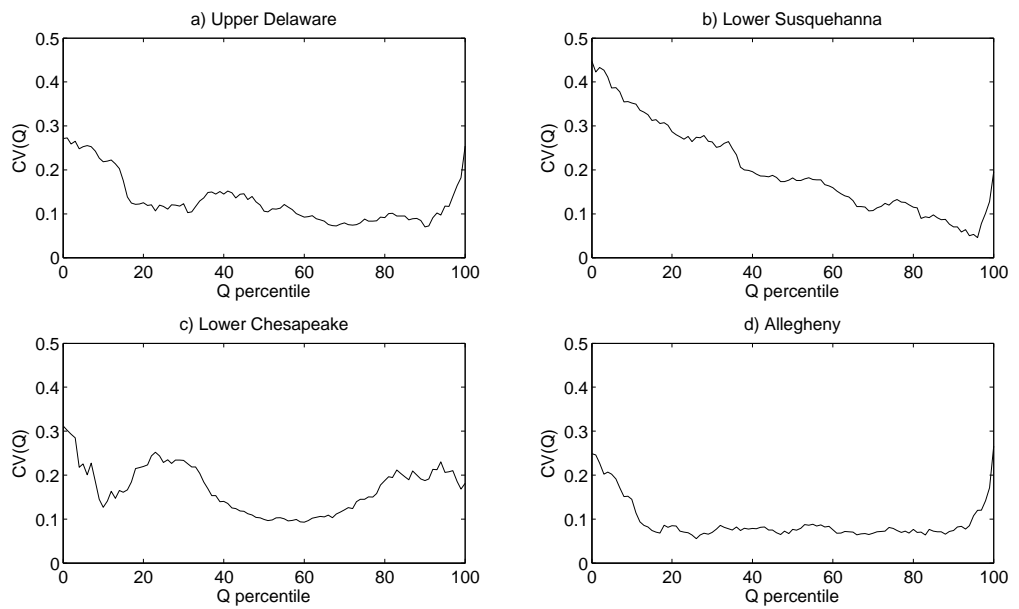


Figure 3.4: Coefficients of variation of catchment streamflow percentiles within a) Upper Delaware, b) Lower Susquehanna, c) Lower Chesapeake, and d) Allegheny basin.

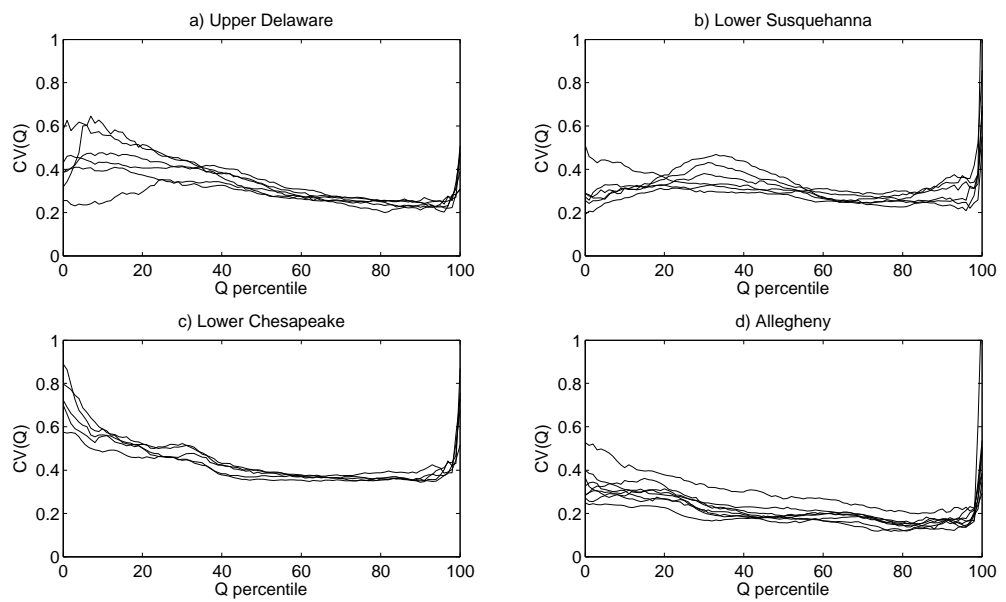


Figure 3.5: Inter-annual coefficients of variation of streamflow percentiles for all the 25 catchments within a) Upper Delaware, b) Lower Susquehanna, c) Lower Chesapeake, and d) Allegheny basin.

Since the CV is a ratio of standard deviation and mean, we also analyze both these entities separately in order to explore the relative influence of each property on the CV values from low to high flow percentiles. **Figure 3.6** shows the spatial mean (solid line) and standard deviation (dashed line) of all the flow percentiles for catchments in each of the four river basins. The mean value varies smoothly across the flow percentiles and appears similar to the flow duration curves shown in **Figure 3.3**. On the other hand, the variations in standard deviation across flow percentiles do not follow the similar pattern as mean values and appear more fluctuating. From low to high flow percentiles, the mean increases at a faster rate than standard deviation, thus decreasing the CV values at higher flow percentiles. However, at extremely high flow percentiles ($> 90\%$), the standard deviation increases at a faster rate than mean, and increases the CV values at those flow percentiles. Similar trends as in **Figure 3.6** are observed for inter-annual variations of mean and standard deviation at individual catchments across flow percentiles (result not shown).

3.5.2 Seasonal variations in the hydrologic similarity among catchments

Next, we seek to identify the seasonal trends in similarity. Within each basin, we select two catchments that are located closest to each other. The condition of closest proximity is to ensure that the catchment pair has a high likelihood of receiving similar rainfall input at daily time-scale. **Figure 3.7** shows the comparison of daily hydrographs of the two selected catchments within each basin for water year 1973. Streamflows of catchments in the Upper Delaware, Allegheny and Lower Chesapeake basins have similar magnitudes and fluctuate almost in unison from mid-November to mid-June period

(**Figure 3.7a, c, d**) when the flow is typically high, and suggests that these catchments are responding to same climatic inputs. On the other hand, the hydrologic response of catchments during the summer and early fall months is dissimilar when the flow is typically low. In contrast to the other three basins, the dissimilarity in streamflows for the catchment pair in Lower Susquehanna basin persists from February to November period (see **Figure 3.7b**).

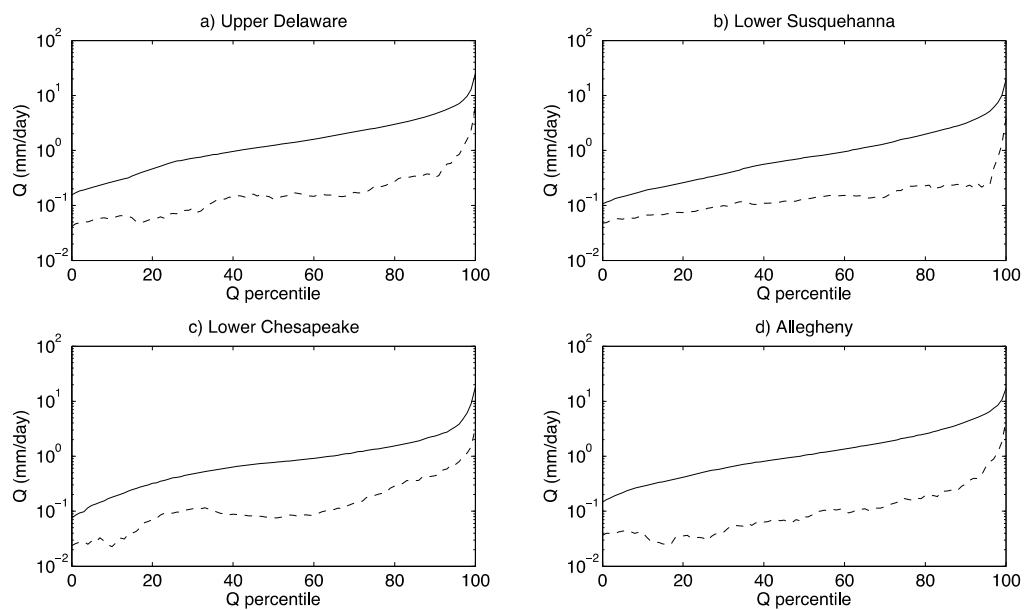


Figure 3.6: Spatial mean (solid line) and standard deviation (dashed line) of catchment streamflow percentiles within a) Upper Delaware, b) Lower Susquehanna, c) Lower Chesapeake, and d) Allegheny basin.

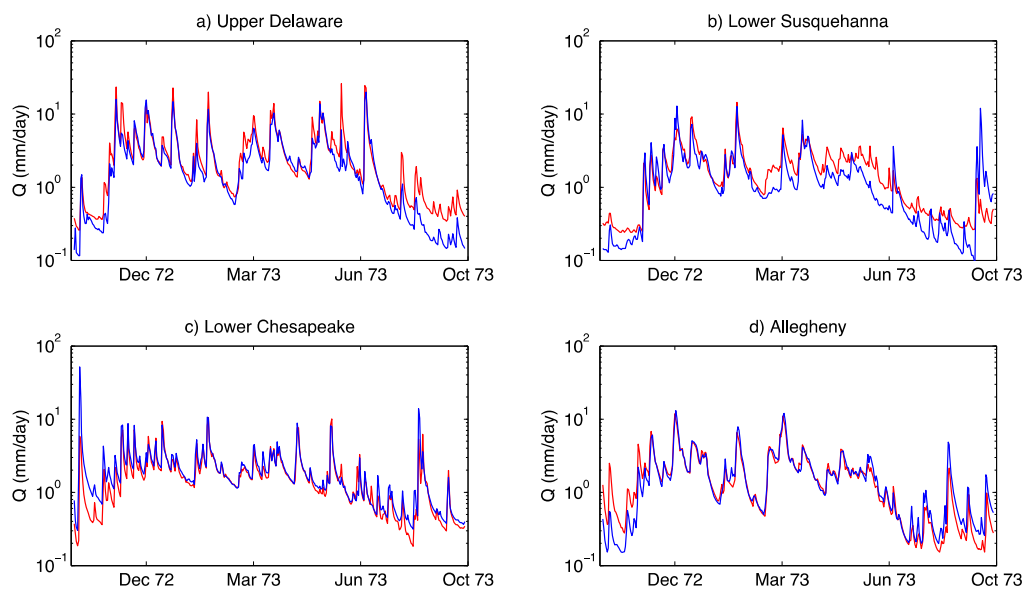


Figure 3.7: Hydrograph comparison of the two selected catchments for water year 1973 within a) Upper Delaware, b) Lower Susquehanna, c) Lower Chesapeake, and d) Allegheny basin.

3.6 Discussion

Results suggest that the hydrologic response of two or more catchments within a region does not remain similar across flow conditions (**Figure 3.4**). The intra-basin variability in streamflow among catchments is high at low flow percentiles, and the variability reduces at higher flow percentiles. The relationship between CV and streamflow percentiles is unique for catchments within each of the four basins (**Figure 3.4**) and is suggestive of the conditions at which the similarity/dissimilarity among the catchments is manifested. As seen in **Figure 3.7**, the hydrographs of catchments in Upper Delaware, Allegheny and Lower Chesapeake basins are similar during the winter and spring periods, while most of the dissimilarity occurs during the low flow period in summer. **Figure 3.8** shows the average monthly values of streamflow, precipitation and PET of a sample catchment within all the four basins. In all the four basins, high flow period is characterized by low ET demand, whereas the low percentile flows mostly occur when the water balance of a catchment is heavily influenced by the high ET demand from atmosphere. Thus, the dominance of ET demand becomes a controlling factor on the magnitude and spatial variability of streamflow during the low flow summer period; whereas the dominance of precipitation input controls the streamflow magnitudes and variability during the higher flow periods in winter. However, the streamflows of catchments in the Lower Susquehanna basin exhibit greater dissimilarity than the catchments in other three basins. As seen in **Figure 3.7b**, the similarity in streamflow is limited only to the early winter period when the ET demand from atmosphere is the lowest. From mid-November to April period, the peaks of hydrographs are similar between the two catchments, but their recession characteristics start to show differences as the year progresses (**Figure 3.7b**). Therefore, dissimilarity in streamflows over a

longer period results in higher CV values across low and intermediate streamflow percentiles within the Lower Susquehanna basin (**Figure 3.4b**).

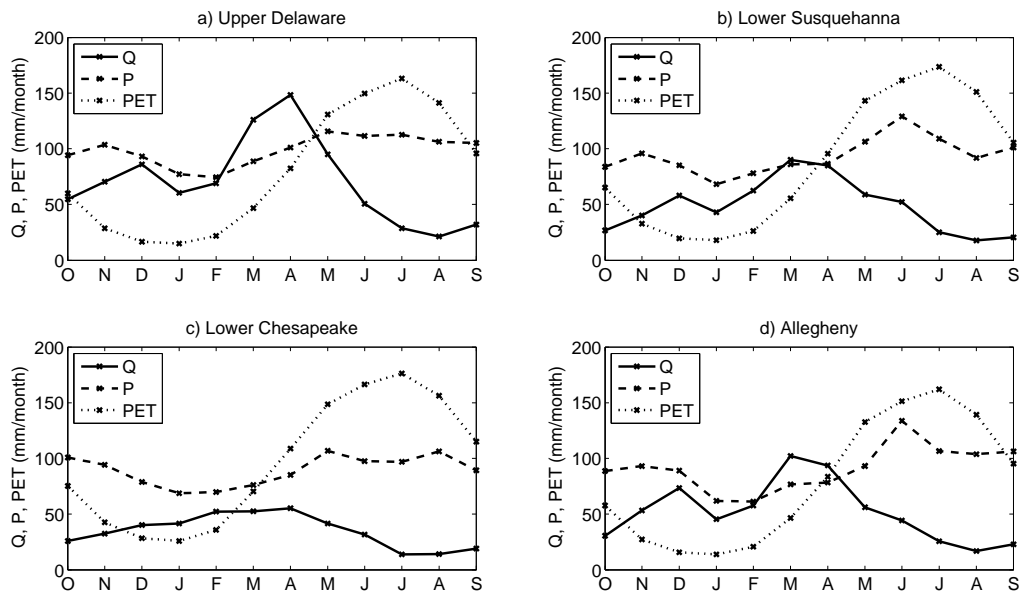


Figure 3.8: Average monthly values of streamflow, precipitation and potential evapotranspiration of a sample catchment in a) Upper Delaware, b) Lower Susquehanna, c) Lower Chesapeake, and d) Allegheny basin.

The seasonal fluctuations in streamflow variability also suggest that different physical factors govern the spatial streamflow patterns at different periods within a year. During low flow conditions, typically in summer when the ET demand is high (**Figure 3.8**), water fluxes are predominantly vertical [*James and Roulet, 2007; Tromp-van Meerveld and McDonnell, 2006*], and the spatial patterns of soil moisture are unorganized and strongly influenced by the local terrain [*Grayson et al., 1997; Stieglitz et al., 2003*]. At these conditions, disparate regions within a catchment are hydrologically disconnected (due to a lack of lateral water movement) and the catchment discharge is most likely controlled by the geologic factors such as the intricacies of landscape micro-topography, subsurface structure, soil texture and structure, etc. This local geologic control on hydrologic conditions can result in higher variability of streamflow response. However, even though geologic properties of the landscape might be playing an important role in streamflow variability at low flow conditions, a further examination of geologic data (permeability, % organic matter, % clay content) in all our 25 study catchments shows that a large variability exists in soil properties within each catchment, and no distinct differences are observed between catchments that can be quantitatively attributed to the variability at low flows. On the other hand, increased similarity among catchments at higher flow percentiles indicates a shift from “local” to “non-local” (climatic) controls as the catchments transition from low flow to high flow conditions. As the atmospheric evaporative demand reduces, a higher proportion of the precipitation gets converted into streamflow (**Figure 3.8**). The high flow conditions reflect the period when the lateral fluxes of water are dominant [*Grayson et al., 1997*], the near surface and subsurface flow paths are connected [*Meyles et al., 2003; Tromp-van Meerveld and McDonnell, 2006*;

Uchida et al., 2004], and the streamflow variability is increasingly controlled by larger scale climatic forcing.

The CV values increase rapidly for the highest flow percentiles (> 90th percentile). This increase is observed not only in the spatial variation of streamflows (**Figure 3.4**) but also in the inter-annual streamflows in individual catchments (**Figure 3.5**). A potential cause for this rapid increase could be that during the very high flow events the hydraulic properties of stream channels of individual catchments play an important role in controlling the streamflow. The control of these hydraulic properties can: 1) increase the variability in space (between catchments) at any given year, and 2) increase the variability in time (year-to-year) within a single catchment. Another potential cause for increased CV values could be the dependence of peak flow variability on catchment drainage areas [*Blöschl and Sivapalan, 1997; Eaton et al., 2002; Smith, 1992*]. However, examination of the relationship between the CV values and drainage areas of our study catchments showed no clear trend in this relationship at any flow condition. We further examined the timing of peak flow events in our catchments to verify whether high flow variability is caused by peak flows occurring in response to local-scale convective storms in summer months; but found that majority of the peak flow events occur during the winter and spring period when larger scale frontal precipitation events are more likely.

Our choice of using CV as variability metric directly affects our interpretation of the controls on streamflow similarity. The CV measures the relative variability (around the mean value), and therefore, high CV at low flow percentiles can be expected due to small mean values. With an increase in streamflow from dry to wet conditions, the mean flow value increases steadily while the standard deviation increases at a much slower rate

and causes the CV value to decrease from low flows to high flows. Although we attribute these changes in CV to shift in hydrologic controls under variable flow conditions, it can be argued that our results do not genuinely reflect the shifting hydrologic controls and are an artifact caused by use of CV as a similarity measure. To test this, we consider 25 synthetically generated random time-series, each representing one of our 25 study catchments by having the same probability distribution (log-normal) as the actual streamflow series. We repeat our analyses on these 25 synthetic time-series to obtain the spatial and temporal CV patterns, similar to those shown in **Figure 3.4** and **Figure 3.5**. **Figure 3.9** shows the spatial and temporal CV patterns of the synthetic time-series within the Lower Susquehanna basin. The synthetic series show that the intermediate percentiles have low CV values, while the extreme percentiles have high CVs. However, when compared with actual streamflow series in Lower Susquehanna basin (**Figure 3.4b** and **Figure 3.5b**), the CV patterns of the synthetic series (**Figure 3.9**) are distinctly different. Specifically, the synthetic time-series is unable to capture the monotonously decreasing spatial CVs of actual streamflows in Lower Susquehanna basin (**Figure 3.4b**). Moreover, the CV patterns obtained by these synthetic series are similar (and indistinguishable) in all the four basins (results not shown) and do not inform us about the differences in CV patterns across the four basins. Therefore, although the random series display somewhat similar CV trends as the actual streamflow series (due to similar probability distributions), the changes in CV values observed in our study (**Figure 3.4** and **Figure 3.5**) are most likely caused due to the underlying shift in hydrologic controls, and not an artifact of our methodology.

The results of this study have ramifications for predicting streamflow in ungauged catchments. Specifically, during low flows, the variability of streamflow among catchments is high, and the predictive capability at ungauged catchments using information from nearby gauged catchments is likely to be low. However, although the relative variability is high at low flows, the variability in absolute streamflow values will be low during the low flow periods. Therefore, depending on the error tolerance that is acceptable to the end user, streamflows at low flow periods can be simulated with limited success. During high flows, the variability of streamflow among catchments is low, which increases the similarity among catchments within a region and improves the prediction capability at ungauged catchments. This suggests that regions with predominantly wet conditions, i.e., humid regions, would be more favorable for information transfer from nearby gauged catchments to the ungauged catchments. In such regions, one can expect a larger range of low variability at intermediate flow percentiles, as observed in the Upper Delaware and Allegheny basins (**Figure 3.4a, d**). Dissimilarity among catchments can also be identified by abnormal CV patterns, as observed in Lower Susquehanna basin (**Figure 3.4b**). High regional variability at low flow and extremely high flow percentiles suggests that similarity in physiographic attributes should be considered while making regionalized predictions at the low flow and extremely high flood events.

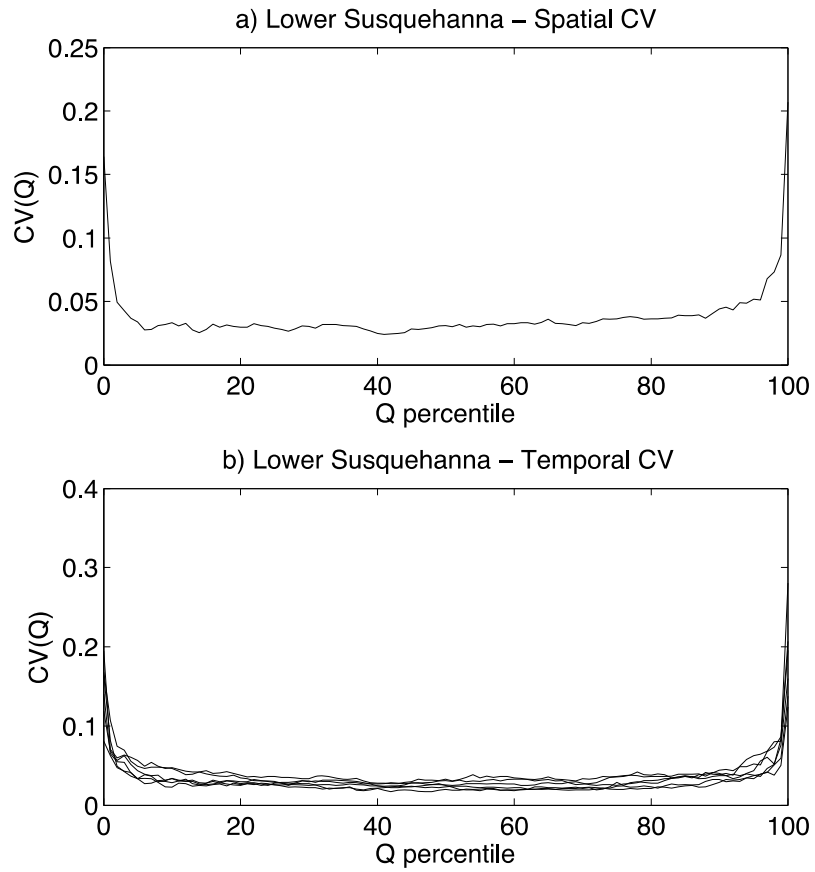


Figure 3.9: CV patterns of synthetically generated random time-series that have the same probability distributions as the streamflows of catchments in Lower Susquehanna basin: a) Spatial CV, b) Temporal CV.

Our *a priori* criteria of catchment selection, i.e., similarity in annual rainfall and runoff, put limits on the size of basins from which the catchments were chosen. We selected basins from the northeast United States since it has the highest density of long-term gauging stations. Although a limited number of gauged catchments are available within each of our four basins, every catchment has a long and consistent hydrologic record (WY 1970 - 1988). Ideally, a larger sample size of gauged catchments (if available) within a basin might provide a clearer picture, in quantitative terms, of spatial variability across flow conditions. However, we think it is unrealistic that we will ever have a large number of gauged catchments within a small basin that satisfies our *a priori* criteria of homogeneity. Moreover, the direct comparison of catchment streamflow and its analysis from an inter-seasonal perspective (**Figure 3.7** and **Figure 3.8**) shows consistency with our observation that regional variability in streamflows is higher at low flow conditions and reduces at higher flows (**Figure 3.4**). Due to the limited number of catchments, the CV patterns in our study might not provide an accurate quantification of variability, but they do provide a preliminary view on the variable nature of hydrologic similarity that is consistent across different basins. In our opinion, one of the main challenges in hydrology, especially from the prediction in ungauged basins (PUB) perspective [Sivapalan *et al.*, 2003], is to work within the constraints of limited measurement locations and learn as much as possible from their observed patterns. We view and interpret the results of this study from that same perspective.

3.7 Summary and Conclusion

This study focused on testing whether stream response similarity among catchments within a region is preserved at all flow conditions. Results show that similarity among catchments is dynamic and highly dependent on the flow conditions. Regional variability in stream response is high at low flow conditions, and it gradually reduces at high flow conditions. Results also suggest that as catchments transition from low to high flow, the dominant control over streamflow variability shifts from evaporative demand to precipitation input. Analysis of the temporal variability of streamflow percentiles shows a similar pattern, i.e., high variability at dry conditions and low variability at wetter conditions. Thus, the evaluation of regional variability over the entire range of streamflow percentiles provides a framework for identifying hydrologic conditions at which stream response among catchments is more likely to be similar. Although our analysis is limited to catchments within the Northeastern United States, the key findings of this study (i.e., dependence of catchment similarity on the flow conditions) should be applicable over a wide range of environments. By identifying the important physical factors that control regional variability in stream response under different wetness conditions, a better understanding and prediction capability of catchment behavior can be achieved at the ungauged sites.

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4. CONTROLS ON HYDROLOGIC SIMILARITY: ROLE OF NEARBY GAUGED CATCHMENTS FOR PREDICTION AT AN UNGAUGED CATCHMENT

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4.1 Abstract

Prediction of streamflows at ungauged catchments requires transfer of hydrologic information (e.g., model parameters, hydrologic indices, streamflow values) from gauged (donor) to ungauged (receiver) catchments. One of the most reliable metrics for selection of ideal donor catchments is the spatial proximity between donor and receiver catchments. However, it is not clear whether information transfer among nearby catchments is suitable across a wide range of climatic and geographic regions. We examine this issue using the data from 756 catchments within the continental United States. Each catchment is considered ungauged in turn and daily streamflow is simulated through distance-based interpolation of streamflows from neighboring catchments. Results show that distinct geographic regions exist in US where transfer of streamflow values from nearby catchments is useful for retrospective prediction of daily streamflow at ungauged catchments. Specifically, the high predictability catchments (Nash-Sutcliffe efficiency $NS > 0.7$) are confined to the Appalachian Mountains in eastern US, the Rocky

Mountains, and the Cascade Mountains in the Pacific Northwest. Low predictability catchments ($NS < 0.3$) are located mostly in the drier regions west of Mississippi river, which demonstrates the limited utility of gauged catchments in those regions for predicting at ungauged basins. The results suggest that high streamflow similarity among nearby catchments (and therefore, good predictability at ungauged catchments) is more likely in humid runoff-dominated regions than in dry evapotranspiration-dominated regions. We further find that higher density and/or closer distance of gauged catchments near an ungauged catchment does not necessarily guarantee good predictability at an ungauged catchment.

4.2 Introduction

Long-term measurements of river streamflow are essential for a number of applications in water resources, such as, planning of water supply and irrigation projects [Dunne and Leopold, 1978; Jain and Singh, 2003], delineation of river floodplains [Merwade et al., 2008; Tate et al., 2002], day-to-day management of dams and canals [Hirsch and Costa, 2004], to name a few. Streamflow measurements are also important for characterizing the hydrologic behavior of river basins within modeling frameworks, so that future assessments of hydrologic behavior in response to climate and/or land-use change can be obtained. However, in many parts of the world, developed as well as developing, rivers are not gauged for continuous monitoring. Developing strategies for prediction at ungauged basins (PUB; Sivapalan et al., [2003]) is therefore required not only for the above practical applications, but also for advancing our process

understanding of the controls on regional variability in landscape hydrologic response [Patil and Stieglitz, 2011; Wagener *et al.*, 2004].

Prediction of streamflows at ungauged basins typically requires transfer of hydrologic information (e.g., model parameters, hydrologic indices, streamflow values) from gauged to ungauged catchments. Transfer of hydrologic model parameters is perhaps the most common procedure [Merz and Blöschl, 2004]. Hydrologic models that have been used extensively for this purpose include: HBV [Göttinger and Bárdossy, 2007; Merz and Blöschl, 2004; Seibert, 1999], IHACRES [Kokkonen *et al.*, 2003; Post and Jakeman, 1996; Schreider *et al.*, 1996], PDM [Kay *et al.*, 2007; Lamb and Kay, 2004]. Alternatively, model-independent methods have been developed that incorporate the spatial variability of streamflow within a region [Archfield and Vogel, 2010; Skøien and Blöschl, 2007; V Y Smakhtin, 1999]. These model-independent methods have the advantage that they can circumvent the deficiencies associated with any particular hydrologic model structure. Smakhtin *et al.* [1997] developed regionalized flow duration curves for catchments in South Africa and estimated streamflows at ungauged catchments through transfer of daily streamflow data from nearby gauged catchments using the interpolation technique described in Hughes and Smakhtin [1996]. Archfield and Vogel [2010] developed the map-correlation method to identify the donor gauged catchment that is likely to have high correlation to the ungauged catchment for direct transfer of daily streamflow time series. Skøien and Blöschl [2007] used the concept of topological kriging, or top-kriging [Skøien *et al.*, 2006], on 376 catchments in Austria to predict hourly and daily streamflow in ungauged catchments.

A common challenge for all information transfer procedures is the search for ideal donor (gauged) catchments from which hydrologic information can be successfully transferred. Recent studies have shown that choosing the donor catchments based on spatial proximity to the ungauged catchment alone is by far the most reliable approach. For example, *Merz and Blöschl* [2004] compared eight parameter transfer methods using the HBV model for 308 catchments in Austria and concluded that methods based on spatial proximity alone performed better than those based on catchment attributes. *Oudin et al.* [2008] compared three different regionalization approaches on 913 French catchments using two hydrologic models and found that the spatial proximity approach outperformed other approaches. *Zhang and Chiew* [2009] obtained similar results using data from 210 catchments in Australia. While these studies aptly demonstrate the advantage of spatial proximity based approach, what is not clear is whether the information transfer from nearby gauged to ungauged catchments is suitable across a wide range of hydro-climatic settings.

In this study, we characterize the transferability of hydrologic information among nearby catchments. Our objectives are to: (1) determine if distinct geographic regions exist where nearby catchments tend to have similar streamflows, so that information can be easily transferred between gauged and ungauged catchments, and (2) identify the physiographic and hydro-climatic conditions that favor streamflow similarity among nearby catchments within a region. We use the data from 756 gauged catchments across the continental United States to simulate daily streamflow through inverse distance weighted (IDW) interpolation of streamflow from neighboring gauged catchments. The prediction efficiency at ungauged catchments is then compared against physiographic and

hydro-climatic properties to identify the conditions that favor high streamflow similarity within a region. In section 2, we describe the 756 catchments chosen for this study and the associated environmental data used for our analysis. In section 3, we outline the distance-based interpolation method used for streamflow simulation, the goodness-of-fit measures used to assess predictability, and metric used to analyze the relationship between predictability and catchment properties. In section 4, we present results of our analysis. Sections 5 and 6 provide the discussion of our results and the conclusions of this study respectively.

4.3 Data

We use the streamflow records of catchments from U. S. Geological Survey's Hydro-Climate Data Network (HCDN) [Slack *et al.*, 1993]. The HCDN database consists of data of 1659 catchments located within the United States that are not severely affected by human activity. The streamflow records in HCDN span from 1874 to 1988. A majority of the catchments have consistent and continuous records from water year 1970 onwards. As such, we consider only those catchments that have a continuous daily streamflow record from water year 1970 to 1988 (i.e., 1st October, 1969 to 30th September, 1988), which reduces the number of acceptable catchments to 756 (see **Figure 4.1**). The drainage area of the catchments ranges from 23 km² to 5000 km², and the median drainage area is 715 km².

Monthly time-series of precipitation and potential evapotranspiration in each of the 756 catchments are obtained from the climate dataset developed by *Vogel and*

Sankarasubramanian [2005]. Estimates of monthly precipitation in this dataset are obtained from the PRISM [*Daly et al.*, 1994] climate analysis system as described in *Vogel et al.* [1999], whereas the monthly potential evapotranspiration estimates are obtained using the formula suggested by *Hargreaves and Samani* [1982]. From the streamflow and precipitation data, we derive five hydrologic indices (or signatures) for each of the 756 catchments. These hydrologic signatures are: baseflow index, runoff ratio, baseflow runoff ratio (baseflow/rainfall), slope of flow duration curve, and inter-annual streamflow elasticity. We also use the data of three physiographic attributes from *Vogel and Sankarasubramanian* [2005] dataset, viz., channel slope, soil permeability, and soil water holding capacity. Details of the methods used for deriving these hydrologic signatures are provided in Appendix 4A.

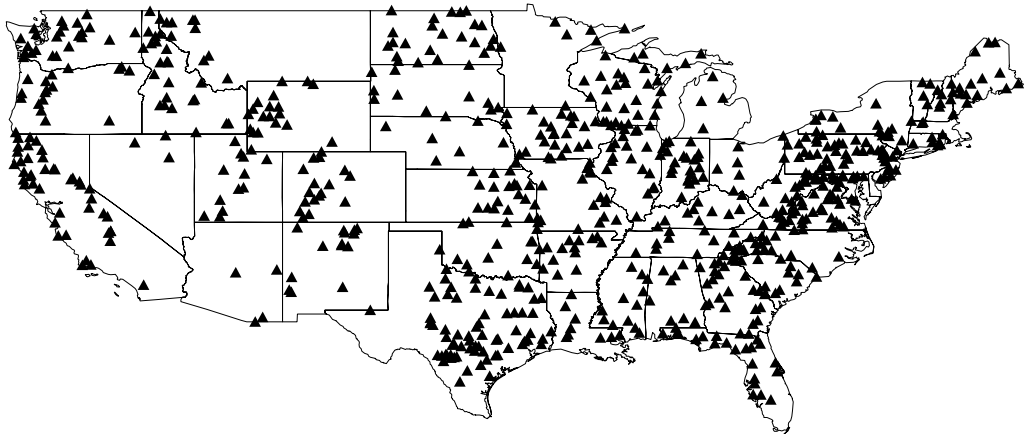


Figure 4.1: Location of all the 756 catchments (black triangles) within the continental United States

As illustrated in **Figure 4.1**, the number of stream gauges is higher in the eastern half of the country than in the western half. Since the regionalized predictions in this study are based on proximity of gauged and ungauged catchments, this variable gauge density may bias our analysis. Thus, in section 4.5.4, we evaluate whether gauge density has an appreciable effect on streamflow predictions at ungauged catchments.

4.4 Methods

In this section, we first outline the distance based interpolation method used for simulating daily streamflows. We then describe the goodness-of-fit measures used for assessing the prediction efficiency, followed by a brief explanation of the metric used for assessing the relationships between prediction efficiency and catchment properties.

The inverse distance weighted (IDW) interpolation is one of the simplest methods to determine whether streamflow values among spatially proximate catchments are similar. Nonetheless, as will be shown in results, this method is highly effective in characterizing the regionalized predictability patterns over the scale of continental US. Comparison of different interpolation methods is beyond the scope of this study. The mathematical expression of the IDW interpolation scheme is as follows:

$$q(x) = \sum_{k=1}^N \frac{w_k(x)}{\sum_{k=1}^N w_k(x)} \cdot q(x_k) \quad (4.1)$$

And,

$$w_k(x) = \frac{1}{d(x, x_k)^p} \quad (4.2)$$

where, $q(x)$ is the discharge value at the ungauged catchment that is located at point x in the region, $q(x_k)$ is the discharge value at neighboring donor catchment k located at point x_k in the region, and N is the total number of neighboring donor catchments considered for the interpolation. The daily streamflow values are normalized by catchment drainage area and have the units of mm/day. Distance between the gauged and ungauged catchment d is calculated individually for each of the N neighboring catchments. d is the distance between stream gauges of the catchments. The interpolation weights w are calculated for all the donor catchments using equation 4.2. The exponent p in equation 4.2 is a positive real number, called as power parameter.

Each of the 756 catchments is considered ungauged in turn (jack-knife procedure), and daily streamflows are simulated using equations 4.1 and 4.2. We use power parameter $p = 2$ (i.e., the inverse square distance weighted method) and vary the number of neighboring donor catchments N from 1 to 50.

Goodness of fit for predicted hydrograph is measured using two metrics: Nash-Sutcliffe efficiency (NS) and water balance error (WBE). These two measures convey different information about prediction performance. The WBE verifies whether long-term differences in the magnitudes of observed and simulated streamflows are within an acceptable range, whereas the NS verifies whether the fluctuations in daily hydrograph are appropriately captured. These metrics have been extensively used in the hydrology literature to determine the simulation efficiency of daily hydrographs. The Nash-Sutcliffe efficiency criterion [Nash and Sutcliffe, 1970] is defined as follows:

$$NS = 1 - \frac{\sum_{i=1}^n (Q_{obs,i} - Q_{pred,i})^2}{\sum_{i=1}^n (Q_{obs,i} - \bar{Q}_{obs})^2} \quad (4.3)$$

where, $Q_{pred,i}$ and $Q_{obs,i}$ are the predicted and the observed stream discharge values on the i^{th} day respectively, \bar{Q}_{obs} is the mean of all the observed discharge values and n is the total number of days in the record.

The water balance error is defined as follows:

$$WBE = 100 \times \left| \frac{\sum_{i=1}^n Q_{pred,i} - \sum_{i=1}^n Q_{obs,i}}{\sum_{i=1}^n Q_{obs,i}} \right| \quad (4.4)$$

We analyze the relationship of prediction efficiency (NS values) with numerous catchment properties. These relationships are analyzed to identify the factors that favor streamflow similarity among nearby catchments. To this end, we use the Spearman's rank correlation [Spearman, 1904], which quantifies the increasing/decreasing trend in a relationship. The formula for Spearman's correlation (ρ) is as follows:

$$\rho = 1 - \frac{6 \cdot \sum d^2}{M \cdot (M^2 - 1)} \quad (4.5)$$

Where, d is the difference between the ranks of each observation on the two variables under consideration, and M is the total number of observation points ($M = 756$ in our case). Spearman's ρ varies from -1 to +1, with -1 being a perfect monotonically decreasing relationship and +1 being perfect monotonically increasing.

4.5 Results

4.5.1 *Choosing the optimal number of donor gauged catchments*

To find the optimal number of donor catchments required for a good streamflow estimate we vary the number of nearest donor catchments from 1 to 50 and calculate the associated NS. This approach for choosing the optimal number of donors has been used previously [Oudin *et al.*, 2008; Zhang and Chiew, 2009]. Figure 4.2a shows the relationship between the number of donor gauged catchments used for simulating daily streamflow and the median NS from each simulation run for all the 756 catchments. The median NS increases sharply from 0.49 to 0.61 as the number of donor catchments increase from 1 to 4 followed by small increases in median NS for subsequent increases in the number of donor catchments. The median NS reaches its highest value of 0.615 at 15 donor catchments. Beyond 15 donor catchments there is decline in simulation efficiency that can be attributed to the relative reduction in influence of the nearby catchments. For subsequent analysis, we therefore limit the number of donors to five nearest gauged catchments and perform the distance based interpolation to simulate daily streamflows. For simulations with five donor catchments, the maximum NS is 0.97, the median value is 0.61, and the 25th percentile value is 0.29. Figure 4.2b shows the 25th and 75th percentile NS values along with median NS against the number of donor catchments. Similar to the median, other percentile values also show that increasing the number of donors far beyond 4 or 5 does not cause an increase in prediction performance. Figure 4.2c shows the distribution of NS values of simulated streamflows using five donor catchments.

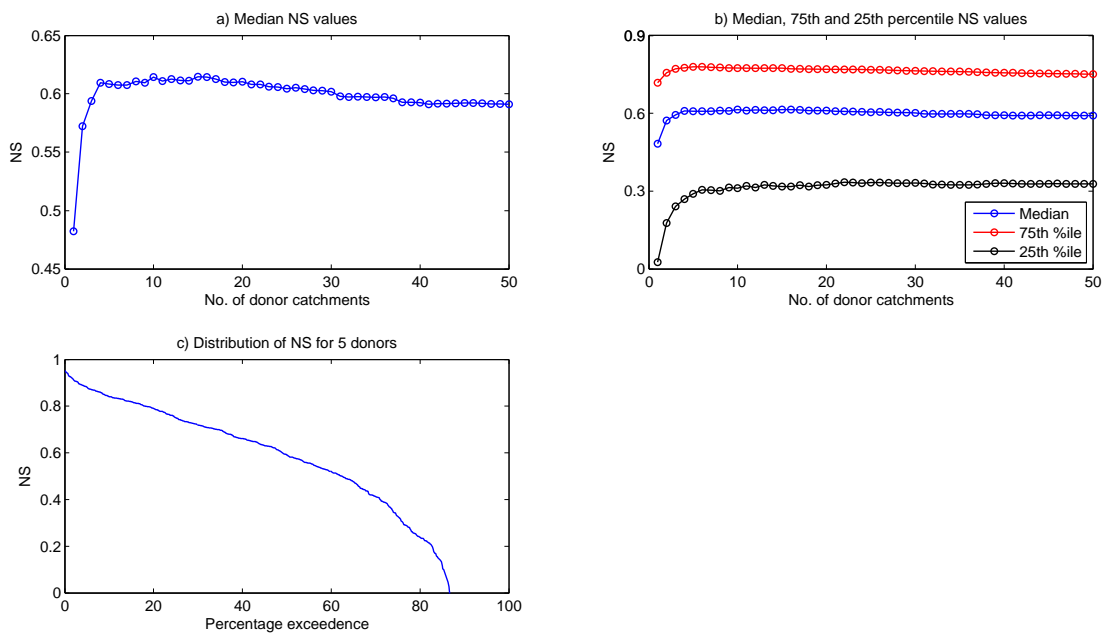


Figure 4.2: a) Relationship between number of donor catchments and median NS, b) relationship between number of donor catchments and median, 75th percentile, and 25th percentile NS, and c) distribution of NS values with five donor catchments

4.5.2 Geographic patterns of streamflow predictions

Distinct geographic patterns are observed in the NS and WBE values of catchment streamflows using the IDW interpolation method (Figure 4.3 and Figure 4.4). For better identification of these geographic patterns, we partition the catchments into three groups: Group 1 for NS greater than 0.7, Group 2 for NS between 0.3 and 0.7, and Group 3 for NS less than 0.3. Figure 4.3a shows the location of all the Group 1 catchments, 288 in total (~ 40%), which have the highest predictability of daily streamflow. The majority of the Group 1 catchments are located in three geographic regions: (1) the Appalachian mountain ranges in the eastern US, (2) the Rocky Mountains, and (3) the Pacific Northwest region to the west of Cascade Mountain range. The remaining Group 1 catchments are located across the eastern half of continental US, especially in the states of Indiana and Illinois (Figure 4.3a). The Group 2 catchments (Figure 4.3b, a total of 277 catchments (~ 35%), are located across the eastern part of the United States. The poorest performers, Group 3 catchments are located in the western half of continental US, especially to the west of Mississippi river (Figure 4.3c). There are 191 catchments (~ 25%) that belong in Group 3 and these are considered as practically unpredictable using the spatial proximity based regionalization method.

For water balance errors (WBE), we group catchments as follows: Group A for $WBE < 20\%$, Group B for $20\% < WBE < 50\%$, and Group C for $WBE > 50\%$. Figure 4.4 shows the geographic patterns of WBE for these three catchment groups. Figure 4.4a shows the Group A catchments, which have the smallest water balance errors. A total of 473 (~ 63%) catchments belong to Group A, and majority of them are located in the eastern part of US and along the west coast. The Group B catchments (152 in total (~

20%), see Figure 4.4b) are spread throughout the US and do not have any preferential geographic patterns. Figure 4.4c shows the Group C catchments, 131 in total (~ 17%), which have the highest water balance errors and are located mostly in drier western part of the US. The geographic patterns of Group C catchments are similar to the catchments with lowest NS values (Group 3, Figure 4.3c).

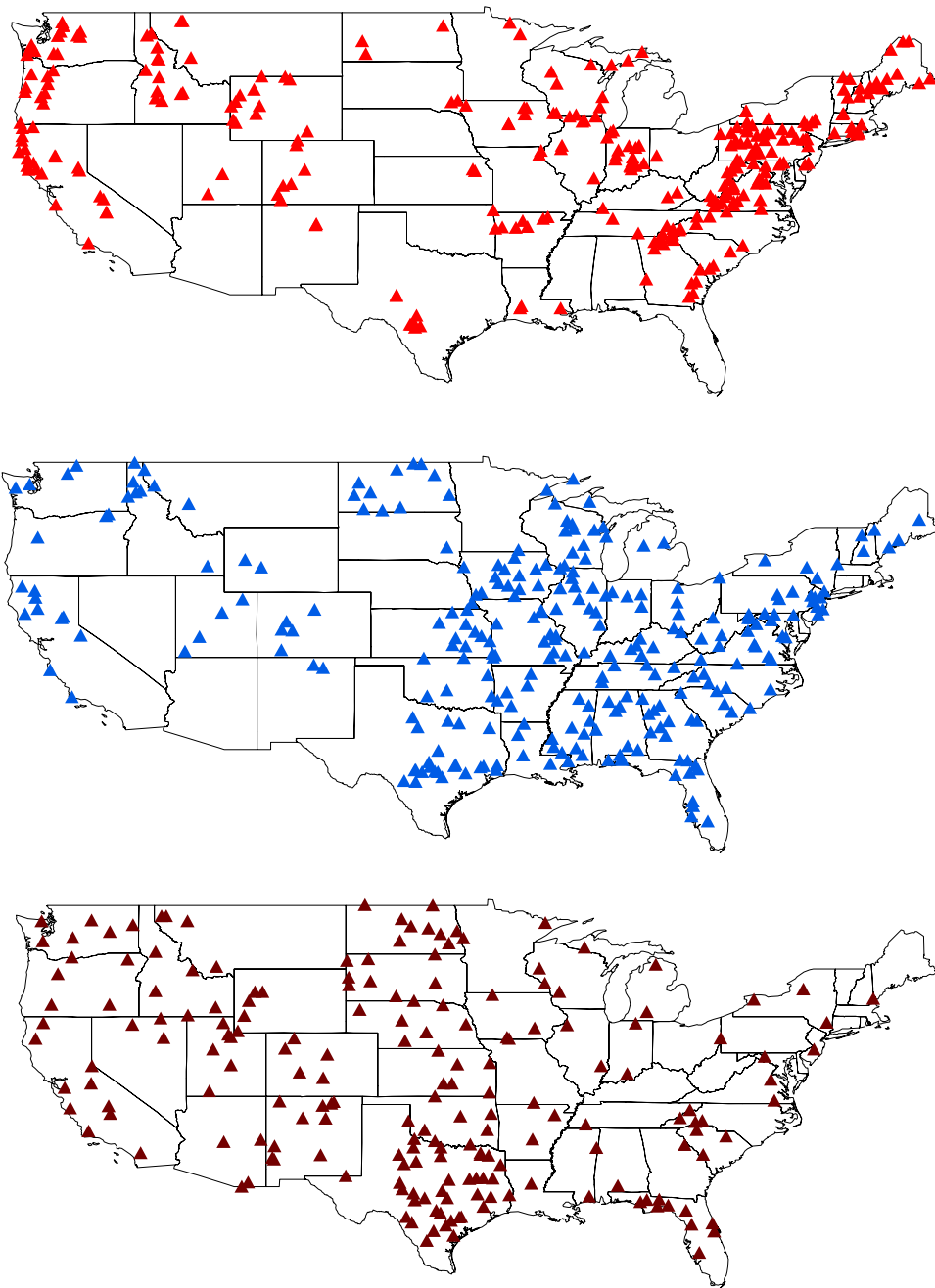


Figure 4.3: a) Group 1 catchments with $NS > 0.7$ (Red triangle), b) Group 2 catchments with $0.3 < NS < 0.7$ (Blue triangle), and c) Group 3 catchments with $NS < 0.3$ (Brown triangle)

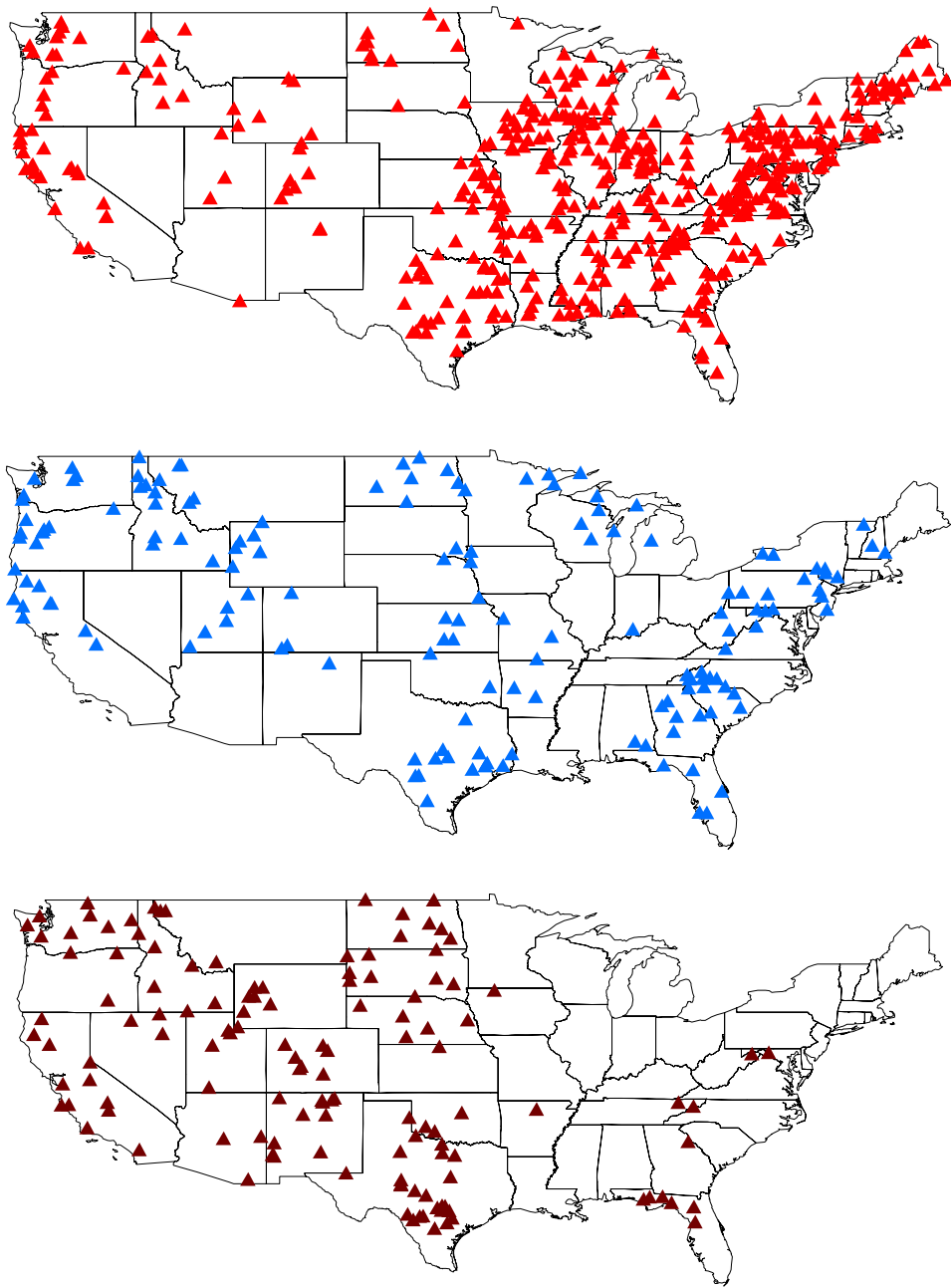


Figure 4.4: a) Group A catchments with $WBE < 20\%$ (Red triangle), b) Group B catchments with $20\% < WBE < 50\%$ (Blue triangle), and c) Group C catchments with $WBE > 50\%$ (Brown triangle)

4.5.3 Impact of catchment proximity on predictability at ungauged catchments

Figure 4.5a shows the relationship of prediction efficiency (NS) with the average distance of donor catchments from the ungauged catchment, while Figure 4.5b shows its relationship with the distance of nearest donor catchment. As expected, the observed trend is that high NS catchments have donor catchments in closer proximity, i.e., smaller distances. The Spearman rank correlation (ρ) for the relationships of NS with the average and minimum distance is -0.44 and -0.41 respectively (p value < 0.01 in both cases). However, at any given NS value, there is a surprisingly wide scatter of distances between donor and receiver catchments (Figure 4.5a, b). This suggests that the donor-receiver catchment proximity alone cannot fully explain the prediction performance at a given location. Among catchments with $NS > 0$, the R^2 value of relationship between NS and average donor distance is 0.12, i.e., the average distance from donor catchments explains only 12% of the spatial variability in NS.

4.5.4 Impact of gauge density on predictability at ungauged catchments

Gauge density is possibly an important factor that can influence the transfer of information to ungauged catchments. If more gauged catchments are present in the vicinity of an ungauged catchment, we can intuitively expect that catchment to have better predictability. Therefore, we test quantitatively whether disparity in gauge density across different regions of the US influences predictability at an ungauged catchment. Gauge density around a catchment is defined as the number of gauged catchments within the 200 km radius of its location. We tested the gauge density metric by varying the search radius from 100 km to 500 km and found that the relationship between NS and

gauge density is not affected by the choice of the search radius (result not shown). Figure 4.6 shows the relationship between NS and gauge density near the ungauged catchment. Contrary to our a priori expectation, high gauge density around an ungauged catchment does not guarantee good predictability. Moreover, there are numerous catchments that have low gauge density in their vicinity and still have high NS values. No significant trend is observed in the relationship between NS and gauge density. Among catchments with $NS > 0$, the R^2 value of relationship between NS and gauge density is 0.06, i.e., the density of gauged catchments surrounding within a region explains only 6% of the spatial variability in NS.

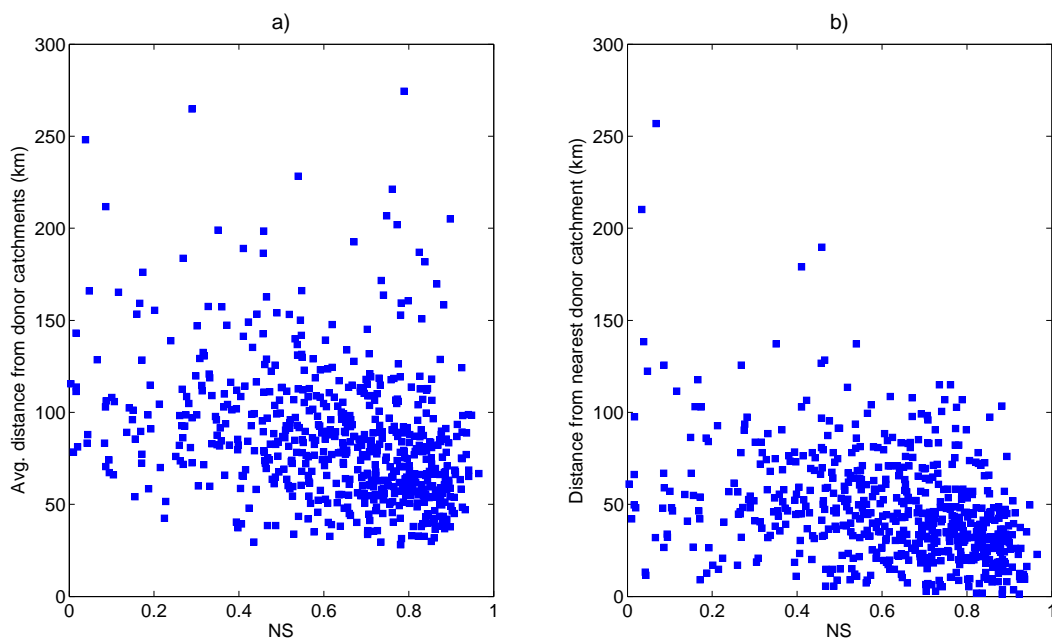


Figure 4.5: Relationship of Nash Sutcliffe efficiency (NS) with a) average distance from donor catchments, and b) distance from nearest donor catchment

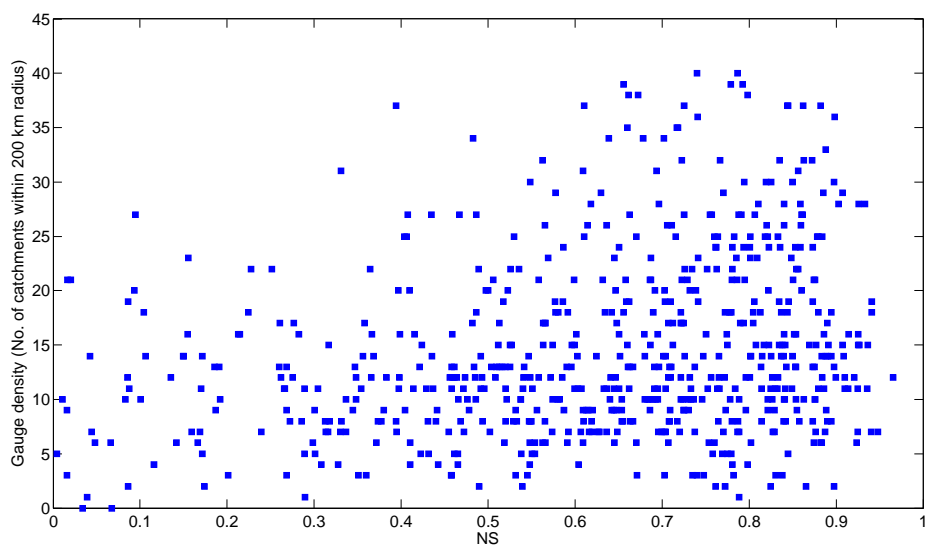


Figure 4.6: Relationship of Nash Sutcliffe efficiency (NS) with gauge density around an ungauged catchment

4.5.5 Impact of climate on predictability at ungauged catchments

We analyze the high and low predictability catchments using the Budyko curve [Budyko, 1974]. A Budyko curve characterizes the relationship between aridity index (PET/P) and evaporation index (ET/P) of the catchments. Figure 4.7 shows the Group 1 catchments (NS > 0.7, blue squares) and Group 3 catchments (NS < 0.3, red squares) on the Budyko curve. Majority of the high predictability catchments (Group 1) have low values of evaporation and aridity indices and are located in the lower portion of the curve. This suggests that the water balance in these high predictability catchments is controlled by energy limitation, i.e., more water is present than can be evaporated. On the other hand, low predictability catchments (Group 3) have higher values of evaporation and aridity indices and are located in the higher portion of the curve. About 48% of the Group 3 catchments have aridity index > 1, suggesting that their water balance is controlled by water limitation, i.e., less water is present than can be evaporated. Thus, the Budyko curve shows that the predictability is higher in regions where the ET of catchments is demand limited (i.e., humid) and low where the ET is supply limited (i.e., arid).

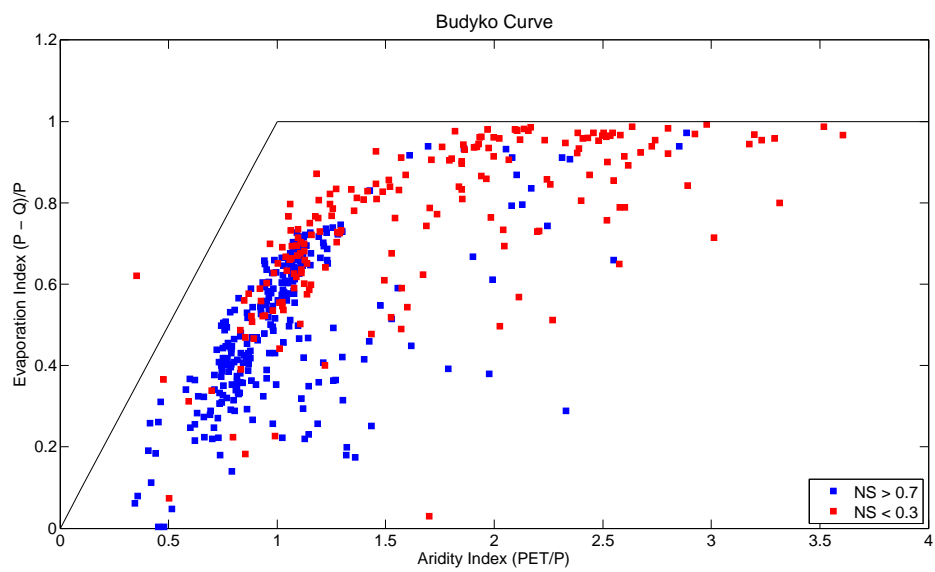


Figure 4.7: Budyko diagram showing the high predictability (NS > 0.7) and low predictability (NS < 0.3) catchments

4.5.6 Physical conditions favoring good predictions at ungauged catchments

To identify the physical conditions that favor high streamflow similarity (and therefore good predictability), we explore the relationships between NS and catchment attributes. Eight catchment properties are considered: three physiographic properties (channel slope, soil permeability, and soil water holding capacity) that are obtained for each catchment from the *Vogel and Sankarasubramanian* [2005] dataset; and five hydrologic signatures (baseflow index, runoff ratio, baseflow runoff ratio, slope of flow duration curve, and inter-annual streamflow elasticity) that are derived from the streamflow and precipitation data (see Appendix 4A for details).

Figure 4.8 shows the relationship between prediction efficiency (NS) and each of the three physiographic properties. While none of these properties have a distinct relationship with NS, a majority of the catchments with higher channel slope ($> 1\%$) have high NS value (Figure 4.8a). This trend is consistent with the observation that a majority of high NS catchments are located along the three large mountain ranges of the US (Figure 4.3a). However, high NS values are not exclusive to catchments with high channel slope. Of the three physiographic properties, only channel slope shows a statistically significant trend in its relationship with NS (Spearman $\rho = 0.21$; see Table 4.1). No distinct trend is observed in soil permeability except that the preference of higher permeability catchments is towards high NS values (Figure 4.8b). No trend whatsoever is observed in the relationship between NS and soil water holding capacity (Figure 4.8c).

Figure 4.9 shows each of the five hydrologic signatures plotted against NS. High scatter is observed in all the five relationships, similar to the observations of

physiographic attributes (Figure 4.8). Nonetheless an increasing trend with respect to NS is observed in the relationships of runoff ratio (Spearman $\rho = 0.51$), baseflow runoff ratio (Spearman $\rho = 0.46$), and slope of FDC (Spearman $\rho = 0.31$) (Figure 4.9a, c, and d respectively). Although many high NS catchments are clustered towards high values of baseflow index (Figure 4.9b), it does not have a significant trend in its relationship with NS. No particular trend (increasing or decreasing) is observed in the relationship between NS and streamflow elasticity (Figure 4.9e).

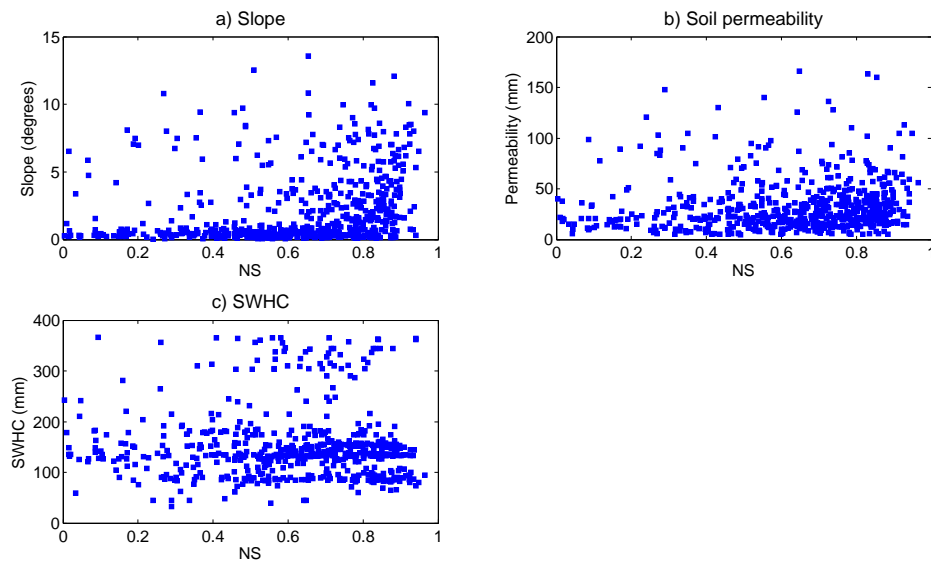


Figure 4.8: Relationship between Nash Sutcliffe efficiency (NS) and a) channel slope, b) soil permeability, and c) soil water holding capacity (SWHC)

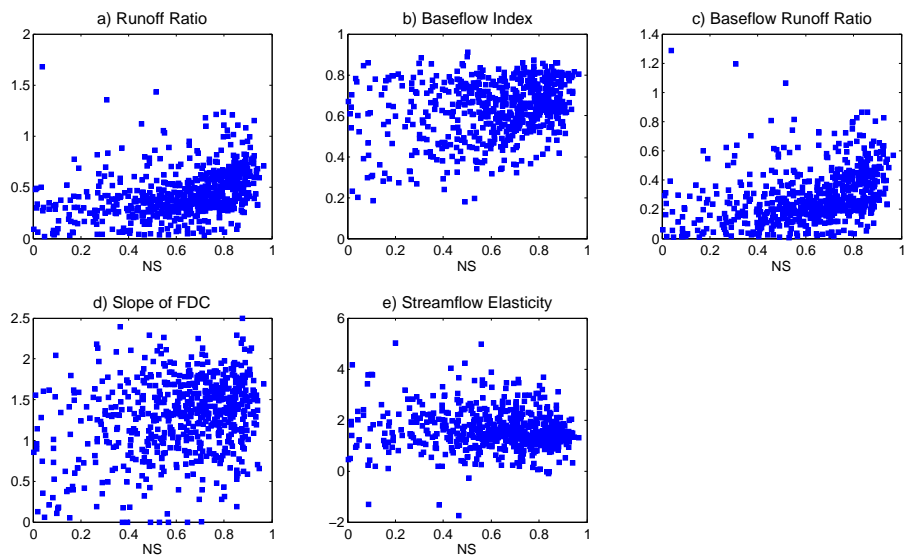


Figure 4.9: Relationship between Nash Sutcliffe efficiency (NS) and a) runoff ratio, b) baseflow index, c) baseflow runoff ratio, d) slope of FDC, and e) streamflow elasticity

Table 4.1: Correlation of catchment properties with Nash-Sutcliffe (NS) efficiency of simulation. Bold and underlined values indicate statistically significant value ($p < 0.01$)

Type	Property	Spearman rank correlation (ρ)	p value
Physiographic	Channel slope	<u>0.21</u>	0.00
	Soil permeability	0.08	0.03
	SWHC	0.04	0.26
Hydrologic	Runoff ratio	<u>0.51</u>	0.00
	Baseflow index	0.03	0.46
	Baseflow runoff ratio	<u>0.46</u>	0.00
	Slope of FDC	<u>0.31</u>	0.00
	Streamflow elasticity	0.01	0.83

4.6 Discussion

Distinct geographic regions exist where transfer of streamflow information from nearby gauged catchments results in good streamflow prediction at an ungauged catchment. High streamflow predictability is obtained in humid mountainous regions, whereas the low predictability catchments are predominantly located in the drier regions (Figure 4.3 and Figure 4.4). To our knowledge, the geographic patterns of streamflow similarity (and predictability at ungauged catchments) shown here not been shown before within the continental US, specifically at a daily time-scale and using an information transfer method. The Budyko curve (Figure 4.7) illustrates the preference of high predictability catchments in humid regions. Our previous work [Patil and Stieglitz, 2011] characterized streamflow similarity among nearby catchments across multiple flow conditions. Patil and Stieglitz [2011] suggested that the competing influences of precipitation and evaporative demand determine the conditions at which streamflow similarity is manifested. Consistent with their suggestion, the results presented here show that streamflow similarity is more likely to occur in regions where annual precipitation exceeds evaporative demand (i.e., low energy environments). The preference for humid environment is further evident from the tendency of high predictability catchments to be located in regions of high forest density. Figure 4.10 shows all the 756 catchments mapped with the forest cover within the US. The forest cover map is obtained from the USGS Global Land Cover Characteristics (GLCC) project [Loveland *et al.*, 1991]. With the exception of catchments in the mid-West, almost all the high predictability catchments (Group 1) are located in regions with high amount of forest cover.

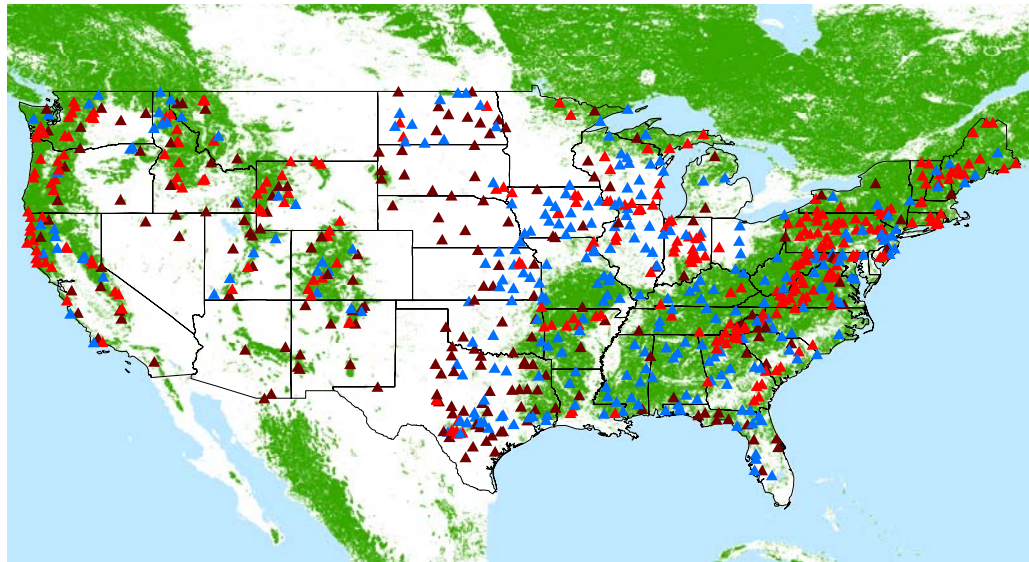


Figure 4.10: All the 756 catchments mapped along with the forest cover within the United States: Group 1 ($NS > 0.7$; Red), Group 2 ($0.7 > NS > 0.3$; Blue), Group 3 ($0.3 > NS$; Brown)

While humid climate is certainly favorable for similarity among nearby catchments, climate alone is not sufficient for identifying regions of high streamflow similarity. The clustering of Group 1 catchments along the mountain ranges suggests that topography is also an important factor in determining streamflow similarity (and predictability). For instance, the catchments in southeastern states of Louisiana, Mississippi, Alabama and Florida have humid climate, but a flatter terrain (and most are Group 2 catchments). Due to the strong connection of predictability with geographic features, we had an a priori expectation that the catchments with high (or low) predictability will have distinct physiographic and hydrologic signatures associated with them. However, the relationship of NS with individual catchment properties is weak. Of the eight catchment properties considered, statistically significant positive trends with respect to NS are observed in only four properties: channel slope, runoff ratio, baseflow runoff ratio, and the slope of FDC (see Table 4.1). These weak relationships are indicative of the difficulties faced by hydrologists in achieving a universally acceptable hydrologic classification of catchments [McDonnell *et al.*, 2007; Wagener *et al.*, 2007].

Although the streamflow predictions in this study are obtained through distance-based interpolation, results show that the distance between donor and receiver catchments cannot fully explain the prediction patterns. It could have been argued that the high NS catchments are preferentially located in humid regions because of the higher gauge density in those regions. However, no clear relationship is found between NS and gauge density (Figure 4.6). This suggests that factors other than the spatial proximity among catchments and gauge density play an important role in regional similarity of streamflows. The higher predictability in humid environments is likely to be due to

similarity in climatic inputs over larger spatial scales. However, low predictability an ungauged catchment can be due to either one of the three primary causes: (1) the ungauged catchment is too far from the donor catchments, or (2) the spatial variability in climatic inputs is high in the region surrounding the ungauged catchment, or (3) the hydrologic behavior of the ungauged catchment is idiosyncratic (and therefore, non-representative of the region surrounding it) either due to contributions from deep groundwater sources, loss of water to regional aquifers, or other complex geologic factors.

4.7 Summary and Conclusion

This study examined whether information transfer from nearby gauged to ungauged catchments is suitable across multiple environments. Distinct geographic patterns of daily streamflow predictability at ungauged catchments were observed within the continental US. Specifically, high predictability catchments are located along the Appalachian Mountains in eastern US, the Rocky Mountains, and the Cascade Mountains in Pacific Northwest, whereas the low predictability catchments are located in the drier regions west of Mississippi river. Identification of these patterns provides essential information regarding the usefulness of gauged catchments within a region for predicting streamflow at a nearby ungauged catchment. While the direct transfer of streamflows is useful for retrospective prediction, future forecasts of streamflows will still require implementation of hydrologic models. Our results suggest that streamflow similarity in the high predictability regions increases the likelihood that gauged and ungauged catchments in those regions will have similar model parameters. However, we suspect

that model regionalization studies will need to additionally consider whether their chosen model structure is suitable for characterizing the hydrologic response within their region of interest.

Comparison of catchments using the Budyko curve suggests that climate has a dominant control over the regional extent of similarity in hydrologic response. Nonetheless, among the humid regions, high predictability catchments are still preferentially clustered among the mountainous environments. This suggests that the topography of the region also has the ability to influence similarity in catchment streamflows. However, analysis of individual catchment attributes provides, at best, a weak picture of the physiographic and hydro-climatic conditions that favor high streamflow similarity (and predictability at ungauged catchments). More importantly, our results show that the spatial proximity between gauged and ungauged catchments alone cannot fully explain the prediction performance at a given location. This suggests that a combined influence of spatial proximity, regional climate variability and geologic settings contributes towards meaningful information transfer between the gauged and ungauged catchments.

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4.8 Appendix 4A: Deriving the hydrologic signatures of a catchment

Five hydrologic indices (or signatures) are derived individually for each of the 756 catchments. These hydrologic signatures are: baseflow index, runoff ratio, baseflow runoff ratio, slope of flow duration curve, and inter-annual streamflow elasticity. *Sawicz et al.* [2011] used four of the above signatures (baseflow index, runoff ratio, slope of flow duration curve, and inter-annual streamflow elasticity) in their catchment classification study and showed that each individual hydrologic signature explains a different aspect of the hydrologic response of a catchment.

The baseflow index (BFI) is defined as the ratio of baseflow to total streamflow of a catchment. We use the one parameter single-pass digital filter method [*Arnold and Allen*, 1999; *Eckhardt*, 2008] to calculate the BFI. The baseflow filter is applied on daily streamflow time-series through the following equation:

$$B_k = \alpha \cdot B_{k-1} + \frac{1-\alpha}{2} \cdot (Q_k + Q_{k-1}) \quad (4A-1)$$

where, B is the baseflow and Q is the total streamflow. The values of filter parameter $\alpha = 0.925$. Equation 4A-1 is applicable provided that $B_k \leq Q_k$ (or else $B_k = Q_k$). After applying the above filter, the baseflow index is calculated as:

$$BFI = \sum_{k=1}^N \frac{B_k}{Q_k} \quad (4A-2)$$

A high value of BFI suggests that the influence of subsurface flow on the overall flow output from a catchment is higher. On the other hand, a low BFI value suggests that the catchment is fast responding.

The runoff ratio (RR) is defined as the ratio of average annual streamflow (Q) to average annual precipitation (P). We consider the annual average values of Q and P over the entire period of WY 1970-1988 to calculate the RR values. The runoff ratio is a metric for partitioning the incoming precipitation input into the fraction that exits the catchment as runoff and the fraction that exits the catchment as evapotranspiration [Sankarasubramanian *et al.*, 2001; Yadav *et al.*, 2007]. Catchments with high RR value are considered to be streamflow dominated, while those with low RR values are evapotranspiration dominated.

The baseflow runoff ratio is the ratio of average annual baseflow and precipitation. It is a similar metric to runoff ratio, but gives a direct estimate of the proportion of incoming rainfall that reaches the catchment outlet through slower subsurface paths. The baseflow runoff ratio is calculated as the product of baseflow index and runoff ratio of a catchment.

The flow duration curve (FDC) of a catchment is a graphical illustration of the amount of time (expressed as a percentage) a specific streamflow value is equaled or exceeded in a catchment within a specified period of hydrologic record [Searcy, 1959; V U Smakhtin, 2001]. The slope of flow duration curve (S_{FDC}) is defined as the slope of the middle section of the FDC (between 33rd and 66th percentile flows) when the curve can be considered as approximately linear [Sawicz *et al.*, 2011; Yadav *et al.*, 2007]. S_{FDC} is calculated using the following formula:

$$S_{FDC} = \frac{\ln(Q_{66}) - \ln(Q_{33})}{0.66 - 0.33} \quad (4A-3)$$

A high value of S_{FDC} indicates that the catchment is subject to high flow variability, while a low S_{FDC} values is typical of catchments with damped response behavior and stable flows.

The inter-annual streamflow elasticity (E_{QP}) is defined as the ratio of percentage change in annual streamflow and the percentage change in annual precipitation. E_{QP} is an indicator of the sensitivity of streamflow to relative changes in precipitation inputs [Sankarasubramanian *et al.*, 2001; Sawicz *et al.*, 2011]. We calculate the E_{QP} using the following formula:

$$E_{QP} = median\left(\frac{dQ}{dP} \cdot \frac{P}{Q}\right) \quad (4A-4)$$

An E_{QP} value of 1 suggests that the relationship between precipitation change and streamflow change is linear. $E_{QP} > 1$ indicates that the catchment is elastic (or more sensitive) to precipitation change, while $E_{QP} < 1$ indicates that the catchment is inelastic.

4.9 References

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5. MODELING DAILY STREAMFLOW AT UNGAUGED CATCHMENTS: WHAT INFORMATION IS NECESSARY?

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5.1 Abstract

Rainfall-runoff modeling at ungauged catchments involves indirect estimation of calibrated parameters, most often by borrowing them from hydrologically similar gauged catchments. In this paper, we hypothesize that reliable estimation of hydrograph recession information alone is sufficient to achieve good model predictability at ungauged catchments. We develop a simple daily time-step rainfall-runoff model that calibrates for the hydrograph recession properties of a catchment and implement it over 756 catchments located across the continental United States. For indirect characterization of hydrologic similarity between the gauged and ungauged catchments, we compare the methods based on physical proximity and spatial proximity measures. Results show that the rainfall-runoff model simulates well at catchments in humid low-energy environments (Nash Sutcliffe efficiency $NS > 0.6$), most of which are located in the eastern part of the US, the Rocky Mountains, and along the west coast (to the west of Cascade Mountains). Within these regions, estimation of the parameter characterizing hydrograph recession provides reliable streamflow predictions at ungauged catchments, with a loss in prediction efficiency of less than 10% in most catchments. Results further show that

borrowing model parameters from gauged catchments based on spatial proximity measures provides better streamflow predictability at ungauged catchments than that based on physical proximity measures.

5.2 Introduction

Rainfall-runoff models are the essential tools for predicting catchment streamflows and are applied for numerous tasks in hydrology. These tasks include: short-term streamflow forecasting [Zealand *et al.*, 1999], flood frequency estimation [R. Merz and Blöschl, 2005], water quality assessment [Krysanova *et al.*, 1998], low flow predictions [Nathan and McMahon, 1990; Smakhtin, 2001], study of ecosystem services linked to catchment hydrologic functioning [Abdelnour *et al.*, 2011; Poff *et al.*, 2010], and assessment of climate change impacts on water availability [Arora and Boer, 2001; Christensen *et al.*, 2004; Hamlet and Lettenmaier, 1999]. Some of the widely used rainfall-runoff models are: TOPMODEL [Beven and Kirkby, 1979], SWAT [Arnold *et al.*, 1998], VIC [Liang *et al.*, 1994], and HBV [Bergström, 1995]. Regardless of the model used, an important prerequisite for streamflow prediction involves calibration of the model parameters with the aid of past streamflow data [Beven, 2001]. However, most catchments throughout the world are ungauged (i.e., they lack streamflow observations). A major challenge, therefore, for hydrologists is to develop strategies for implementing the rainfall-runoff models at these ungauged catchments [Sivapalan *et al.*, 2003; Wagener and Montanari, 2011].

Streamflow modeling at ungauged catchments is typically performed using the following procedure [Oudin *et al.*, 2010]: (1) model parameters are calibrated at a gauged catchment using the past streamflow data, and (2) the calibrated parameters are then used at an ungauged catchment that is perceived to be hydrologically similar to the gauged catchment. Here, we define hydrologic similarity as two or more catchments having similar streamflow response. Since streamflow data is not available at the ungauged catchments, surrogate metrics are required for identifying hydrologic similarity among gauged and ungauged catchments [Blöschl, 2006]. Numerous studies over the years have focused on indirect characterization of hydrologic similarity to ensure that the model parameters are appropriately estimated at the ungauged catchments [Burn and Boorman, 1993; Ralf Merz and Blöschl, 2004; Mosley, 1981; Oudin *et al.*, 2008]. Two prominent approaches that use surrogate metrics for identifying hydrologic similarity have been shown to work successfully across a large number of catchments: the spatial proximity approach and the physical proximity approach. In the spatial proximity approach, catchments that are located in close proximity to each other are assumed to be hydrologically similar [Ralf Merz and Blöschl, 2004; Mosley, 1981; Vandewiele and Elias, 1995; Vandewiele *et al.*, 1991]; whereas in the physical proximity approach, catchments that are nearest in the physical attribute domain are assumed to be hydrologically similar [Burn and Boorman, 1993; Oudin *et al.*, 2010]. Results from the studies that have compared these two approaches show that no approach has a clear advantage over the other in terms of estimating parameters at an ungauged catchment. For example, Parajka *et al.* [2005] used an 11 parameter HBV model on over 300 catchments in Austria and found that the physical proximity approach slightly

outperformed the spatial proximity approach for catchments in Austria. On the other hand, *Oudin et al.* [2008] and *Zhang and Chiew* [2009] found that the spatial proximity approach performed marginally better than the physical proximity approach for estimating model parameters at ungauged catchments in France and Australia respectively.

In our previous work [*Patil and Stieglitz*, 2011], we focused on identifying the geographic regions within the continental US where nearby catchments are more likely to be hydrologically similar (i.e., have similar daily streamflows). The results of this study showed that, regardless of the high diversity in physiographic properties, most of the high streamflow similarity regions are located in the wet parts of the US and are characterized by an energy-limited environment [*Budyko*, 1974]. *Patil and Stieglitz* [2011] further suggested that, within the regions of high streamflow similarity, the parameters of a rainfall-runoff model that are calibrated at gauged catchments should be readily applicable to nearby ungauged catchments. On the other hand, in regions with low streamflow similarity, the calibrated parameters of a gauged catchment will most likely be useless for application at a nearby ungauged catchment.

In the present study, we hypothesize that: (1) a simple rainfall-runoff model is sufficient for obtaining good predictions in regions with humid energy-limited environment (where *Patil and Stieglitz* [2011] identified high streamflow similarity), and (2) reliable estimation of the hydrograph recession information alone is sufficient for predicting at ungauged catchments in those regions. We develop a simple daily time-step rainfall-runoff model that calibrates for the hydrograph recession properties of a catchment and implement it over 756 catchments across the continental United States.

We then compare three different approaches (spatial proximity, physical proximity, and the combination of those two) to determine the best surrogate metric for characterization of hydrologic similarity between the gauged and ungauged catchments.

The remainder of the paper is organized as follows: In section 5.3, we describe the 756 catchments and their associated climatic and physiographic data. In section 5.4, we describe the rainfall-runoff model, the objective function used for calibration, and the three surrogate metrics used for indirect characterization of hydrologic similarity between gauged and ungauged catchments. In section 5.5, we present the results showing model predictability at gauged catchments (with calibration) and ungauged catchments (with information transfer). Sections 5.6 and 5.7 provide the discussion of results and the conclusions of this study respectively.

5.3 Data

We use the streamflow data of 756 catchments from U. S. Geological Survey's Hydro-Climate Data Network (HCDN) (*Slack et al.*, [1993]; see **Figure 5.1**). This dataset has been used previously by *Patil and Stieglitz* [2011], and consists of catchments that have a continuous daily streamflow record from water year 1970 to 1988 (i.e., 1st October, 1969 to 30th September, 1988). The drainage area of the catchments ranges from 23 km² to 5000 km², whereas the average annual precipitation at the catchments ranges from 320 mm to 3300 mm.

Historical daily air temperature and precipitation data are obtained from the dataset developed by *Maurer et al.* [2002]. This data is gridded at 1/8 degree (about 14

km) spatial resolution and covers the entire continental United States. Estimates of soil permeability are obtained from the STATSGO database gridded at 1 km resolution for the continental United States [Wolock, 1997]. The median value of soil permeability among all the catchments is 1268 mm/day, whereas the 25th and 75th percentile values are 775 mm/day and 2722 mm/day respectively.

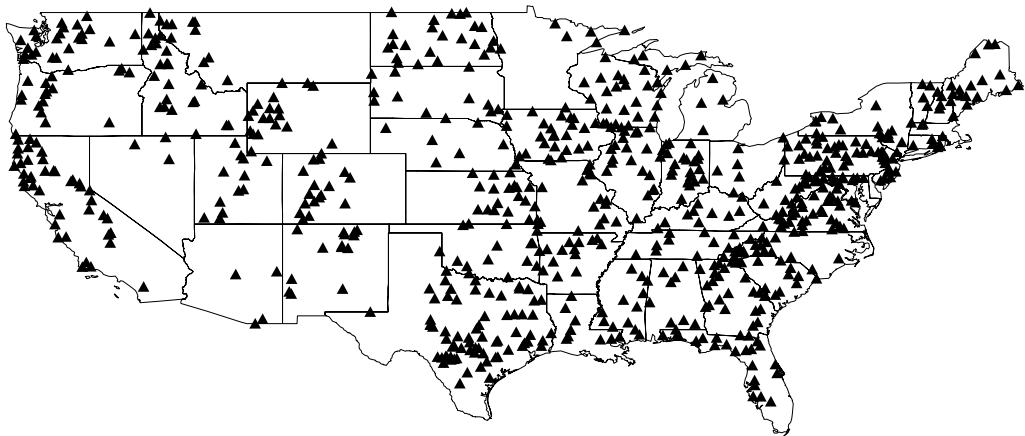


Figure 5.1: Location of the 756 study catchments within the continental United States.

5.4 Methods

5.4.1 Rainfall-Runoff Model

A simple daily time-step rainfall-runoff model is developed that conceptualizes the catchment as a bucket store (**Figure 5.2**). The water balance equation of the catchment bucket is as follows:

$$\frac{dS}{dt} = P_r + M - ET - Q_{surf} - Q_{sub} \quad (5.1)$$

Where, S is the water stored in catchment bucket (unit: mm), P_r is the precipitation that falls as liquid rainfall (unit: mm/day), M is the snowmelt that occurs from the snow accumulation store (unit: mm/day). The snowmelt is modeled using a simple thermal degree-day model whose details are provided in Appendix 5A. ET is the evapotranspiration (unit: mm/day), Q_{surf} and Q_{sub} are surface and subsurface runoff respectively (unit: mm/day). Surface runoff Q_{surf} occurs only when the bucket storage S exceeds bucket capacity S_{max} . The daily streamflow at catchment outlet is the sum of Q_{surf} and Q_{sub} .

Evapotranspiration is calculated using the following formula adopted from *Abdelnour et al.* [2011]:

$$ET = PET \cdot (1 - \exp(-c_{ET} \cdot (S / S_{max}))) \quad (5.2)$$

where, $c_{ET} = 5$, and PET is the potential evapotranspiration (unit: mm/day) that is obtained from daily air temperature using Hamon's formulation [*Hamon*, 1963]:

$$PET = 29.8 \cdot D \cdot \frac{e_{sat}(T_a)}{T_a + 273.2} \quad (5.3)$$

where, D is the day length (unit: hours), and e_{sat} is the saturation vapor pressure (unit: kPa), calculated as:

$$e_{sat}(T_a) = 0.611 \cdot \exp\left(\frac{17.3 \cdot T_a}{T_a + 237.3}\right) \quad (5.4)$$

The amount of subsurface runoff depends on the amount of water stored in the catchment bucket and is calculated as:

$$Q_{sub} = Q_{max} \cdot \exp(-f \cdot (S_{max} - S)) \quad (5.5)$$

where, Q_{max} is the maximum lateral subsurface runoff produced (unit: mm/day) when the bucket storage reaches its maximum capacity, and f is the parameter controlling the storage-dependent decline in lateral subsurface runoff (unit: 1/mm).

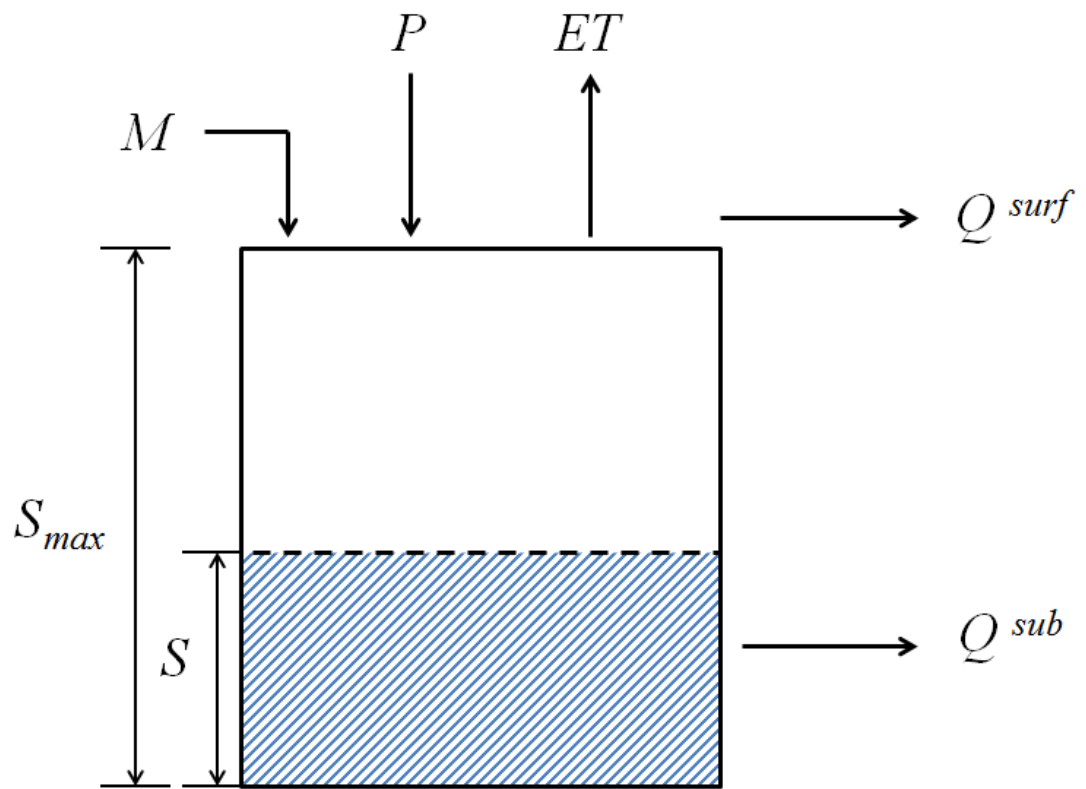


Figure 5.2: Schematic representation of the rainfall-runoff model.

5.4.2 Model calibration

The rainfall-runoff model contains four main parameters: f , Q_{\max} , S_{\max} , and D_f (the thermal degree-day factor; see Appendix 5A), of which we only calibrate for f and D_f with the streamflow data. Q_{\max} for each catchment is assumed to have the soil permeability value obtained from STATSGO database. The catchment bucket capacity S_{\max} is kept constant at 500 mm for all the catchments. In section 5.6, we discuss how streamflow predictability at a catchment is affected if we implement S_{\max} and Q_{\max} as free calibration parameters.

Nash Sutcliffe efficiency [Nash and Sutcliffe, 1970] of square root values of daily streamflow is used as the objective function for model calibration:

$$NS = 1 - \frac{\sum_{i=1}^n (\sqrt{Q_{obs,i}} - \sqrt{Q_{pred,i}})^2}{\sum_{i=1}^n (\sqrt{Q_{obs,i}} - \sqrt{\bar{Q}_{obs}})^2} \quad (5.6)$$

where, $Q_{pred,i}$ and $Q_{obs,i}$ are the predicted and the observed streamflow values on the i^{th} day respectively, \bar{Q}_{obs} is the mean of all the observed streamflow values and n is the total number of days in the record.

5.4.3 Parameter estimation at ungauged catchments

To predict streamflow at ungauged catchments, we first identify a gauged catchment that is hydrologically similar to the ungauged catchment. Then we use the calibrated parameters (f and D_f) of the gauged catchment to predict at the ungauged catchment. Three different approaches that use a surrogate metric for characterizing

hydrologic similarity between the gauged and ungauged catchments are considered: (1) physical proximity approach, (2) spatial proximity approach, and (3) combined approach. In the physical proximity approach, physiographic and climatic attributes of each catchment are obtained, and the catchment that is closest to the ungauged catchment in physical attribute domain is chosen as hydrologically similar catchment. We consider five catchment attributes: drainage area, channel slope, soil permeability, aridity index (P/PET), and mean elevation above sea level. The attribute distance between the catchments is calculated as follows:

$$dist_{a,b} = \sqrt{\sum_{j=1,J} \left(\frac{X_{a,j} - X_{b,j}}{\max(X_j) - \min(X_j)} \right)^2} \quad (5.7)$$

Where, J is the total number of catchment attributes ($J = 5$ in our case), $X_{a,j}$ is the value of an attribute at catchment a , and $\max(X_j) - \min(X_j)$ is the range of that attribute among all the catchments considered. The gauged catchment with the lowest value of $dist$ is chosen as the hydrologically similar catchment.

In the spatial proximity approach, only geographic distance among catchments is considered. We use the Euclidean distance between the stream gauge locations to quantify spatial proximity. Gauged catchment that is located closest to the ungauged catchment is identified to be hydrologically similar.

In the combined approach, we basically implement the physical proximity approach again for finding the hydrologically similar catchment. However, the search for gauged catchments is restricted to a 500 km radius surrounding the ungauged catchment. This adds an element of spatial proximity consideration for characterizing hydrologic

similarity by making sure that the chosen gauged catchment is within 500 km distance from the ungauged catchment of interest.

5.5 Results

5.5.1 Model calibration and performance at gauged catchments

We first test the model performance at gauged catchments by calibrating the parameters with streamflow data from water years 1971-75 and then use the calibrated parameters for water years 1976-88 for validation. **Figure 5.3a** shows the boxplot of the NS values of all the 756 catchments for the calibration and validation periods. The median NS value for the calibration and validation period is 0.44 and 0.40 respectively. **Figure 5.3b** shows the relationship of NS values for the calibration and validation periods, where the data points are scattered evenly around the 1:1 line. Similar results were obtained when parameters were calibrated with streamflows from different periods (results not shown), suggesting that the calibrated model parameters are fairly stable.

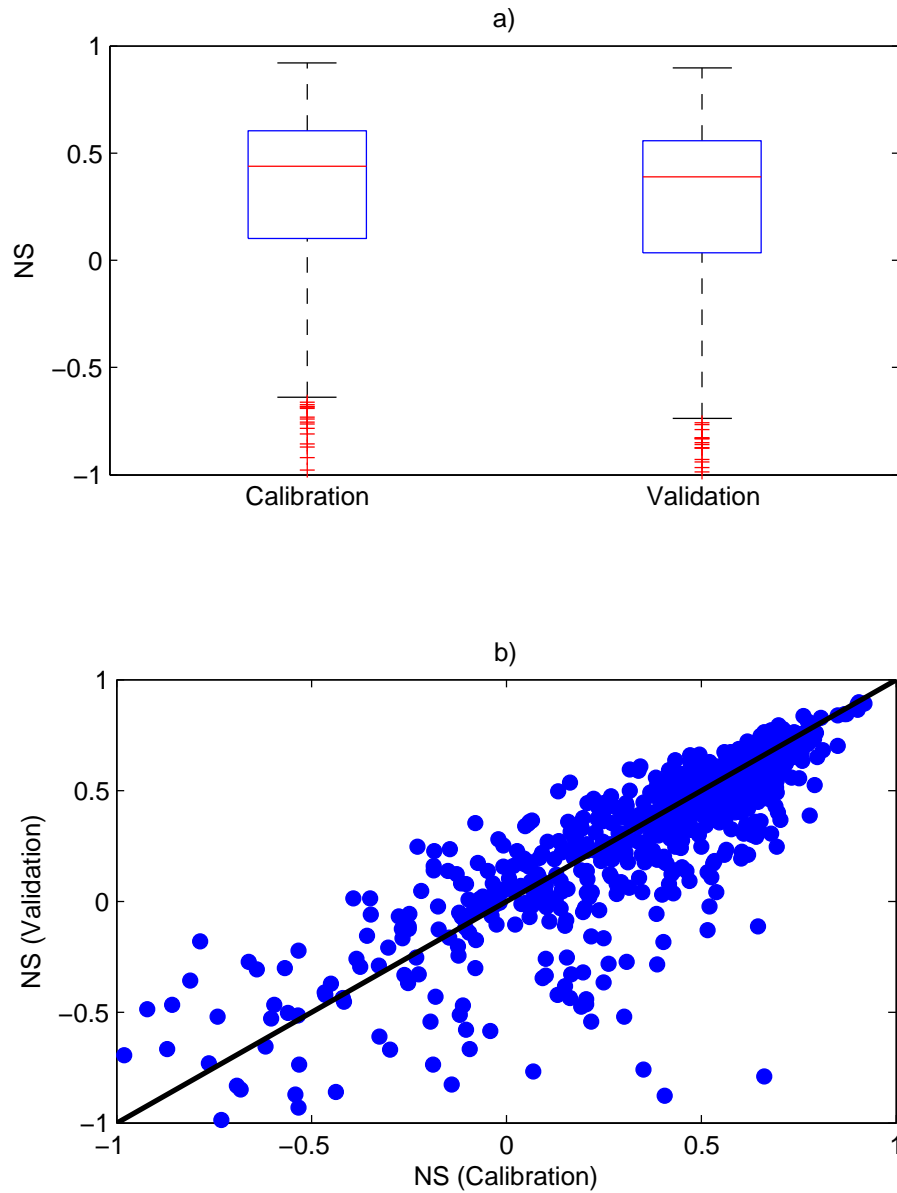


Figure 5.3: a) Box-plot of the NS values of catchments for the calibration and validation periods, and b) Relationship between the NS values of catchments for the calibration and validation periods.

To obtain the parameter values for implementation at the ungauged catchments, we calibrate the rainfall-runoff model for all the 19 years of streamflow data. For calibration with the entire record, median NS value of simulated streamflows among the 756 catchments is 0.43. We classify catchments into three groups based on model performance; Group 1: $NS > 0.6$, Group 2: $0.3 < NS < 0.6$, and Group 3: $NS < 0.3$. **Figure 5.4** shows the location of catchments belonging to each of these groups. The criteria for good predictability chosen here ($NS > 0.6$) is different than the criteria chosen in Chapter 4. This difference exists because the NS in this study is calculated using the square root Q values whereas the NS in Chapter 4 is calculated directly from the Q values. About 23% of the catchments (173 in total) belong to Group 1, which consists of catchments whose streamflows can be modeled with high accuracy. The Group 1 catchments are mainly located: (1) in the eastern half of the US mainly along Appalachian Mountains, (2) along the Rocky Mountains, and (3) to the west of Cascade Mountain range in the Pacific Northwest. **Figure 5.5** shows the observed vs. simulated hydrographs for two Group 1 catchments where the model captures hydrologic response well, especially for hydrograph recession. Most of the Group 2 catchments in eastern US are located in close proximity to the Group 1 catchments. The remaining Group 2 catchments are located along the Rocky Mountains. Group 3 catchments are located mainly along the drier parts of western and central US. In eastern US, Group 3 catchments are located in the Florida panhandle and in regions east of the Appalachian Mountain range.

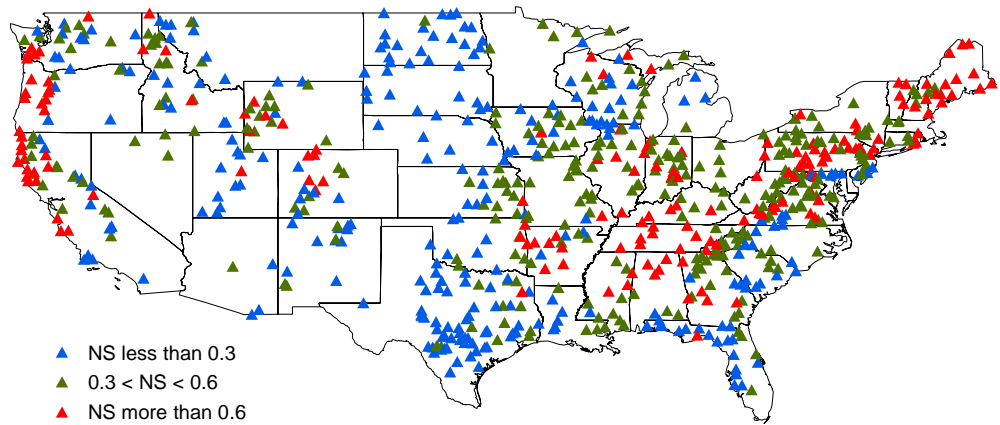


Figure 5.4: Classification of the 756 catchments based on their prediction efficiency (NS values) with calibrated parameters.

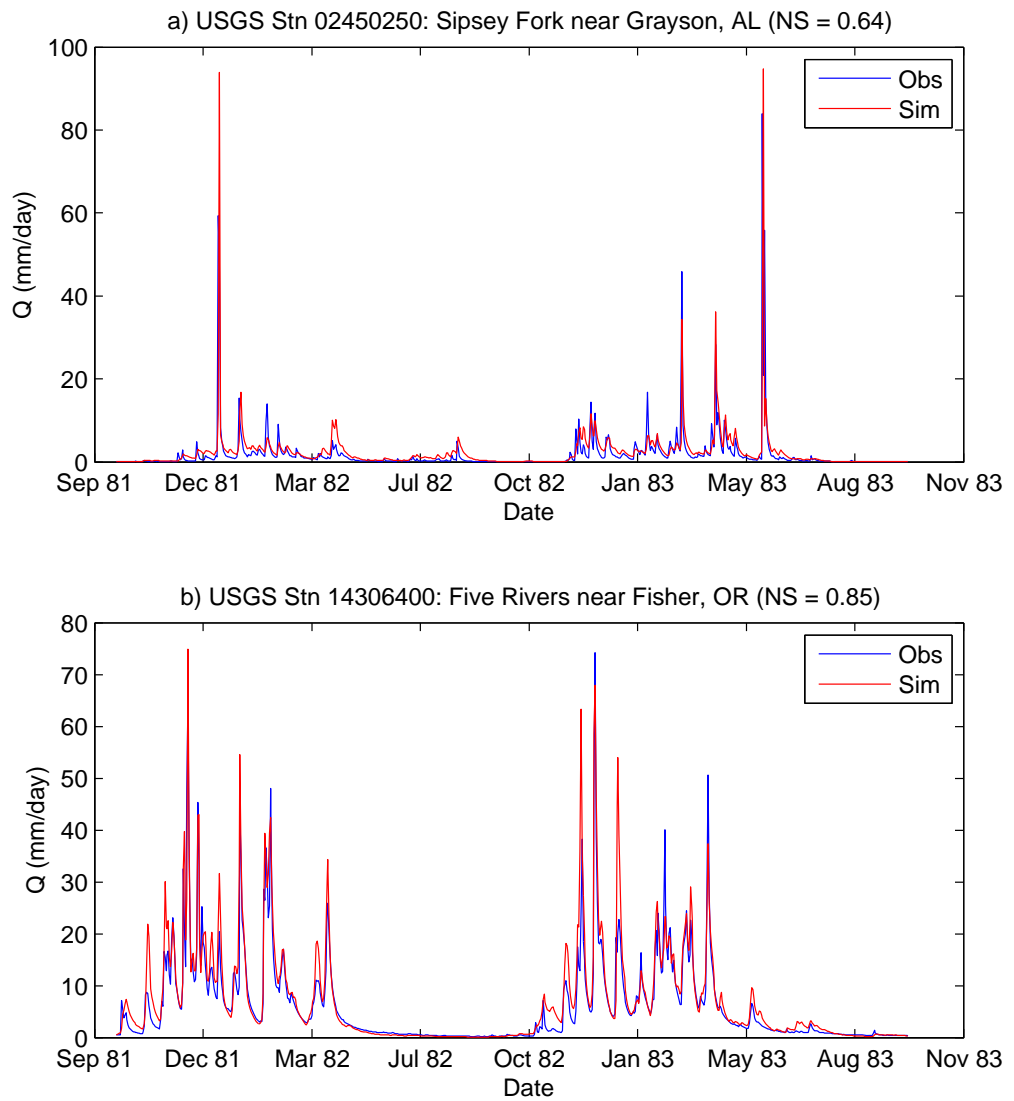


Figure 5.5: Observed vs. simulated hydrographs of a catchment in a) Alabama and b) Oregon.

We next analyze the geographic patterns of calibrated parameters f and D_f . For this analysis we only consider Group 1 catchments ($NS > 0.6$), since the rainfall-runoff model has demonstrated high performance in those catchments. **Figure 5.6a** shows the calibrated f values of Group 1 catchments. The f value of catchments is mainly divided between the eastern and western halves of US, with eastern catchments having high f values ($> 0.025 \text{ mm}^{-1}$) and the western catchments having low f values ($< 0.025 \text{ mm}^{-1}$). **Figure 5.6b** shows the calibrated D_f values of Group 1 catchments. Catchments with low D_f values ($< 1.5 \text{ mm/day/}^\circ\text{C}$) are located mostly along the Rocky Mountains and the coast of northern California. Catchments with high D_f values are located in the eastern half of US and to the west of Cascade Mountains in the Pacific Northwest.

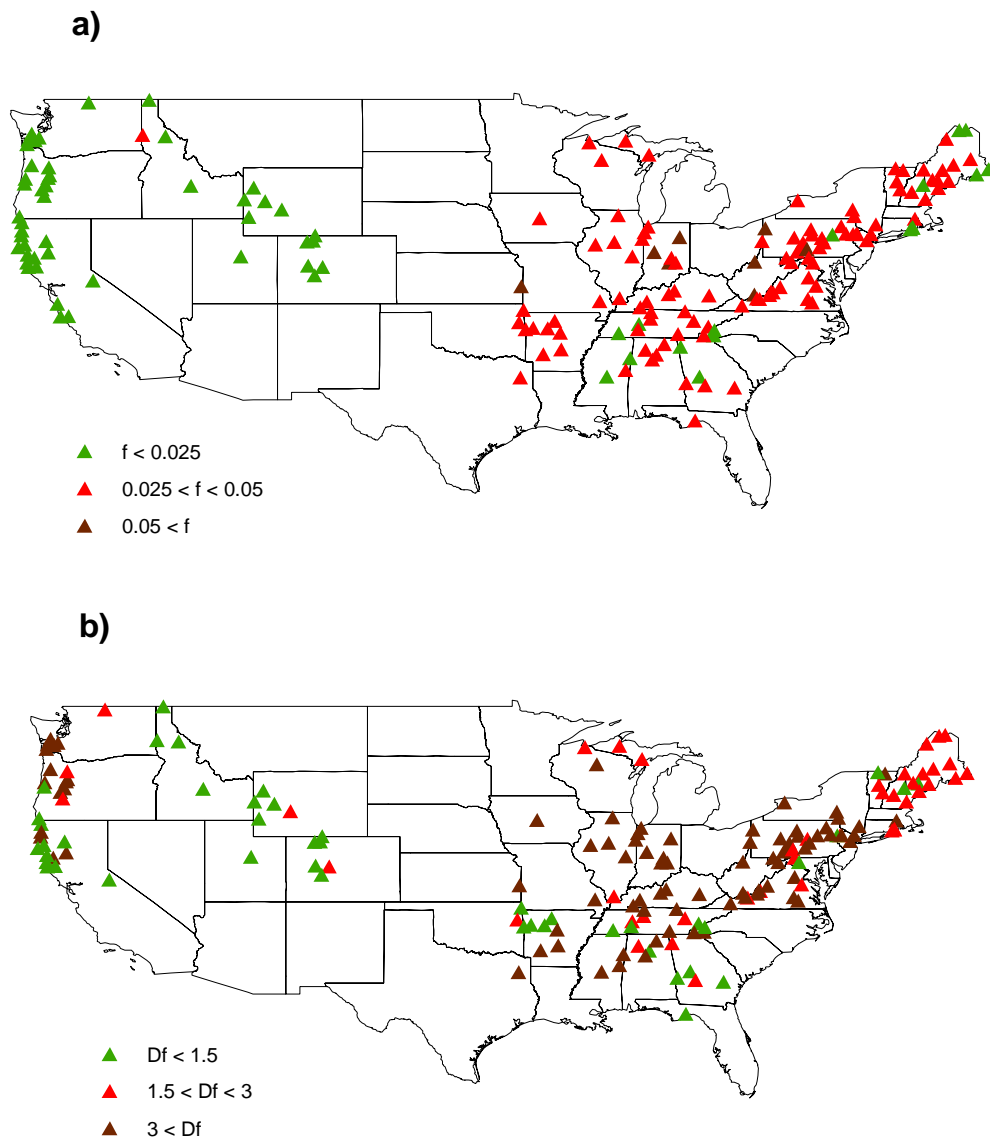


Figure 5.6: Spatial distribution of a) parameter f , and b) parameter D_f .

5.5.2 Model performance at ungauged catchments

For implementing the rainfall-runoff models at ungauged catchments, we consider only the 173 Group 1 catchments where the model performs with $NS > 0.6$ and omit the remaining catchments where the model predictability is low. Each of the 173 catchments is considered ungauged in turn and a gauged catchment that is hydrologically similar to it is identified. Then, parameters from the gauged catchment are used to model streamflow at the ungauged catchment. For each ungauged catchment, hydrologically similar gauged catchment is chosen using the three methods described in Section 5.4.3. **Figure 5.7** shows comparison of the three methods using CDF plot of NS values. The blue line in **Figure 5.7** is the CDF of NS values using the original calibrated parameters, which is the best performance that can be obtained at the 173 catchments using the bucket model. The median NS value among the 173 catchments for calibration case is 0.67. The CDFs of NS values for the ungauged case, i.e., using parameters from hydrologically similar gauged catchments (black, red, and green lines), show the deterioration in simulation efficiency. Among the three approaches, the spatial proximity approach (red line) provides the best performance, with median NS value of 0.64. The physical proximity approach provides the worst performance, with median NS value of 0.60. The model performance using the combined approach (green line) is a slight improvement over the physical proximity approach (with median NS value of 0.62).

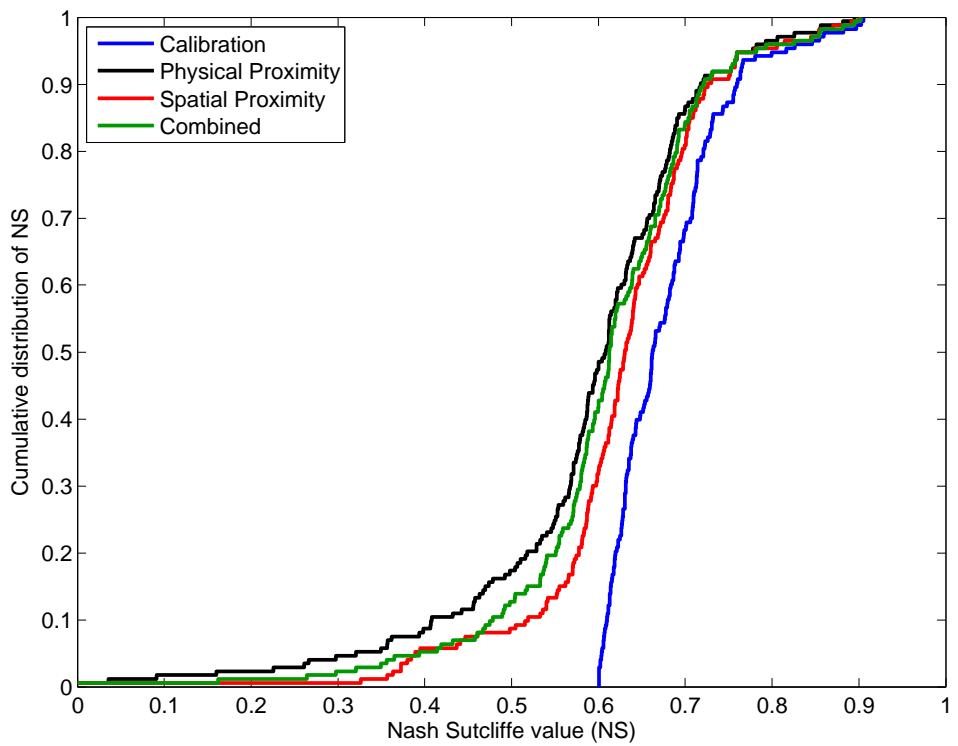


Figure 5.7: CDF plots of NS values of 173 catchments for parameters obtained with calibration, physical proximity approach, spatial proximity approach, and the combined approach.

Focusing exclusively on the spatial proximity approach now, we test whether estimating the model parameters at ungauged catchments by borrowing them from multiple donor gauged catchments provides better model performance than borrowing from a single gauged catchment. Parameter estimation from a single donor gauged catchment is the same as described in section 5.4.3. For parameter estimation from multiple donors, if N donors are considered, first we identify N nearest catchments to the ungauged catchment of interest. Then f and D_f at the ungauged catchment are calculated by inverse distance squared interpolation of the parameter values from N nearest catchments. We varied N from 2 to 10 and found that using 5 nearest donors provided the best overall model performance at ungauged catchments. **Figure 5.8** shows the comparison of simulation results using single donor and 5 donors with the CDF plot of NS values. Estimating parameters from multiple gauged donors provides slight improvement in model performance at ungauged catchments. With a single donor, 37 out of the 173 catchments showed deterioration in simulation efficiency greater than 10% (when comparing model performance using calibrated parameters against the borrowed parameters). On the other hand, with 5 donors, only 27 catchments showed deterioration in simulation efficiency greater than 10%.

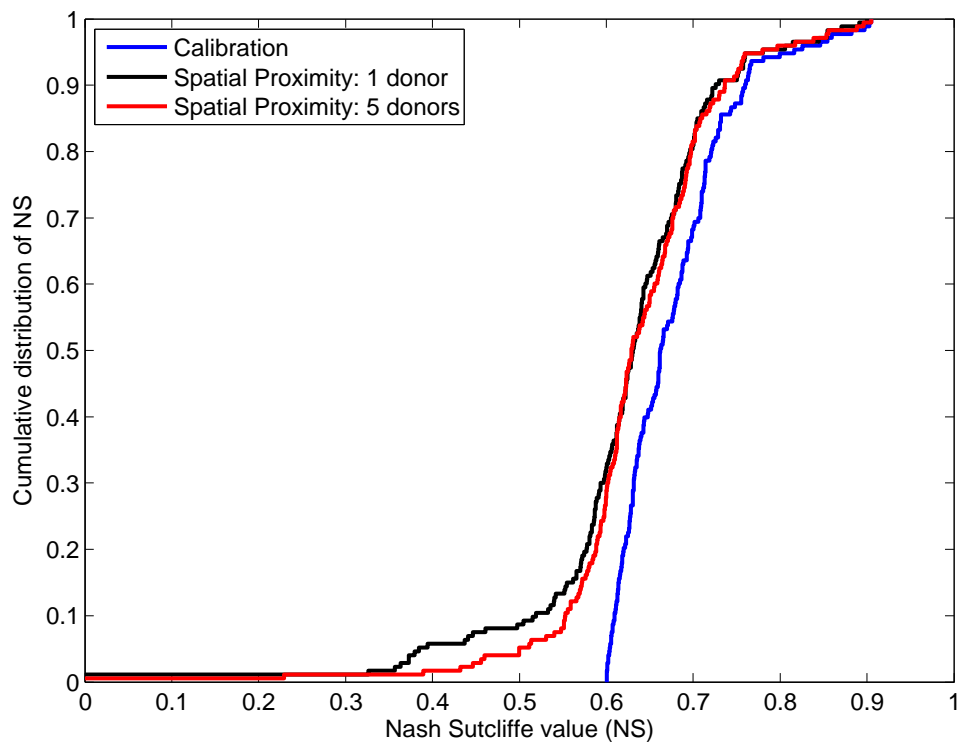


Figure 5.8: CDF plots of NS values of 173 catchments for parameters obtained with calibration, spatial proximity approach with 1 donor, and spatial proximity approach with 5 donors.

5.6 Discussion

The rainfall-runoff model developed in this study, in essence, calibrates for one parameter (f) in rain-dominated catchments and two parameters (f and D_f) where snow accumulation and melt also affect streamflow fluctuations. Both these parameters contain information pertaining to hydrograph recession properties of a catchment. The parameter f controls the rapidity of water storage fluctuations within the catchment bucket. **Figure 5.9** shows how different f values affect the decline in subsurface runoff contribution as the bucket storage decreases. If f is high, subsurface runoff declines more rapidly with decrease in catchment storage and results in a fast hydrograph recession. On the other hand, a low f value results in a longer hydrograph recession, specifically due to higher subsurface runoff when the bucket water storage is low. Interestingly, a clear geographic divide is observed among catchments with high and low f values (**Figure 5.6a**). Catchments in eastern half of the US have higher f values, suggesting that their hydrographs have a tendency to be flashier. On the other hand, the catchments in western half of US have low f values and have hydrographs that tend to have longer recession times.

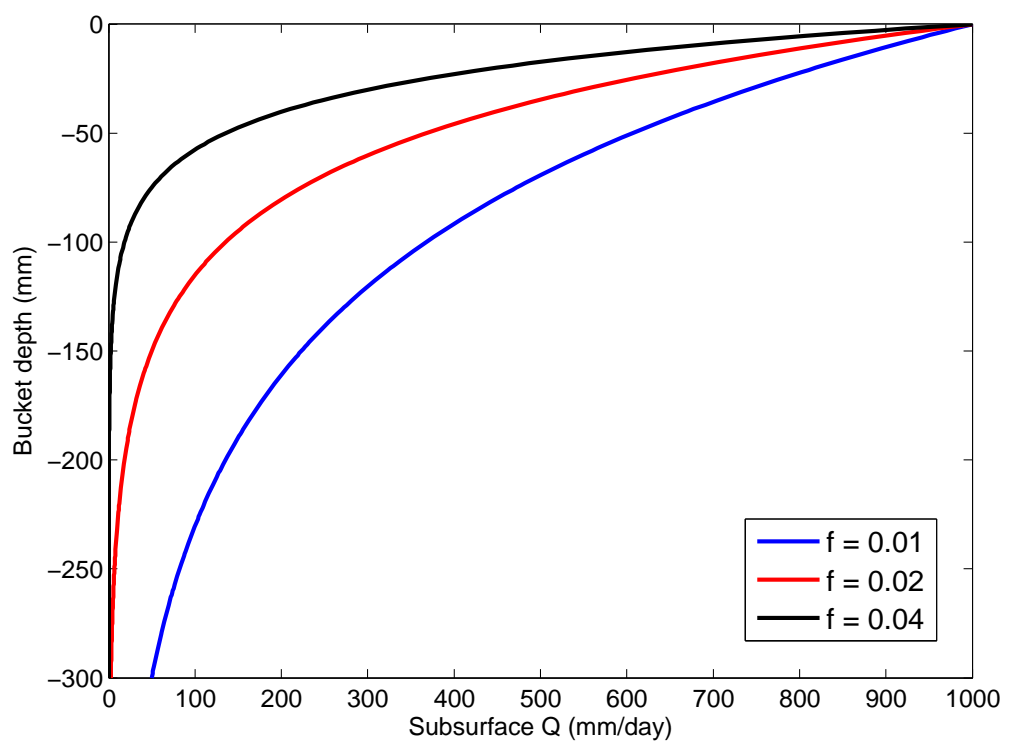


Figure 5.9: Depth-dependent variation in subsurface runoff for different values of the f parameter.

The parameter D_f controls the melting of snow that has accumulated in the snow bucket over the winter period. A low (high) value of D_f will release snow into the catchment bucket at a slower (faster) rate, thereby resulting in slow (fast) hydrograph recession. **Figure 5.6b** shows the optimal D_f values in Group 1 (NS > 0.6) catchments. Among the catchments in **Figure 5.6b**, there are two main regions that contain snow-dominated catchments: Northeast US and the Rocky Mountains. The catchments in northeast US have high D_f values compared to catchments along the Rocky Mountains. Although both these regions are located in same latitudes, the catchments in Rocky Mountains have greater elevation above sea level than those in northeast US. The snow accumulation and melting processes in high-altitude regions are highly influenced by orographic effects and temperature gradients [Fontaine *et al.*, 2002; Hartman *et al.*, 1999]. It is likely the thermal degree-day model (see Appendix 5A) used to simulate the snow accumulation and melt might be insufficient to accurately represent the snow processes for catchments in the Rocky Mountains.

Unlike f and D_f , the other two parameters of the rainfall-runoff model (viz., S_{\max} and Q_{\max}) were not calibrated with past streamflow measurements. S_{\max} represents the maximum capacity of the catchment bucket and Q_{\max} is the maximum lateral subsurface runoff produced when the bucket storage reaches S_{\max} . We use $S_{\max} = 500$ mm for all the 756 catchments, whereas we use the soil permeability values of STATSGO database to estimate Q_{\max} . **Figure 5.10** shows the effect of varying each of the 4 parameters (S_{\max} , Q_{\max} , f , and D_f) individually (while keeping the other parameters fixed) on NS value at a catchment in the northeast US. For smaller values of S_{\max} , NS is very low (**Figure 5.10a**). However, NS increases rapidly with increase in S_{\max} and stabilizes beyond ~450

mm. Further increases in S_{\max} do not significantly affect NS. For Q_{\max} , a large variation in value from 500 mm/day to 3000 mm/day causes miniscule fluctuation in NS (**Figure 5.10b**). On the other hand, fluctuations in f (**Figure 5.10c**) and D_f (**Figure 5.10d**) away from the optimal values result in significant decline of NS, suggesting that these parameters are far more sensitive than Q_{\max} and S_{\max} . Therefore, rough estimation of S_{\max} and Q_{\max} parameters do not significantly affect streamflow predictions in a catchment, whereas rough estimation of f (and D_f in snow-dominated regions) might not guarantee good model predictability. It should be noted that the sensitivity of parameter D_f decreases as we move towards more rain-dominated catchments. In other commonly used rainfall-runoff models, the number of parameters used to capture the recession information varies according to their structural complexity. For instance, in IHACRES model [Kokkonen *et al.*, 2003; Post and Jakeman, 1996] recession is controlled by 4 calibration parameters (for rain-dominated catchments only), whereas the GR4J model [Oudin *et al.*, 2008; Perrin *et al.*, 2003] controls it with 2 calibration parameters.

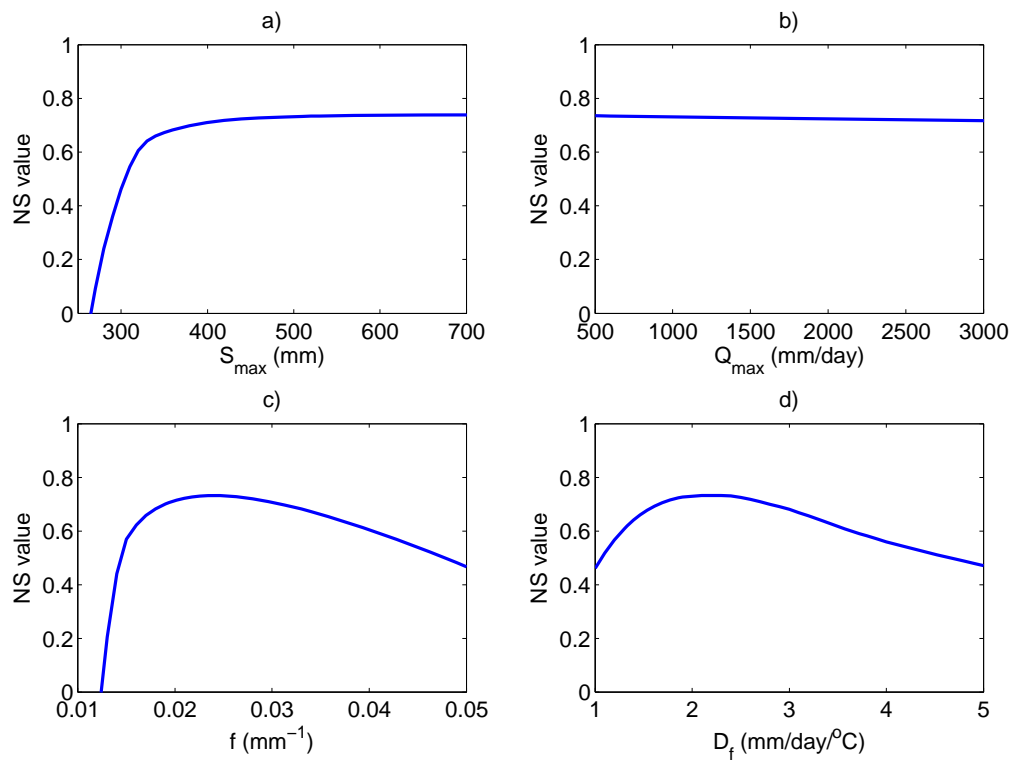


Figure 5.10: Sensitivity of NS values to fluctuations in a) S_{\max} , b) Q_{\max} , c) f , and d) D_f .

The geographic patterns of streamflow predictions at gauged catchments provided by our rainfall-runoff model are consistent with previous modeling studies within the continental US [Hay and McCabe, 2002; Martinez and Gupta, 2010]. However, it should be noted that studies by Hay and McCabe [2002] and Martinez and Gupta [2010] used monthly time-step hydrologic models, whereas our study has used a daily time-step model. The smaller time-step reduces the percentage of catchments that provide satisfactory model performance with our model. Patil and Stieglitz [2011] performed distance-based interpolation of daily streamflows with the same 756 catchments that are used in this study and identified the regions where nearby catchments have high streamflow similarity. They observed that regions where nearby catchments have similar streamflows are mainly along the Appalachian Mountains, the Rocky Mountains, and the Cascade Mountains. As shown in **Figure 5.4**, regions where our rainfall-runoff model performs well have a considerable overlap with regions where Patil and Stieglitz [2011] demonstrated high streamflow similarity. Overall, the model performs better in humid runoff-dominated regions than in the drier evapotranspiration-dominated regions.

For application at ungauged catchments, we tested three different approaches that used surrogate metrics for identifying hydrologic similarity between the gauged and ungauged catchments. Results show that indirectly ascribing hydrologic similarity among catchments based on spatial proximity alone slightly outperforms the approaches based on proximity in physiographic attributes. This is consistent with previous studies that have compared different approaches for estimating model parameters at ungauged catchments [Oudin *et al.*, 2008; Zhang and Chiew, 2009]. It must be noted, nonetheless, that although spatial proximity approach performs best for our study catchments, the

approaches using proximity in physical attributes provide almost similar predictability at ungauged catchments. In regions with more homogenous hydro-climatic conditions, (e.g., United Kingdom) studies have shown that the physical proximity approach is highly suitable for estimating model parameters at ungauged catchments [Kay *et al.*, 2006; Young, 2006]. Close proximity between the gauged and ungauged catchments implies that those catchments are more likely to have similar climatic regime and geomorphic development. However, incorporating the catchment properties directly into the similarity framework does not improve predictability at ungauged catchments. Although adding a spatial proximity component in the physical proximity approach (i.e., the combined approach) slightly improves the model performance, it still does not improve on the simpler spatial proximity approach. This suggests that the currently used catchment properties (drainage area, elevation, channel slope, etc.) do not convey complete information regarding catchment similarity.

Within the spatial proximity based approach, we further showed that borrowing calibrated parameters from multiple donor catchments provides slight improvement in model predictability compared to borrowing from a single donor catchment. This suggests that some of the methods using information transfer from single donor (e.g., Archfield and Vogel, [2010]) can improve their reliability by considering multiple donor gauged catchments. When parameters are borrowed from 5 nearest donors, only 15% of the catchments show decrease in model performance greater than 10% (compared performance with calibrated parameters). Most of these catchments are snow-dominated and located along the Rocky Mountains (see **Figure 5.11**). Interestingly, the model performance of the snow-dominated catchments in northeast US did not deteriorate

significantly. This suggests that the high-altitude catchments in Rocky Mountains region might need a better representation of snow processes, preferably through a snow model that considers altitude gradients within the catchment.

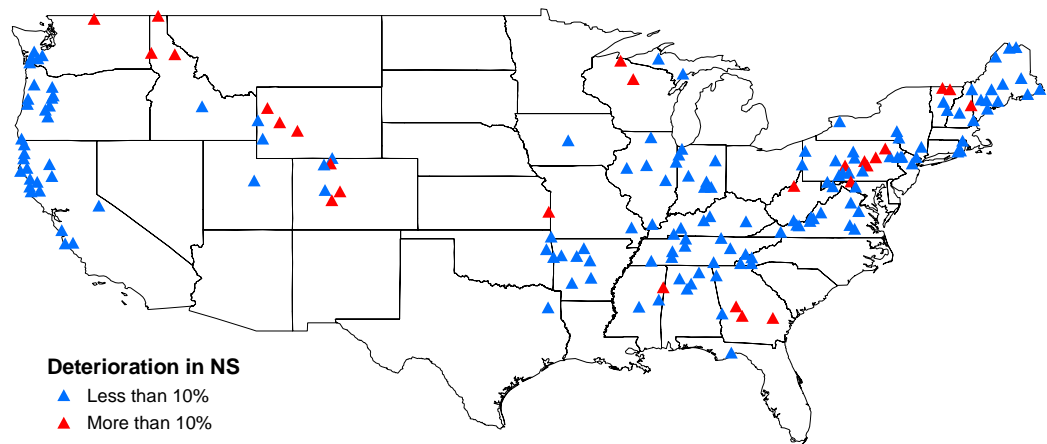


Figure 5.11: Deterioration in prediction efficiency (compared to the calibration case) when model parameters are borrowed from 5 nearest gauged catchments.

The main insight from this study is that the transmissivity feedback, i.e., subsurface runoff fluctuations when bucket water storage changes (controlled by parameter f), is the single most important process that must be captured well to achieve good streamflow predictability. In our rainfall-runoff model this feedback is characterized with an exponential decline in hydraulic conductivity (Equation 5.5). This feedback mechanism was first introduced in TOPMODEL [Beven and Kirkby, 1979] and has since been shown to perform well for numerous catchments throughout the world [Beven *et al.*, 1984; Franchini *et al.*, 1996; Stieglitz *et al.*, 2003]. A strong physical basis exists for assuming a depth dependent decline in lateral hydraulic conductivity. Specifically, the plant roots and earthworms, as well as the chemical and physical soil processes lead to the development of near surface macropores, and increase the hydraulic conductivity. At high soil depth, these activities and processes are reduced and soils are compacted, thus reducing flow rates by several orders of magnitude.

Alternative functional forms of the transmissivity feedback (e.g., linear, hyperbolic, cubic) have also been proposed [Duan and Miller, 1997; Iorgulescu and Musy, 1997] and shown to perform well for catchments with peculiar characteristics [Ambroise *et al.*, 1996]. Our results further show that reliable estimation of this feedback can lead to improved streamflow predictions at ungauged catchments (by transferring f from nearby gauged catchments). However, characterization of the transmissivity feedback does not provide good predictability across all types of catchments. Most of the high predictability catchments are located in humid mountainous regions where this feedback might be the primary driving mechanism. Interestingly, our previous study [Patil and Stieglitz, 2011] observed that high streamflow similarity exists mostly among

catchments in humid mountainous regions. These results suggest that the interaction between climate and topography influences the geographic patterns of both, streamflow predictability and similarity. Nonetheless, our previous analysis has shown at best weak relationships between streamflow similarity and physiographic features (such as channel slope, soil permeability, etc.). Results from this study also show that characterization of hydrologic similarity based on a simple distance measure still performs better than based on the physical properties. Thus, we think that our current understanding of this interaction might be insufficient to isolate the influence of climate from the topography and quantify them separately.

5.7 Summary and conclusion

This study focused on identifying what constitutes the critical information that needs to be reliably estimated at ungauged catchments to achieve good model predictability. To this end, we developed a simple daily time-step rainfall-runoff model with minimal calibration requirement and implemented it over 756 catchments across continental United States. This model produced geographic patterns of streamflow predictability that were similar to those obtained in previous modeling studies within the continental US. Based on the results, we conclude that hydrograph recession is the most critical piece of information that must be captured in any modeling framework, and good estimation of this information alone is sufficient for predicting at ungauged catchments. Results also show that estimation of model parameters by borrowing them from hydrologically similar gauged catchments is a reliable strategy. However, for indirect characterization of hydrologic similarity among gauged and ungauged catchments,

metrics based on spatial proximity measures perform better than those based on physical proximity measures. Moreover, when borrowing parameters from nearby gauged catchments, using multiple donor catchments is more reliable than using a single donor catchment.

5.8 Appendix 5A: Snow sub-routine

The rainfall-runoff model contains two buckets, a catchment bucket and a snow accumulation bucket. Only the precipitation that is considered as snowfall accumulates in the snow bucket, whereas the rainfall accumulates directly in the catchment bucket. The daily precipitation P is classified as snowfall or rainfall based on the following conditions:

If $T_a < -1$ °C,

$$P_s = P; P_r = 0 \quad (5A-1a)$$

Else,

$$P_s = 0; P_r = P \quad (5A-1b)$$

Where, P_s is snowfall in mm/day, P_r is rainfall in mm/day, and T_a is daily air temperature in °C. Water balance of the snow bucket is as follows:

$$\frac{dS_{snow}}{dt} = P_s - M \quad (5A-2)$$

Where, S_{snow} is the storage in snow bucket (unit: mm), and M is the snowmelt (unit: mm/day). The amount of snowmelt M is modeled using the thermal degree-day concept as follows:

If $S_{snow} > 0$ and $T_a > T_{melt}$

$$M = \min [S_{snow} ; D_f \cdot (T_a - T_{melt})] \quad (5A-3a)$$

Else,

$$M = 0 \quad (5A-3b)$$

where, D_f is the thermal degree-day factor (unit: mm/day/°C), and T_{melt} is the temperature threshold above which accumulated snow begins to melt (= 0 °C). The snowmelt M from the snow bucket is input to the catchment bucket.

5.9 References

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6. CONCLUSIONS AND FUTURE RESEARCH

This dissertation attempts to gain an in-depth understanding of the physical and climatic controls on hydrologic similarity among catchments. An understanding of these controls is essential to achieve reliable streamflow predictions at ungauged catchments. In this Chapter, I present some of the caveats and assumptions in my analyses, the main conclusions reached from the results, and the future research that can be pursued based on the insights gained in this dissertation.

6.1 Caveats and Assumptions

The results from this dissertation provide insights into the conditions at which hydrologic similarity among catchments is likely to be manifested, and are helpful for improving predictability at ungauged catchments. However, there are caveats and assumptions in my analysis that are discussed below.

In Chapter 3, the hydrologic similarity at variable flow conditions is analyzed within four river basins in the northeast United States. All the four basins are located in humid part of the country where the streamflow values are typically high. These four basins were chosen such that they contain at least 5 gauged catchments, all of which are similar to each other in terms of long-term rainfall and runoff. The results showed that streamflow similarity among catchments mostly exists at medium to high flow conditions. However, due to the low gauge density in dry regions, I could not choose any

river basin with arid climate for the analysis. Therefore, it is still not clear whether hydrologic similarity at medium to high flows will be observed in dry regions where the evaporative demand dominates the hydrologic balance of catchments over a longer period. In Chapter 4, daily streamflow at each catchment is simulated through distance based interpolation from 5 nearest gauged catchments. Results show that the high predictability catchments are located mainly in humid, mountainous environments. However, while choosing 5 nearest donors provides good predictability in most of the 756 catchments, it is likely that the optimal number of donors will be different for each individual catchment. In Chapter 5, model parameters are transferred from gauged to ungauged catchments. This spatial transfer of model information certainly increases the uncertainty in streamflow predictions. Results suggest that our confidence in model predictability should be higher in humid runoff-dominated regions. However, my analysis does not quantify the uncertainty in streamflow predictability at ungauged catchments. This uncertainty can potentially be quantified by considering probabilistic climate inputs and exploring the entire range of variability in the climatic regime. To ascribe hydrologic similarity among the gauged and ungauged catchments, I consider five catchment attributes in the physical proximity method. The choice of these attributes is governed by both, availability of the appropriate data for all the 756 catchments and the attributes commonly used by previous studies. Nonetheless, it is not clear yet whether the use of additional physical catchment information will improve the characterization of hydrologic similarity among catchments. The results from Chapters 4 and 5 suggest that high streamflow similarity (and predictability) can be expected in humid runoff-dominated regions, whereas low similarity is more likely in dry evapotranspiration-

dominated regions. However, exceptions can be found in either of these climatic regimes. Analysis of 756 catchments enables a general understanding of where streamflow similarity is more likely to be dominant. But from operational point of view, smaller regions will have to be analyzed individually in order to determine the likelihood of obtaining reliable streamflow predictions at the ungauged catchments of interest.

6.2 Conclusions

Based on the results obtained from the three independent research studies (Chapters 3, 4, and 5), the following conclusions have been reached:

1. Streamflow similarity among catchments is dynamic and highly dependent on the flow conditions. Specifically, the results from Chapter 3 show that spatial variability in stream response is high at low flow conditions. On the other hand, the spatial variability reduces with increasing streamflow values.
2. Among the four river basins in northeast United States (Chapter 3), climate controls are such that rainfall is relatively constant throughout the year, whereas the evapotranspiration varies (low in winter and high in summer). Moreover, the streamflow values are high during the winter and spring seasons and low during the summer and fall seasons. This suggests that high streamflow similarity during winter is primarily due to the dominance of precipitation input in water balance whereas the low similarity during summer is due to the dominance of evaporative demand.

3. Within the continental United States (Chapter 4; 756 catchments), high streamflow similarity among nearby catchments is more likely in low energy environments, specifically, humid runoff-dominated regions with mountainous terrain and extensive vegetation cover. Such regions are primarily confined to the Appalachian Mountains in eastern US, the Rocky Mountains, and the Cascade Mountains in the Pacific Northwest. On the other hand, streamflow similarity among nearby catchments is less likely in high energy environments, i.e., the dry evapotranspiration-dominated regions. These regions tend to be located in the central parts of the US to the west of Mississippi River.
4. While the streamflow interpolation from spatially proximate gauged catchments provides good streamflow predictions at many catchments, high gauge density and/or closer distance of gauged catchments near an ungauged catchment do not necessarily guarantee good predictability.
5. Results from Chapter 5 suggest that embedding a simple representation of the hydrograph recession information within a hydrologic model structure provides good streamflow prediction in numerous humid catchments. Transfer of this recession information alone from gauged to ungauged catchments is sufficient for achieving reliable streamflow predictability in humid regions.
6. While it may seem counter-intuitive, transferring model parameters from gauged to ungauged catchments based on spatial proximity provided better streamflow

predictions than transfer based on physical proximity. Improved characterization of the catchment physiographic properties might be useful in improving predictability. However, limited data availability is always a concern in the physical proximity approach.

7. Using data from multiple donor catchments is more likely to provide better streamflow predictability at ungauged catchments than using a single donor catchment. However, as shown in Chapter 4, too many donor catchments will deteriorate the prediction performance at an ungauged catchment, most likely due to the addition of noise from catchments that will be located further away.

6.3 Future Research

The results presented in this study suggest a strong connection between hydrologic similarity and streamflow predictability. Specifically, both hydrologic similarity and predictability are more likely among catchments in humid, energy-limited environments.

However, a challenge, going forward, is to determine how predictions can be made within a region in the absence of hydrologic similarity, specifically in the dry regions. I think that future progress can be achieved through a combination of improvements in measurement of physiographic properties, and in the structure of rainfall-runoff models. Heterogeneity in physiographic properties (e.g., soil depth, permeability, slope, vegetation cover) makes it almost impossible to ascribe a single

quantitative value over the scale of a typical catchment ($\sim 100 - 1000 \text{ km}^2$). This is one of the potential reasons for weak relationships between model parameters and physical attributes. Development of novel metrics, that can implicitly quantify the mean state as well as the heterogeneity in a property, could potentially improve the correlation between physical attributes and hydrologic response. Improvements in rainfall-runoff models will most likely be achieved by first classifying the catchments into different groups based on climate and topography, and then focusing on the dominant hydrologic processes within each group exclusively. Hydrologic classification of catchments is a research area that is increasingly gaining importance in hydrology [Sawicz *et al.*, 2011; Wagener *et al.*, 2007], and has the potential to change our perspective on how hydrologic models can be developed in the future.

Non-stationarity of climate and land-use will most likely change the hydrologic behavior of catchments and can impact the hydrologic similarity among catchments within a region. Impacts of climate change on hydrology of river basins have been studied extensively for almost two decades, mostly through the use of large-scale hydrologic models [Christensen *et al.*, 2004; Hamlet and Lettenmaier, 1999]. However, an important limitation here is that the hydrologic models are calibrated over the limited historical range of climate variability. If the variability in future climate scenarios exceeds the bounds set by historical data, the uncertainty in hydrologic predictions will increase accordingly. Therefore, a better understanding of the feedbacks between climate variability and hydrologic variability is necessary to improve our confidence in future hydrologic forecasts. Land-use change will also change the response behavior of catchments and impact the hydrologic similarity among catchments. As urbanization

increases in most parts of the world, a challenge for hydrologists is to determine whether the process understanding obtained at one catchment is transferrable to other places. Therefore, studying the effects of non-stationary climate and land-use patterns on hydrologic predictability is an exciting new frontier for hydrologists.

6.4 References

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VITA

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