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Regionalization of Hydrologic Response in the Great Lakes Basin: Considerations of Temporal Variability

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REGIONALIZATION OF HYDROLOGIC RESPONSE IN THE GREAT LAKES BASIN:

CONSIDERATIONS OF TEMPORAL VARIABILITY

by

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ABSTRACT

REGIONALIZATION OF HYDROLOGIC RESPONSE IN THE GREAT LAKES BASIN: CONSIDERATIONS OF TEMPORAL VARIABILITY

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Methods for predicting streamflow in areas with limited or nonexistent measures of hydrologic response commonly rely on regionalization techniques, where knowledge pertaining to gaged watersheds is transferred to ungaged watersheds. Hydrologic response indices have frequently been employed in contemporary regionalization research related to predictions in ungaged basins. In this study, regionalization models were developed using multiple linear regression and regression tree analysis to derive relationships between hydrologic response and watershed physical characteristics for 163 watersheds in the Great Lakes basin. These models provide a means for predicting runoff in ungaged basins at a monthly time step without implementation of any process-based rainfall-runoff model. Major findings from this research study include (1) Monthly runoff in ungaged watersheds was predicted with reasonable skill using regression-based relationships between runoff ratio and watershed physical characteristics; (2) Predictions in ungaged watersheds were highly influenced by the temporal characterization of runoff ratio used to condition the regression models; (3)

Watershed classification using regression tree and multiple linear regression techniques resulted in comparable model predictive skill.

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1. Introduction

1.1 Predictions in ungaged basins

Water resource research and management objectives require knowledge of hydrological processes spanning both gaged and ungaged watersheds. Hydrological processes include precipitation, runoff, and the routing, storage and loss of water by intervening media. Research and management objectives include lake level forecasting, nonpoint source pollution loadings, the effects of land use/land cover change on streamflow and coastal ecosystems, and net water supply availability for irrigation, hydropower, and human consumption.

Addressing water quantity and quality issues is possible in gaged watersheds, where historical time series of streamflow observations can be used to calibrate and validate hydrologic models designed to represent the hydrological processes being studied. The need to address these issues over spatial domains with limited or nonexistent stream gage observation networks motivated the International Association of Hydrological Sciences Prediction in Ungaged Basins (PUB) initiative (Sivapalan et al., 2003). While PUB research is typically conducted at local or regional scales, the challenges of understanding hydrological processes in data-sparse locations are global. In fact, the least developed gaging networks are generally found in those regions most susceptible to hydrologic impacts from expanding populations and changes in land use and climate (Sivapalan et al., 2003).

Figures 1 illustrates some fundamental elements of a watershed, in this case the Milwaukee and Menomonee Rivers watershed in southeastern Wisconsin. Red triangles indicate locations of stream gages, which provide continuous observations of the volume of water passing that point per unit of time. The area of Figure 1 shaded green represents the gaged portions of the watershed, that is, the drainage area upstream from a gage. The area shaded grey represents the ungaged portion of the watershed, that is, the drainage area downstream from all stream gages. Consequently, the amount of water generated by the land upstream from a gage is known, but not how much water is flowing into Lake Michigan from the land downstream of the gages.

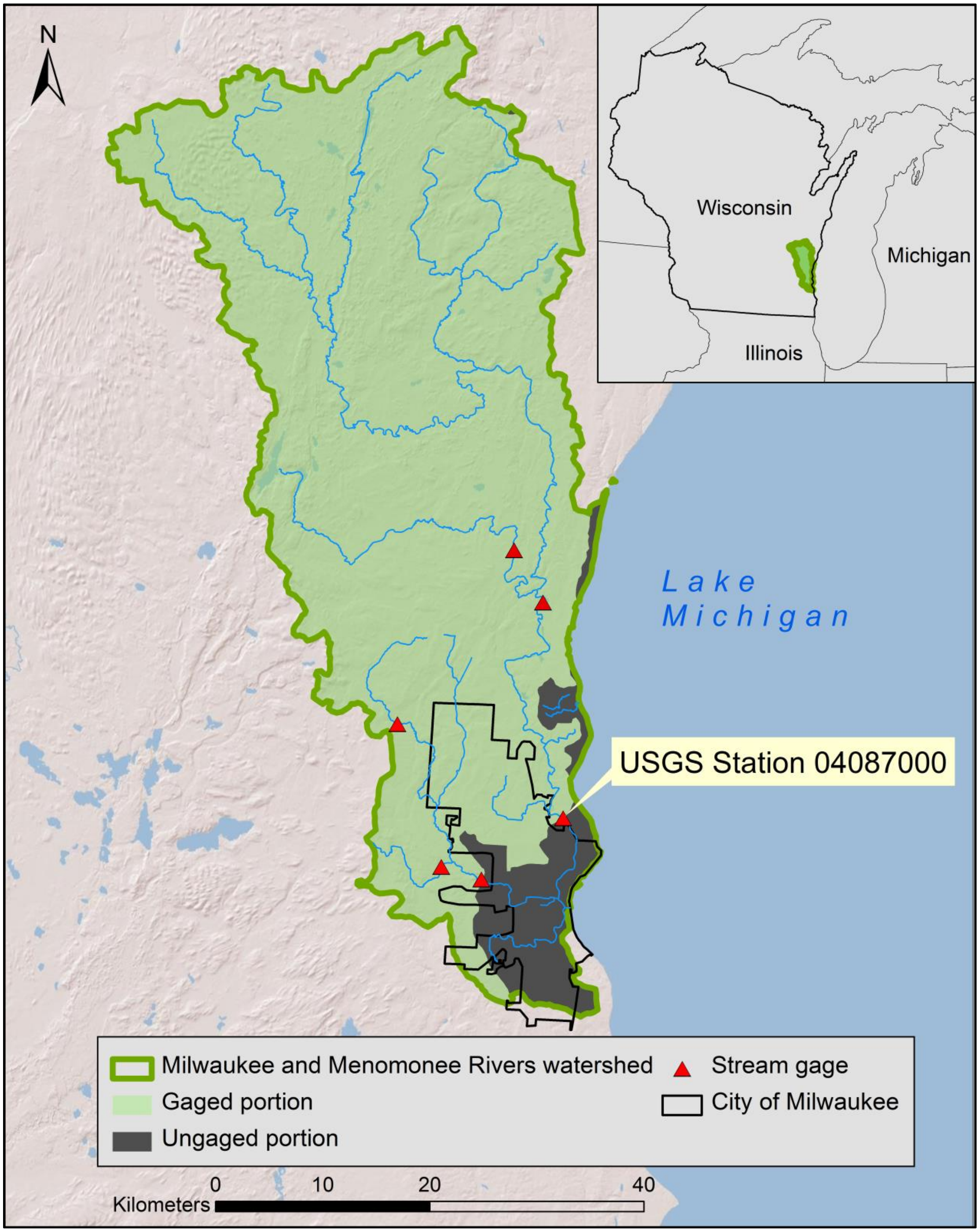

Figure 1 Milwaukee and Menomonee Rivers watershed in southeastern Wisconsin. Stream gages are indicated by red triangles. The area shaded green represents the gaged portion of the watersheds, while the grey area is ungaged.

1.2 Regionalization as a solution to the PUB problem

Traditional approaches to making predictions in ungaged basins (PUB) invoke the concept of regionalization (Vogel, 2006; Wagener et al., 2004). The term originates from the need to apply a locally calibrated hydrologic model to a larger region of interest. More generally, regionalization can be thought of as the spatial interpolation of hydrologic variables or observations from gaged watersheds to ungaged watersheds.

A great deal of research has explored the means and physical rationale for this transfer of hydrologic information across space. Returning to Figure 1, a simple regionalization approach could extrapolate the total watershed's outflow based solely on drainage area. Since the gaged portion covers 92 percent of the watershed's drainage area, we might assume it contributes 92 percent of the total watershed runoff.

This straightforward regionalization approach is based on the geographic phenomenon of spatial autocorrelation, that is, the correlation of a variable with itself over space (Cliff and Ord, 1973). While spatial autocorrelation is a common feature of many physical and human processes, the assumption of similar hydrologic response based on spatial proximity is frequently unjustified. Hydrologic response refers to the way a watershed translates rainfall into runoff, for example by surface runoff, soil infiltration, evapotranspiration, and ultimately outflow from the watershed.

Table 1: Land cover type for gaged versus ungaged portions of the Milwaukee and Menomonee Rivers watershed.

Land cover type	Gaged area (km^2)	Percent of gaged area	Ungaged area (km^2)	Percent of ungaged area
Water	22	1	1	1
Open/low developed	387	18	67	39
Medium/high developed	135	6	84	49
Forest	266	13	6	4
Shrub/grassland	34	2	2	1
Agriculture	979	47	6	4
Wetlands	270	13	5	3
Total	2093		171	

For example, Table 1 compares the predominance of different land cover types in the gaged and ungaged portions of the Milwaukee and Menomonee Rivers watershed. Compared to the upstream gaged area, the downstream ungaged area features higher percentages of impervious surfaces influencing fast runoff in developed areas, lower percentages of vegetation for plant uptake and transpiration, and lower percentages of wetlands for short-term water storage. In short, the ungaged and gaged portions of the Milwaukee and Menomonee Rivers watershed would not be expected to exhibit similar hydrologic response despite their physical proximity.

In addition to spatial variability, hydrologic response can exhibit substantial temporal variability. Table 2 presents summary statistics for monthly streamflow at United States Geological Survey (USGS) gaging station 04087000 on the Milwaukee River (see Figure 1) for water years (WY) 1915-2012 (USGS, 2013). The data in Table 2 indicate considerable seasonal and interannual variability of hydrologic response (here, quantified as streamflow) for the Milwaukee River watershed. The temporal trends evident in Table 2 (and present to varying degrees throughout the Great Lakes basin) are discussed in greater detail in Section 6.1.

Table 2: Monthly streamflow statistics for the Milwaukee River at USGS gaging station 04087000 for WY 1915-2012.

	Streamflow (cubic meters per second)			
Month	Min	Max	Mean	Standard deviation
Jan	1.3	30.6	7.6	5.5
Feb	1.3	62.3	11.3	9.6
Mar	5.1	100.4	30.0	17.9
Apr	6.7	85.6	28.2	15.9
May	2.4	73.5	15.8	10.5
Jun	1.6	84.3	12.9	13.3
Jul	0.7	35.5	6.9	6.4
Aug	0.5	83.1	6.2	8.9
Sep	0.8	65.2	7.3	9.8
Oct	1.5	37.3	7.8	7.0
Nov	1.8	55.4	9.8	7.5
Dec	1.2	27.8	8.7	6.0

1.3 Research questions and methodology overview

This research considers both the spatial and temporal variability of hydrologic response in the Great Lakes basin with the goal of predicting runoff from ungaged areas at a monthly time step. The following questions are addressed:

1. Can an index of hydrologic response be used to predict monthly runoff in ungaged watersheds?
2. How does the temporal variability of hydrologic response affect monthly runoff predictions?
3. How does watershed classification using a regression tree technique compare to the more commonly used linear regression technique?

In order to answer these research questions, the following methods are employed:

- Perform exploratory analysis of the spatial and temporal variability of hydrologic response in the Great Lakes basin, using monthly runoff ratio as an index of hydrologic response;
- Develop two contrasting regression-based models relating hydrologic response with watershed physical characteristics (that is, comparing monthly runoff ratio with information on watershed climate, soils, land cover and topography);

- Use the models to predict streamflow in ungaged basins at a monthly time step without implementation of a physically-based rainfall-runoff model; and
- Assess model predictive skill by comparing model predictions to actual observations.

Section 2 introduces the watershed as the fundamental areal unit in hydrology and discusses attempts to define hydrologic similarity or derive watershed classification systems as bases for transferring knowledge between watersheds. Section 3 provides a literature review of regionalization techniques used to make predictions in ungaged watersheds, including contemporary research gaps to be addressed. The Great Lakes basin study area is described in Section 4. Section 5 presents the data and methods used to develop the regionalization models. Results are given in Section 6. Section 7 provides a discussion of the significance of these results in the context of water resources research and management in the Great Lakes basin and worldwide. Answers to the research questions posed above are provided in Section 8.

2. The role of watersheds in hydrology

2.1 The watershed as a geographic and geomorphic unit

In the middle of the 20th century, hydrology emerged as a unique scientific pursuit consequent to increased specialization within geomorphology. By this point, the drainage basin had been well established as a fundamental landscape unit in geomorphology (Davis, 1899) and was readily adopted as the fundamental areal unit in hydrology (Chorley, 1969). Drainage basins, also referred to as watersheds or catchments, can be defined as the area of land for which surface and near surface water flows to a common location. The drainage basin has served as an important geographical unit for applications in ecology (Omernik and Griffith, 1991), engineering and reclamation (Graf, 1999), and water quality impacts from non-point source pollution (He and DeMarchi, 2010), among many others.

In all cases, the drainage basin constitutes a geographic unit within which both hydrological processes and their resulting land surface forms may be examined (Gregory and Walling, 1973). Hydrological processes include precipitation, runoff, and the routing, storage and loss of water by intervening media. Resulting landforms include river channels, flood plains, and erosional features, while topographic characteristics include basin area, relief, slope, aspect, and drainage density.

One important benefit of the drainage basin concept is that watersheds are naturally scalable to any spatial resolution as they are solely determined by land surface topography. This nesting of spatial units allows for the study of hydrological processes at multiple scales and is the basis for the USGS Hydrologic Unit Code (HUC) system (USGS, 2012). This scalability has resulted in hydrologic research conducted at a range of spatial resolutions, from highly discretized process studies in small "experimental watersheds" (Hewlett et al., 1969; Slaughter et al., 2001) to studies of continental and global scale runoff (Njissen et al., 1997; Njissen et al., 2001).

However, there are important limitations to the drainage basin concept. For example, groundwater basin boundaries are frequently different from the surface water basin boundaries dictated by topography (Feinstein et al., 2010). In addition, Omernik and Bailey (1997) discuss many situations where watershed delineations dictated by topography alone may not be the best spatial unit for ecosystem management and developed the concept of ecoregions as an alternate geographic unit for analysis. A final limitation, and one that is particularly relevant for making predictions in ungaged basins, is the lack of a formal watershed classification system. This issue is discussed in the following section.

2.2 Watershed similarity and classification

Wagener et al. (2007) review the many existing approaches to defining hydrologic similarity or devising watershed classification systems. The authors observe that as a relatively young science, hydrology has yet to develop a unified watershed classification system. Wagener et al. (2007) contrast the current state of classification in hydrology with the well-established and well-defined systems found in biology (i.e. Linnaean taxonomy) and chemistry (i.e. the periodic table).

The need for a unified watershed classification system has been established (Wagener et al., 2007), and much research undertaken toward this goal (Sawicz et al., 2011; Sivakumar and Singh, 2012; Winter, 2001; Wolock et al., 2004). Winter (2001) presented the concept of hydrologic landscapes "as a framework for objectively conceptualizing the movement of ground water, surface water, and atmospheric water in different types of terrain" (336). Subsequently, Wolock et al. (2004) used geographic information systems and statistical techniques to group 43,931 small U.S. watersheds into 20 hydrologic-landscape regions based on similarities in land-surface form, geology, and climate. Sawicz et al. (2011) developed a classification scheme for watersheds in the eastern U.S. based on statistical analysis of an ensemble of hydrologic response indices.

Attempts at watershed classification must address the wide range of variables that influence watershed response (see Section 5.2). Climate, vegetation, land use and land cover, soils, geology, topography, and human modifications to the landscape are all physical characteristics influencing rainfall-runoff processes in a watershed. The potential combinations of these physical characteristics are indicative of the "uniqueness of place" concept as applied to watersheds (Beven, 2000; see section 3.2). In light of these difficulties for establishing watershed similarity, a variety of regionalization techniques have been developed to transfer information from gaged to ungaged watersheds.

3. Regionalization approaches for making predictions in ungaged basins

3.1 Rainfall-runoff model-dependent regionalization approaches

Traditionally, regionalization approaches for predicting streamflow in ungaged basins begin by calibrating a chosen rainfall-runoff model in watersheds where observations are available. Recalling the definition of hydrologic response as the translation of rainfall into runoff via routing, storage, and loss processes, rainfall-runoff models attempt to represent these processes by way of formal mathematical relationships.

Figure 2 shows a representative structure for such a process-based rainfall-runoff model. Rainfall-runoff models translate incoming precipitation into runoff via numerous surface and subsurface processes (the right side of the diagram), while accounting for losses of water from the system (the left side of the diagram). The boxes in Figure 2 represent the short- and long-term storage of water in the system. The internal components and structure of this "cascading tank" type of model are adaptable to a wide variety of research and management objectives, including lake level forecasting, sediment or contaminant transport, flood and drought mitigation, and net water supply availability for irrigation, hydropower, and human consumption.

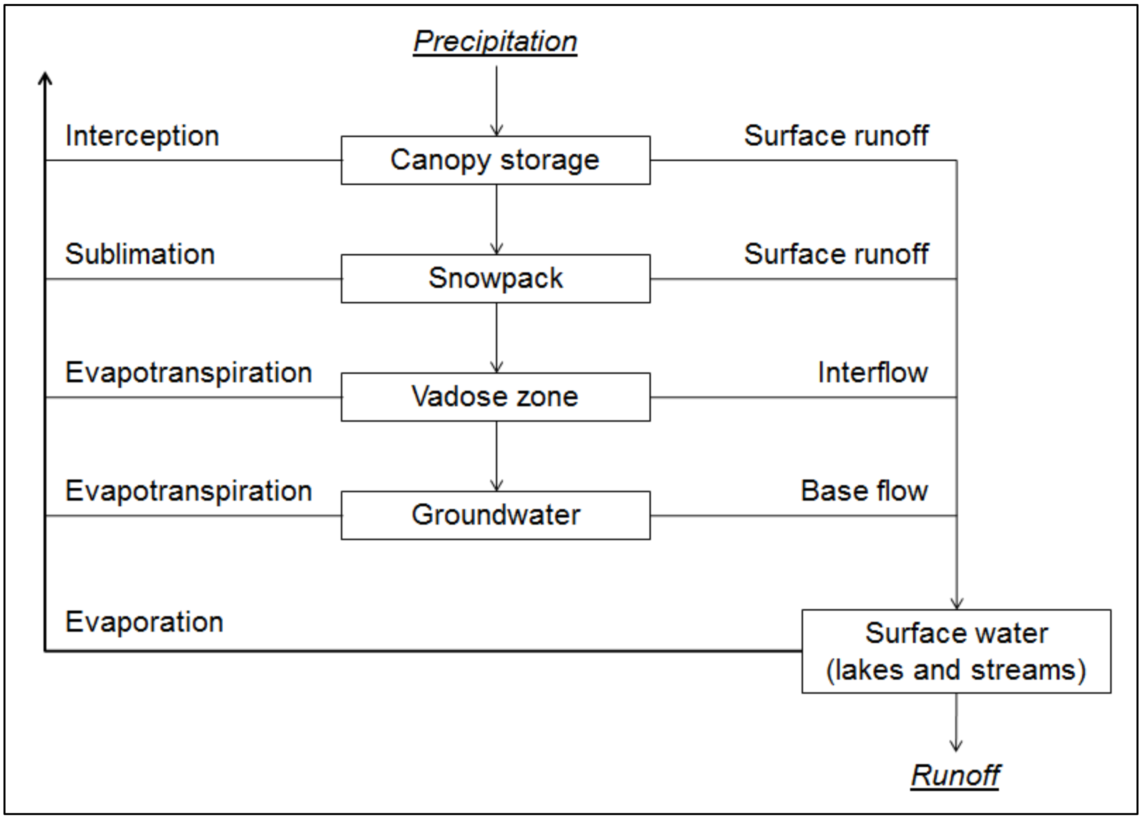

Figure 2: Representative components of a process-based rainfall-runoff model.

The rainfall-runoff model calibration process typically seeks to find an optimal set of model parameters based on observed system inputs (e.g. precipitation and temperature) and outputs (e.g. streamflow). Such parameters are associated with the routing, storage and loss processes included in the model structure, that is, the boxes and arrows of Figure 2.

In ungaged watersheds, streamflow observations are not available for estimating these parameters. Consequently, a variety of regionalization techniques have been developed to establish parameter sets at ungaged sites based on parameter sets calibrated at gaged sites. Assuming model inputs such as temperature and precipitation are available for the ungaged watershed, the rainfall-runoff model can then be applied to predict runoff from the ungaged area. This methodology reflects the origins of the term regionalization, that is, finding a way to make a locally calibrated rainfall-runoff model applicable to a larger region of interest.

In many studies, parameter sets are estimated at ungaged sites based on statistical relationships between calibrated parameters and watershed physical characteristics at gaged sites (Abdulla and Lettenmaier, 1997; Kokkonen et al., 2003; Post and Jakeman, 1999; Sefton and Howarth, 1998; Seibert, 1999). For example, a model parameter related to direct surface runoff could be related to information on land cover, such as the percent of agriculture, impervious surfaces, or wetlands in the watershed. These statistical relationships can then be applied to ungaged areas, resulting in a new parameter set based on the physical characteristics of the ungaged watershed.

Abdulla and Lettenmaier (1997) obtained parameter values for the gridded Variable Infiltration Capacity rainfall-runoff model based on regression relationships between calibrated parameters and watershed soils, topography, and climate. Results indicated that this method provided better streamflow simulations than an approach based on linearly interpolating calibrated parameters over the grid. Post and Jakeman (1999) used a similar procedure to predict daily streamflow in 16 small Australian watersheds using the IHACRES rainfall-runoff model. They found that some relationships between model parameters and watershed physical characteristics were better defined than others, leading to a range of predictive skill for simulating streamflow.

Alternately, a parameter set may be inferred for an ungaged watershed based on its spatial proximity or physical similarity to gaged watersheds (McIntyre et al., 2005; Merz and Blöschl, 2005; Njissen et al., 2001; Parajka et al., 2005; Reichl et al., 2009). For example, Njissen et al. (2001) used climate characteristics as a basis for transferring parameters for the Variable Infiltration Capacity model from nine large river basins to 17 other continental river basins. Parajka et al. (2005) explored a variety of regionalization approaches for transferring parameters of a conceptual rainfall-runoff model among 320 Austrian watersheds. Two regionalization approaches performed best: (1) spatial interpolation of model parameters using a kriging technique and (2) transfer of complete model parameter sets based on similarity of watershed physical characteristics. McIntyre et al. (2005) developed a method to predict runoff in ungaged watersheds using an ensemble of candidate models from the most similar gaged watersheds, where similarity was based on a set of 17 watershed physical characteristics. Results indicated that this ensemble approach performed better than an approach based on regression relationships between model parameters and watershed physical characteristics.

3.2 Limitations of rainfall-runoff model-dependent approaches

In practice, the three regionalization schemes described above (based on spatial proximity, physical similarity, and regression on calibrated parameters) are frequently explored in tandem (e.g. Bao et al., 2012; Kay et al., 2006; Kokkonen et al., 2003; Merz and Blöschl, 2004; Oudin et al., 2008). Comparisons of regionalization approaches indicate there is no optimal approach for estimating model parameters for ungaged watersheds. Kay et al. (2006) found the optimal regionalization scheme depended on the rainfall-runoff model employed for calibration. Bao et al. (2012) observed that the accuracy of different approaches varied between humid and arid regions. Oudin et al. (2008) found spatial proximity to be optimal for their regionalization study in France, but predicated their findings on the presence of a dense gaging station network.

There are many explanations for this inability to identify an optimal regionalization approach. Beven (2000) argues that "a fully reductionist approach to describe the uniqueness of individual catchment areas by the aggregation of descriptions of small scale behavior will be impossible given current measurement technologies" (203). In other words, the scale at which watersheds exhibit unique behavior is finer than the scale at which physical measurements can feasibly be obtained. This "uniqueness of place" paradigm has been well documented as a major obstacle for contemporary regionalization studies (Beven, 2000; McDonnell et al., 2007).

Further, the regionalization approaches discussed so far are all rainfall-runoff model-dependent, that is, they all implement some rainfall-runoff model for generating runoff predictions. Such models invariably contain “structural uncertainty introduced through simplifications and/or inadequacies in the description of real world processes” (Wagener et al., 2004, p.5). The model structure in Figure 2 illustrates this simplification of the real world. For example, surface runoff is treated as a single process, when in fact numerous sub-processes are involved in this translation of rainfall into runoff.

Moreover, Wagener and Wheater (2006) argue that implementations of rainfall-runoff models introduce location-specific model structural uncertainty. That is, a model structure that appears representative of hydrological processes in one location (e.g. a gaged watershed) may not be suited for the same processes occurring at another location (e.g. an ungaged watershed).

Finally, for any given rainfall-runoff model structure, the potential for multiple equally acceptable parameters sets has been well established (Bárdossy, 2007; Beven, 2006; Sorooshian and Gupta, 1983). In other words, considering Figure 2, there will be multiple ways for the model structure to translate observed precipitation into observed streamflow, with no objective way to discern which pathway most closely represents the actual flow of water in the system.

3.3 Rainfall-runoff model-independent approaches

In response to the limitations of model-dependent regionalization approaches, recent studies have developed regionalization schemes that are model-independent (that is, they can be applied to any rainfall-runoff model). Wagener and Montanari (2011) review emerging methods wherein model-independent measures of hydrologic response in gaged watersheds (other than direct streamflow observations) are employed to establish a regionalization scheme.

Hydrologic response refers to the translation of rainfall into runoff via watershed routing, storage and loss processes. Hydrologic response indices are attempts to implicitly quantify hydrological processes (contrasted with explicit representation in rainfall-runoff models). A wealth of indices (see Olden and Poff, 2003) has been derived to implicitly quantify these processes. Examples include watershed input-output relationships (e.g. runoff ratio), hydrograph analytics (e.g. rising limb density) and metrics characterizing the magnitude, frequency, duration and timing of flow events (e.g. baseflow index and flood frequency).

Examination of one commonly used response index, runoff ratio (also referred to as runoff yield), is instructive for demonstrating the concept of hydrologic response. Runoff ratio is a dimensionless index obtained by dividing total watershed runoff by total watershed precipitation over an equivalent time period. Low values are indicative of arid environments or drought conditions, while values greater than one represent surplus conditions, for example due to snowpack ablation or reservoir releases. Whereas a rainfall-runoff model would try to represent the surface, soil and groundwater processes occurring within a watershed (see Figure 2), an index like runoff ratio simply characterizes the watershed based on the percent of incoming precipitation that ultimately becomes runoff.

Olden and Poff (2003) note the dramatic increase in recent years of hydrologic response indices developed and applied for streamflow characterization. They present a comprehensive review of 171 indices from the literature, providing a framework for identifying high-information and non-redundant indices for hydroecological research. Yadav et al. (2007) review contemporary research employing hydrologic response indices for studying seasonal changes in evapotranspiration, biological assessment in ungaged basins, and annual temperature and streamflow regimes.

Yadav et al. (2007) presented a rainfall-runoff model-independent approach to making predictions in ungaged basins based on empirical relationships between watershed physical characteristics and a variety of hydrologic response indices. Three response indices (runoff ratio, high pulse count and the slope of the flow duration curve) were shown to be useful for constraining ensemble predictions at ungaged sites. Shamir et al. (2005) developed two hydrograph-based response indices (rising and declining limb density) to improve the identification of optimal parameters for a rainfall-runoff model.

A case study employing this method indicated improved model reliability and predictive skill. Sawicz et al. (2011) developed a classification scheme for watersheds in the eastern U.S. that incorporated six hydrologic response indices observed to vary along a climate gradient: runoff ratio, baseflow index, snow day ratio, slope of the flow duration curve, streamflow elasticity, and the rising limb density.

Relationships between hydrologic response indices and watershed physical characteristics are typically used to provide ancillary information for rainfall-runoff modeling. For example, Bulygina et al. (2009) used this information to constrain the range of allowable values for model parameters. Alternately, this information can be used to develop an ensemble of predictions based on the likelihoods of candidate models (McIntyre et al., 2005; Reichl et al., 2009).

Finally, some hydrologic response indices (e.g. runoff ratio) can be applied directly to simulate runoff in ungaged watersheds, as is demonstrated in this research. Unlike those presented above, this approach is rainfall-runoff model-independent in the sense that runoff is predicted without implementation of a process-based rainfall-runoff model.

3.4 Temporal characterization of hydrologic response

Hydrologic response indices have traditionally been developed to describe a watershed's typical behavior over a given period of time. Again, runoff ratio provides a salient example. Yadav et al. (2007) define runoff ratio as average annual runoff divided by average annual precipitation. Berger and Entekhabi (2001) and Sawicz et al. (2011) define it more generally as the ratio of long-term runoff to long-term precipitation. Similarly, nearly all of the 171 response indices reviewed by Olden and Poff (2003) are derived as long-term mean values, representing the average watershed behavior over a given time period. Moreover, despite the fact that hydrologic response can exhibit substantial seasonal variability (see Section 6.1), runoff ratio has typically been defined at an annual time step. As a result, contemporary research utilizing hydrologic response indices has addressed the spatial, but not temporal, variability in watershed behavior.

This research gap is addressed by developing and regionalizing two different temporal characterizations of runoff ratio, addressing the research question of how temporal variability in hydrologic response affects predictions in ungaged basins.

4. Study area

4.1 The Great Lakes basin

The Great Lakes basin (Figure 3) drains 522,000 km^2 of land in the United States and Canada featuring varied land cover, climate, subsurface properties, and human activity. The lakes themselves cover an area of 244,000 km^2 and constitute the largest system of fresh surface water on Earth, containing more than 80 percent of the U.S. supply and nearly 20 percent of the global supply. The Great Lakes support a multi-billion dollar fishing industry, recreation and tourism opportunities, major shipping routes and harbors for international commerce, and a source of freshwater for industry and consumption.

The basin is home to over 30 million residents, many of whom live in highly urbanized areas adjacent to the lakes. Temperature and precipitation variability is a function of both latitudinal and lake effects (Choi et al., 2012; Norton and Bolsenga, 1993). Significantly different subsurface properties exist throughout the basin as a result of the geologic formation of the Great Lakes. At the scale of the Great Lakes basin, this variability results in a wide range of potential watershed behavior spanning both gaged and ungaged catchments.

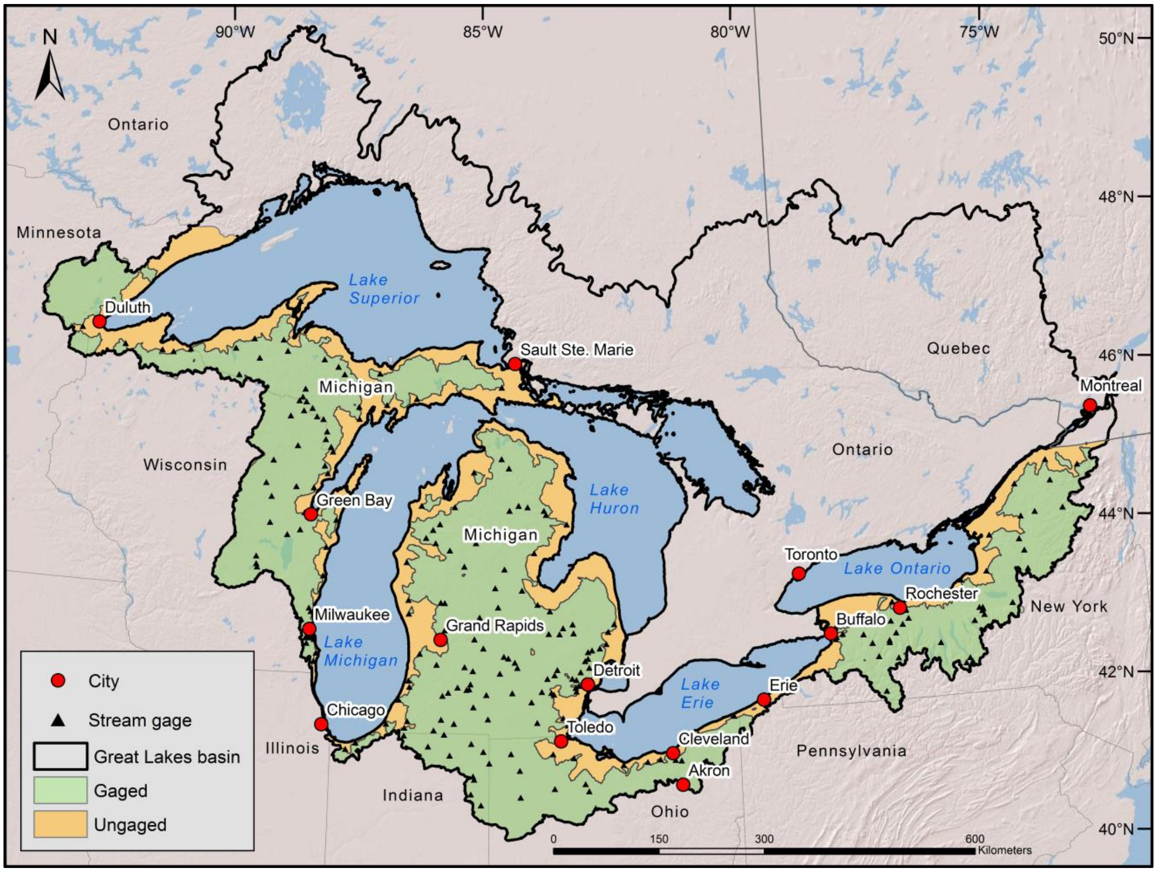

Figure 3: The Great Lakes basin study area. Gaged watersheds in the U.S. portion of the basin are colored green, while ungaged areas are colored orange.

Figure 4 shows the dominant land cover for USGS 12-digit Hydrologic Unit Code sub-watershed delineations (USGS, 2012). Land cover types are based on classifications from the 2006 National Land Cover Dataset (Fry et al., 2011). Wetlands and forests constitute the dominant land cover in northern Minnesota, Wisconsin, and Michigan, while agriculture is prevalent throughout most of central Wisconsin and Michigan and northern Indiana and Ohio. Major urban areas featuring high levels of development are primarily situated along the coasts of the lakes.

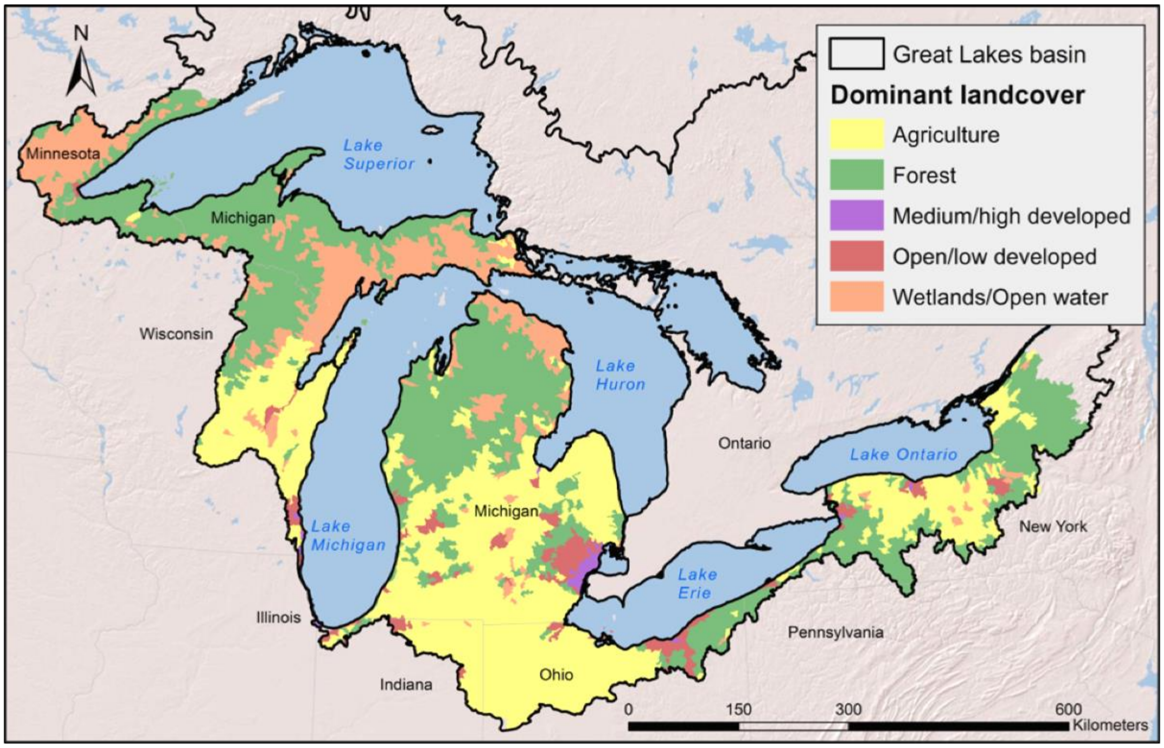

Figure 4: Dominant land cover for USGS sub-watershed delineations.

Predictions in ungaged basins are important at both local and regional scales for a variety of research and management objectives in the Great Lakes basin. For example, complete spatial coverage of runoff estimates throughout the Great Lakes basin is critical for preparing reliable water level forecasts and for understanding the mechanisms involved in fluctuating water levels. The transportation industry relies on maintenance of water levels sufficient for freight traffic and continued use of docks and harbors. Fluctuations in water levels affect the 17,000 km of shoreline by impacting hydropower potential, beach and recreational areas, near-shore wetland habitats, and water quality at municipal water intakes (Gronewold et al., 2011; Lee et al., 1997).

Additional research and management objectives include the effects of land use and land cover change on coastal and near-shore environments (Wolter et al., 2006); the transport of nonpoint source pollution from agriculture and urban runoff (He and DeMarchi, 2010); and net water supply availability for irrigation, hydropower, and human consumption (Changnon, 1987; He, 1997).

4.2 Hydrologic modeling in the Great Lakes basin

As a study area, the Great Lakes basin poses unique challenges for making predictions in ungaged watersheds. For example, there is a clear siting bias in the U.S. stream gage network, with coastal areas primarily ungaged and inland areas predominantly gaged (see Figure 3). Although it represents only 27 percent of the total drainage area, these ungaged areas are frequently unique from neighboring inland regions in a number of ways, including the presence of the region's most highly urbanized areas, coastal wetland ecosystems, or even local climate related to lake effect processes.

Moreover, due to its large size and transnational regulation and data coordination efforts, many models have been applied within the Great Lakes basin to individual tributaries or portions of the basin within national boundaries, but few estimates of runoff to the entire system exist (Coon et al., 2011). Two of the most widely used basinwide products include (1) the conceptual Large Basin Runoff Model (LBRM) developed by the National Oceanic and Atmospheric Administration's Great Lakes

Environmental Research Laboratory (NOAA-GLERL; Croley and Hartmann, 1986) and (2) the physically-based Modeling Environment Community Surface Hydrological (MESH) model developed by Environment Canada (Pietroniro et al., 2007). LBRM and MESH are process-based rainfall-runoff models of the type discussed in Section 3.1.

An alternate regionalization approach involving a simple area ratio method (ARM) has served as a cornerstone of Great Lakes regional hydrologic research for several decades (Croley and Hartmann, 1986; Fry et al., 2012). The basis of this method is the simple extrapolation of runoff by drainage area, as described for the Milwaukee and Menomonee Rivers watershed in Section 1.2. As implemented by NOAA-GLERL, the ARM identifies the most downstream gage(s) for each of 121 subbasins spanning the Great Lakes basin and extrapolates streamflow from gaged to ungaged regions based on the ratio of gaged to total subbasin drainage area.

Advantages of the ARM include the high temporal resolution of the data (daily streamflow observations) as well as computational and conceptual simplicity. The primary disadvantage of the area ratio approach lies in its assumption of spatial homogeneity among the watershed physical characteristics influencing hydrologic response.

Both the ARM and the models developed in this research involve regionalization of hydrologic response (streamflow and runoff ratio, respectively), resulting in empirical rather than process-based rainfall-runoff models. The methods differ in their assumptions concerning the spatial heterogeneity of watershed physical characteristics known to influence hydrologic response. The regionalization models developed in this study take into account the spatial heterogeneity of watershed physical characteristics not explicitly accounted for by the area ratio method.

With the background provided in Sections 2 through 4, the first two research questions posed in Section 1.3 are now specified in greater detail. The regression techniques referred to in the third research question are explained in Sections 5.3 and 5.4.

1. Can an index of hydrologic response be used to predict monthly runoff in ungaged portions of the Great Lakes basin, without implementation of a process-based rainfall-runoff model?

2. How does the temporal variability of hydrologic response, quantified as monthly runoff ratio, affect runoff predictions?

3. How does watershed classification using a regression tree technique compare to the more commonly used linear regression technique?

5. Data and methods

5.1 Monthly runoff ratio

Monthly runoff ratio (monthly runoff divided by monthly precipitation) was calculated for 225 Great Lakes basin watersheds with continuous flow records for water years 2001-2010. USGS streamflow and NOAA precipitation data for each watershed were obtained from NOAA-GLERL. All runoff ratios were log transformed prior to developing the regression relationships.

For a gaged watershed *w* with observations covering *t* years, monthly runoff ratio (MRR) was defined at two temporal scales (Table 3). These temporal characterizations of hydrologic response are derived by (1) treating monthly runoff ratios as individual observations (MRR_i) and (2) using the mean of those runoff ratios as a representative observation (MRR_m).

In the table, *Y* represents the total number of MRR observations for all months over all watersheds contributing to the regionalization scheme. For this study, *t* = 10 years (WY 2001-2010) and *w* = 225 watersheds. Of the 225 watersheds, 163 were used to develop the regionalization scheme, and 62 watersheds used to validate the models.

Table 3: Definition and description of monthly runoff ratio (MRR) at two temporal scales. *Y* represents the total number of MRR observations for 12 months over all years *t* for all watersheds *w* contributing to the regionalization scheme.

<table>
<tr><th>Monthly runoff ratio (MRR) temporal characterization</th><th colspan="2">MRR_i</th><th colspan="2">MRR_m</th></tr>
<tr><td>MRR derivation</td><td colspan="2">12 monthly runoff ratios computed for each year i in (i = 1,2,...t)
MRR = monthly runoff divided by monthly precipitation</td><td colspan="2">Mean of t observed MRR_i values</td></tr>
<tr><td>MRR contribution to model</td><td colspan="2">Each observed MRR contributes to the model ($Y = 12wt$)</td><td colspan="2">A single mean MRR contributes to the model ($Y = 12w$)</td></tr>
<tr><td>Number of observations</td><td>Model development: Y = 1630</td><td>Model validation: Y = 620</td><td>Model development: Y = 163</td><td>Model validation: Y = 62</td></tr>
<tr><td>Interpretation as independent variable, y, for modeling</td><td colspan="2">y : full variability of watershed hydrologic response</td><td colspan="2">y : average watershed hydrologic response</td></tr>
<tr><td>Applications</td><td>Short-term lake level forecasts; extreme/rare event predictions</td><td colspan="2">Near-shore wetland habitats, freight traffic, hydropower potential, municipal and agricultural consumption, synthetic runoff series for calibrating hydrologic models</td><td>Long-term lake level forecasts; beach and recreational areas</td></tr>
<tr><td>Limitations</td><td colspan="2">Potential for overly conservative management decisions</td><td colspan="2">Knowledge of model uncertainty may be insufficient for sensitive applications or use with calibrating rainfall-runoff models</td></tr>
<tr><td>Usage in contemporary PUB research</td><td colspan="2">Rarely used in PUB research</td><td colspan="2">Frequently used: hydrologic response indices are typically based on long-term averages of their parameters</td></tr>
</table>

Since these runoff ratio observations are used to develop regionalization schemes for predicting runoff in ungaged watersheds, the distinction between temporal scales can be viewed as a distinction in water resource research and management objectives. Some common research and management objectives are listed in Table 3 under "Applications" in relation to the perceived appropriateness of temporal scale. The last row in the table recalls the fact that long-term averages of hydrologic response have dominated contemporary PUB-related research.

The monthly time step selected for this research is a compromise: predictions at longer time steps (e.g. annual) have limited use for most water quality and quantity applications, while predictions at shorter time steps (e.g. daily) would be computationally demanding, with reduced tractability for the relationships between watershed response and physical characteristics. Moreover, the Large Basin Runoff Model computes runoff at a monthly time step, facilitating potential comparison between two very different approaches to PUB in the Great Lakes basin.

5.2 Watershed physical characteristics

Watershed physical characteristics were obtained from the Geospatial Attributes of Gages for Evaluating Streamflow (GAGES-II) dataset (USGS, 2011). The geospatial data contained in GAGES-II include several hundred variables related to land cover, soils, topography, geomorphology, and anthropogenic modifications for 450 gaged watersheds within the Great Lakes basin. Criteria for inclusion in the dataset were gages with at least 20 complete years of discharge record since 1950, or currently active gages as of water year 2009. Table 4 lists all watershed physical characteristics from GAGES-II considered for inclusion in the regionalization models.

In GAGES-II, land cover variables are derived from the 2006 National Land Cover Dataset (NLCD) and soils variables from the State Soil Geographic (STATSGO) database. A wide range of variables describing watershed geomorphology, hydrology and topography are derived from national hydrography and Digital Elevation Model datasets. Additional data related to anthropogenic modifications (such as freshwater withdrawals, canals, and dams) are also included in the GAGES-II dataset.

Climate variables within the GAGES-II dataset are derived from PRISM Climate Group datasets. Percent snow is defined as the ratio of annual snow water equivalent to annual precipitation, thus serving as proxy to seasonal snowpack accumulation and

Table 4: Watershed physical characteristics considered for inclusion in the regionalization schemes. Variables contributing to monthly multiple linear regression models at the $p < 0.05$ significance level are denoted with dots. Black and red dots refer to the MRR_i and MRR_m temporal characterizations, respectively (see Table 3). The characteristics highlighted in grey were retained for developing the regionalization schemes based on the criteria in Section 5.2.

		Variable significant at $p < 0.05$ ● MRR_i 🔴 MRR_m											
Watershed physical characteristic[a]	Class	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep
Mean annual precipitation	Climate		● 🔴	● 🔴	●	●	●	●	● 🔴		●	●	●
Average annual temperature	Climate	●	●		🔴	●		●		●	●	●	●
Percent snow	Climate	●	●	● 🔴	🔴		●	● 🔴	● 🔴	●			●
Monthly wetness index	Climate		●	● 🔴			● 🔴	● 🔴		●			●
Monthly precipitation	Climate	🔴	●	● 🔴			● 🔴	● 🔴		●			●
Monthly average temperature	Climate		●	●	🔴	●	● 🔴	● 🔴					●
SPEI[b]	Climate	●	●	●	●	●	●	🔴	● 🔴	●	●	●	
Precipitation seasonality index	Climate	● 🔴	🔴	● 🔴	🔴	● 🔴	● 🔴		●		●	●	
Day of first frost	Climate	● 🔴			●		●		●	●	●		
Day of last frost	Climate	● 🔴	●		●		●	●	●	●	●		🔴
Relative humidity	Climate							●	●		●		
Latitude	Climate			● 🔴	🔴		●						●
% developed	Land cover			●		●			● 🔴				
% impermeable surface	Land cover	●	●	●	●	●	●	●	● 🔴	●	●	● 🔴	●
% forest	Land cover		● 🔴					🔴	🔴				
% agriculture	Land cover	●			●	●					●	●	●
% pasture	Land cover	●			●	●					●	●	●
% crops	Land cover	●			●	●					●	●	●
% shrubland	Land cover	●	● 🔴	● 🔴	● 🔴	● 🔴	●		● 🔴		●	●	●
% grassland	Land cover									●	●	●	●
% woody wetlands	Land cover							●		●			
% open water	Land cover										●	●	
% developed - riparian	Land cover							●					
% forest - riparian	Land cover	🔴	🔴		●		● 🔴	● 🔴	● 🔴				
% agriculture - riparian	Land cover											●	●
Drainage area	Land form			●	●								
Stream density	Land form	🔴	● 🔴	● 🔴	●	●	● 🔴	● 🔴	● 🔴	●	● 🔴		🔴
Basin compactness	Land form	●								●	●	● 🔴	●
Strahler stream order	Land form										●	●	●
Dam storage	Modifications	● 🔴	● 🔴	●			● 🔴						
Major dam density	Modifications										●		
Percent streams as canals	Modifications					●						●	●
Freshwater withdrawal	Modifications										●		
Available water capacity	Soils	●	● 🔴		●		●	●				🔴	
Permeability	Soils			🔴	●		●	●				●	
Bulk density	Soils	●	●	●	●		●	●				●	●
Percent clay	Soils			● 🔴	● 🔴	●		●				●	
Percent sand	Soils			🔴	● 🔴						●	●	●
Erodibility (K) factor	Soils						●					●	
Erosivity (R) factor	Soils	● 🔴	● 🔴	● 🔴		●	🔴	● 🔴	● 🔴	● 🔴	● 🔴	●	● 🔴
Bedrock permeability class	Subsurface	●					●				●		●
Subsurface flow index	Subsurface			●									
Slope	Topography				●	●	● 🔴	● 🔴	● 🔴	● 🔴	● 🔴	●	●
Topographic wetness index	Topography	●	● 🔴	🔴	🔴	🔴			🔴		● 🔴	● 🔴	● 🔴
Aspect northness	Topography	●	🔴	🔴	🔴			●	🔴	● 🔴	●	🔴	
Aspect eastness	Topography			●				●	●		🔴		

[a]from GAGES-II dataset (USGS, 2011)

[b]Standardized precipitation evapotranspiration index (Vicente-Serrano et al., 2009)

ablation processes. The precipitation seasonality index ranges from zero to one, with higher values indicating higher seasonality of precipitation.

Derivations and sources of variables in the GAGES-II dataset are documented in detail by USGS (2011). The two exceptions are (1) a monthly wetness index computed as the ratio between monthly precipitation and potential evapotranspiration and (2) the Standardized Precipitation-Evapotranspiration Index (SPEI) developed by Vicente-Serrano (2010). Both the wetness index and SPEI were calculated in `R` with the `SPEI` package.

The wetness index and SPEI both characterize water balance surplus-deficit conditions at a monthly time step. SPEI additionally considers surplus-deficit conditions from prior months in its derivation. The variables percent snow, precipitation seasonality index, wetness index, and SPEI are included as attempts to address seasonal water balance dynamics obscured by binning precipitation and runoff by month.

To develop the models, 12 variables (highlighted in grey in Table 4) were retained based on (1) variable significance at the $p < 0.05$ level over most of the year based on fitting monthly linear models; (2) minimal redundancy among variables, informed by assessing Pearson correlation coefficients; (3) representation of climate, soils, land cover, topography and geomorphology variables; and (4) prevalence of land cover types in the region. These criteria are discussed in greater detail in the following section.

Figure 5 illustrates the spatial distribution for one of these physical characteristics, the percent of annual precipitation falling as snow. In addition to the expected latitudinal gradient, lake effect snowfall is also visible, for example east of Lakes Erie and Ontario.

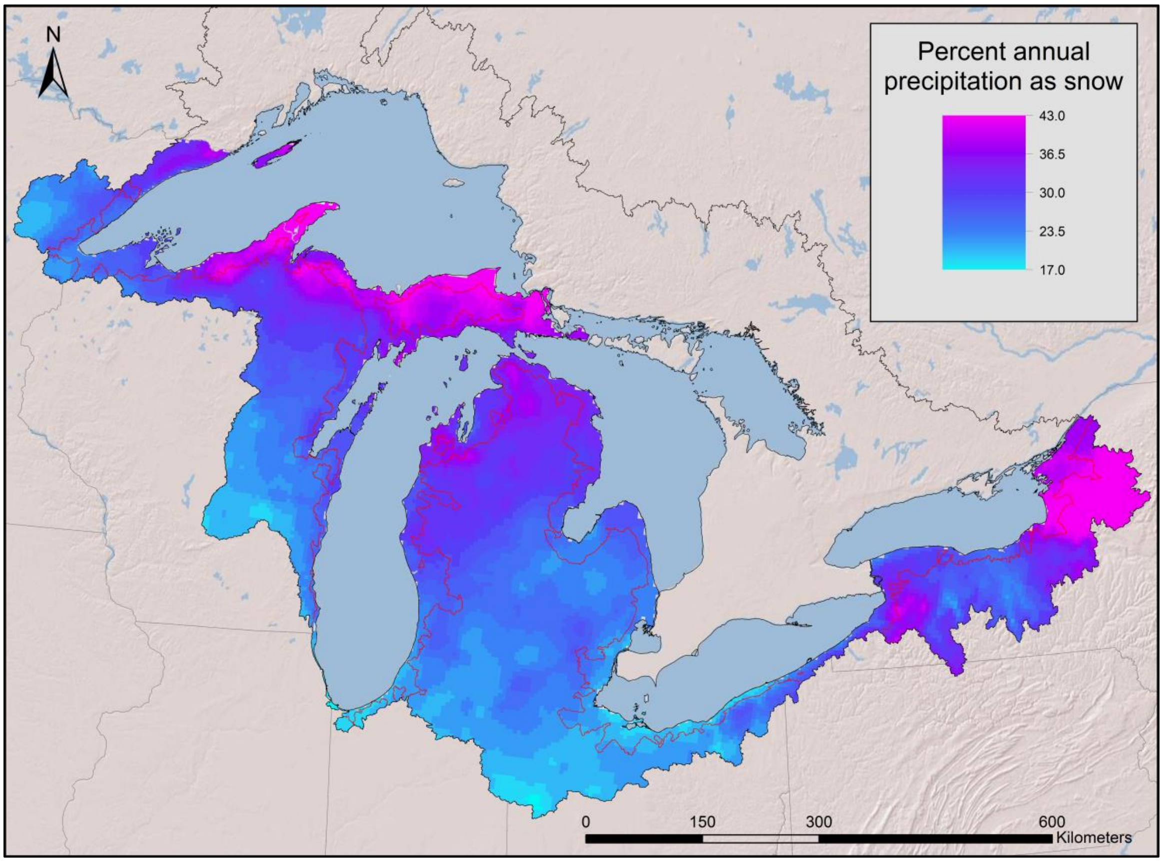

Figure 5: Percent annual precipitation falling as snow in the Great Lakes basin. Data are from the GAGES-II dataset (USGS, 2011).

5.3 Multiple linear regression

Multiple linear regression is a statistical technique commonly used to model relationships between two or more explanatory (independent) variables and a response (dependent) variable based on observed data. The relationships are of the form

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_n x_n + \varepsilon \, . \qquad \text{(Equation 1)}$$

In the present case, the response variable, *y*, is monthly runoff ratio and the explanatory variables, *x*, are the *n* = 12 watershed physical characteristics. Regression coefficients are denoted by the β terms, while *ε* is an error term, or residual, representing the difference between modeled and actual runoff ratio values.

Examples of linear relationships between mean monthly runoff ratio (MRR_m) and selected watershed physical characteristics are given in Figure 6. The four months (columns) were chosen to represent each season, while the watershed characteristics (rows) were chosen to represent climate, land cover, and topography variables. For purposes of visualization, the panels show relationships from simple linear regression, that is, Equation 1 reduced to the form

$$y = \alpha + \beta x + \varepsilon \, . \qquad \text{(Equation 2)}$$

The strongest relationship found in Figure 6 is between mean April runoff ratio and the percent of annual precipitation falling as snow. A physical interpretation of this statistical result is that watersheds receiving higher amounts of their annual precipitation as snow are likely to exhibit higher runoff ratios in April as winter snowpacks melt. The relationship is reversed in the winter, where a higher percent snow tends to result in lower runoff ratios as precipitation is stored in the snowpack.

Many of the plots indicate only weak or moderate linear relationships between long-term hydrologic response (MRR_m) and individual watershed characteristics. Table 4 presents the results of linear fits between 46 watershed physical characteristics and each temporal characterizations of monthly runoff ratio (MRR_m and MRR_i). Dots indicate a probability of less than five percent ($p < 0.05$) that the relationship could have been derived by chance. Compared to the relationships developed using mean monthly runoff ratio (MRR_m), Table 4 illustrates how strong linear relationships developed using all individual monthly observations (MRR_i) are far more prevalent. This is expected, however, since the determination of *p*-values in linear regression analysis is contingent upon the original variability in the data.

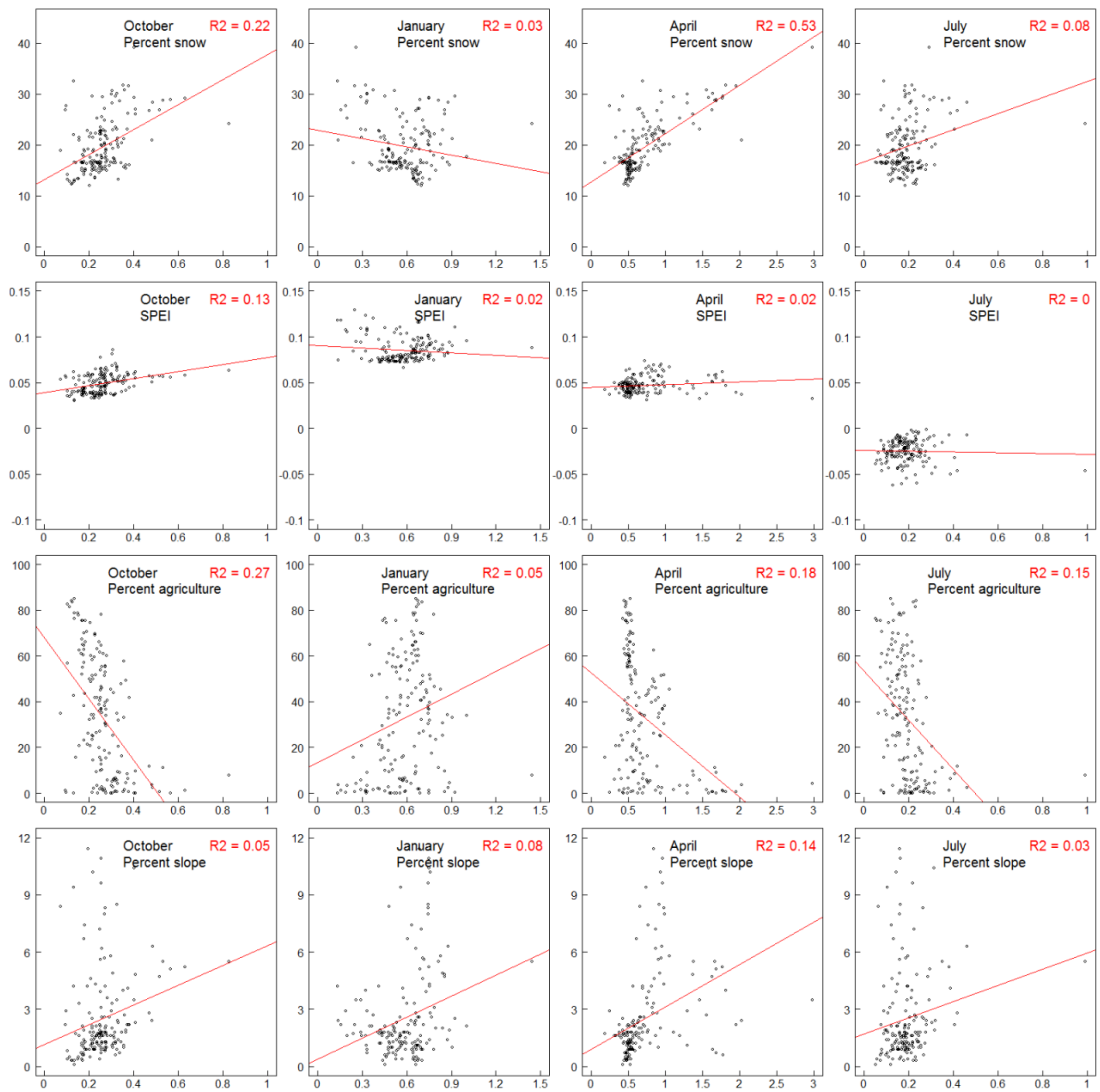

Figure 6: Linear relationships between mean monthly runoff ratio (MRR_m) and selected watershed physical characteristics.

5.4 Variable selection process

The results shown in Table 4 provide a starting point for selecting a more parsimonious set of watershed physical characteristics for the development of the regionalization scheme. This exploratory analysis indicates the notable prevalence of climate variables as good linear predictors. On the other hand, variables such as freshwater withdrawal and subsurface flow time rarely appear linearly related to monthly runoff ratio. Additionally, this analysis indicates that some watershed physical characteristics can be related to hydrologic response consistently throughout the year (e.g. percent impermeable surface and SPEI), while other characteristics only express a linear relation to response seasonally (e.g. percent agriculture and dam storage).

The next step in the variable selection process identified representative and non-redundant watershed physical characteristics. Many of the variables in Table 4 are highly correlated, particularly those of the same class. Examples include large positive Pearson correlation coefficients between percent impervious and percent developed land cover (r = 0.97) and between permeability and percent sand (r = 0.93). Aggregation redundancies exist as well, for example, percent agriculture is a composite of pasture and crop land cover. Correlation matrices for the climate, soils, and land cover classes of variables are given in Appendix B.

Final considerations in the variable selection process were based on the prevalence of land cover types in the region. For example, percent shrubland demonstrated strong linear relationships with monthly runoff ratio throughout the year, while percent wetlands rarely appeared linearly related to monthly runoff ratio. However, shrubland only makes up 2 percent of Great Lakes basin land cover, while wetlands constitute 15 percent. Additionally, shrubland is not a dominant land cover in any of the 225 watersheds used in this study, with a median of less than one percent and a maximum of only 14 percent. On the other hand, wetlands are dominant surface features in many watersheds throughout the basin, with a median of 12 percent and a maximum of over half the watershed's area. Table 5 provides summary statistics for the 12 watershed physical characteristics used to develop the regionalization models.

Table 5: Summary statistics for the 12 watershed physical characteristics selected for the regionalization models.

Watershed physical characteristic	Units	Mean	Median	Standard deviation	Minimum	Maximum
Annual average precipitation	mm	910	878	107	736	1349
Annual average temperature	°C	7.8	8.2	1.7	3.8	10.4
Percent precipitation as snow	Percent	19.9	18.7	5.0	12.1	39.1
Precipitation-evapotranspiration index	NA	0.05	0.06	0.07	-0.19	0.25
Percent impermeable surface	Percent	4.2	1.4	8.1	0.0	49.7
Percent agriculture	Percent	31.8	31.8	26.2	0.0	84.9
Percent woody wetlands	Percent	12.7	11.5	9.8	0.0	51.4
Drainage area	km^2	1725	561	2937	6	16,409
Stream density	km/km^2	0.66	0.61	0.22	0.13	1.38
Available water capacity	in/in	0.14	0.15	0.03	0.07	0.25
Erosivity (R) factor	NA	99	95	17	65	153
Slope	Percent	2.4	1.7	2.2	0.0	11.4

5.5 Model development

Two contrasting regression techniques were developed in the R software environment to relate monthly runoff ratio with watershed physical characteristics. Each regression model is developed with both temporal characterizations of hydrologic response (MRR_i and MRR_m), resulting in four regionalization models designed to predict runoff ratio at a monthly time step. Predicted runoff ratio multiplied by observed precipitation yields predicted runoff.

The first regression technique is multiple linear regression, as described in Section 5.3. In that section, the goal of the regression was exploratory, and involved all the watershed physical characteristics listed in Table 4. In order to develop the regionalization scheme, multiple linear regression was conducted again, this time using only the set of 12 watershed physical characteristics selected in Section 5.4. In other words, for each month of the year, runoff ratio is modeled as a linear combination of watershed characteristics known to influence hydrologic response.

However, many hydrological processes are known to exhibit highly nonlinear behavior (Kundzewicz and Napiórkowski, 1986; Sivakumar and Singh, 2012; Wittenberg, 1999). For this reason, regression tree analysis was performed as an alternate technique to potentially capture nonlinear watershed behavior. Unlike linear models, regression tree models have rarely been used in regionalization studies. One notable exception is the Spatial Regression-Tree Analysis method of Robertson and Saad (2003) for extrapolating water quality data from monitored to unmonitored streams. Regression tree analysis, as implemented in `R` using the `rpart` package, is discussed in detail in the next section.

5.5.1 Regression tree analysis with `rpart`

Regression tree analysis involves the partitioning of a dataset into clusters of observations. The partitions are based on algorithms designed to identify differences among explanatory variables, in this case, watershed physical characteristics. In this way, the method can be considered a data mining technique. Unlike linear regression, regression tree analysis does not model the response variable as a linear combination of the explanatory variables. Rather, it seeks to identify clusters of observations, in this case watersheds, with similar attributes. In this way, the method can be considered a watershed classification technique as well.

Regression tree routines in package `rpart` (Therneau and Atkinson, 2011) are based largely on the Classification and Regression Tree methodology of Breiman et al. (1984). Trees in `rpart` are grown so as to maximize differences in watershed characteristics at each branching in a simple analysis of variance. The resulting trees are then pruned to minimize the risk of misclassifying an observation while avoiding excessive model complexity or overfitting. Outputs from the regression tree analyses in `rpart` are monthly decision trees, with binary splits based on values of watershed physical characteristics, and terminal nodes grouping the 163 gaged watersheds into clusters (ideally) exhibiting similar hydrologic response. From the PUB perspective, `rpart` can then assign cluster membership to an ungaged watershed based on its physical characteristics.

An example of this process is illustrated in Figures 7 and 8. Figure 7 shows a regression tree grown and pruned with `rpart` for the month of July, with mean monthly runoff ratio as the dependent variable. The process begins with all 163 watersheds. The algorithms in `rpart` partition the set of 163 observations into all possible combinations of binary groupings, then search for the threshold value among all watershed physical characteristics that produces the greatest between-group sum-of-squares for runoff ratio. For example, the first branching partitions the 163 watersheds into two groups based on a threshold of 20.5 percent agricultural land cover. The process is then repeated for both resulting partitions. Additional partitioning occurs until a group contains less than a user-defined number of watersheds or until further splits do not result in reduced error based on a leave-one-out cross-validation. The final partitions are terminal nodes, or clusters. In Figure 7, the regression tree has been pruned to six clusters, where each cluster contains n watersheds with a mean of $\bar{y}$. The criteria for the pruning process are discussed next.

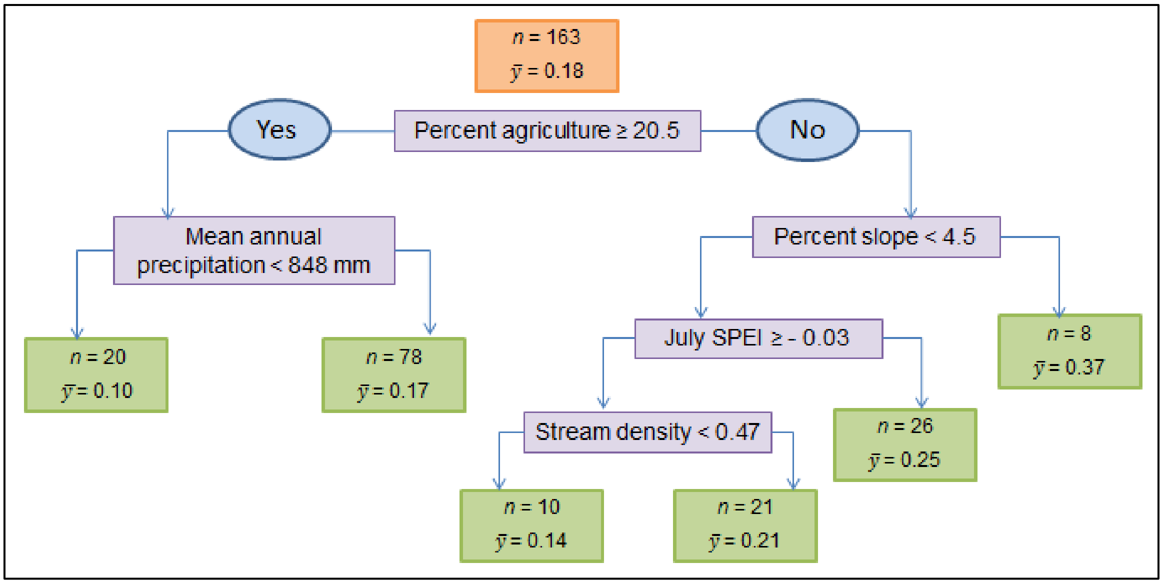

Figure 7: Monthly regression tree grown and pruned with `rpart` using the MRR_m temporal characterization for the month of July.

Figure 8 illustrates the rationale for pruning the trees. Black lines refer to models conditioned on MRR_i, while red lines refer to models developed with MRR_m. For every month, the reduction in cross-validation error (the risk of misclassification) is plotted against model complexity (the number of clusters). Plots of risk (y-axis) versus complexity (x-axis) typically exhibit an initial decay followed by a plateau and then a slow rise (Therneau and Atkinson, 2011). Optimal model complexity can be considered the point on the plot where the reduction in misclassification error becomes small. These points are indicated by the black and red dots in Figure 8, where a threshold of less than a 0.01 reduction in risk was chosen to determine their locations. Trees were then pruned to contain this optimal number of clusters, indicated by the point's x-value on the plots.

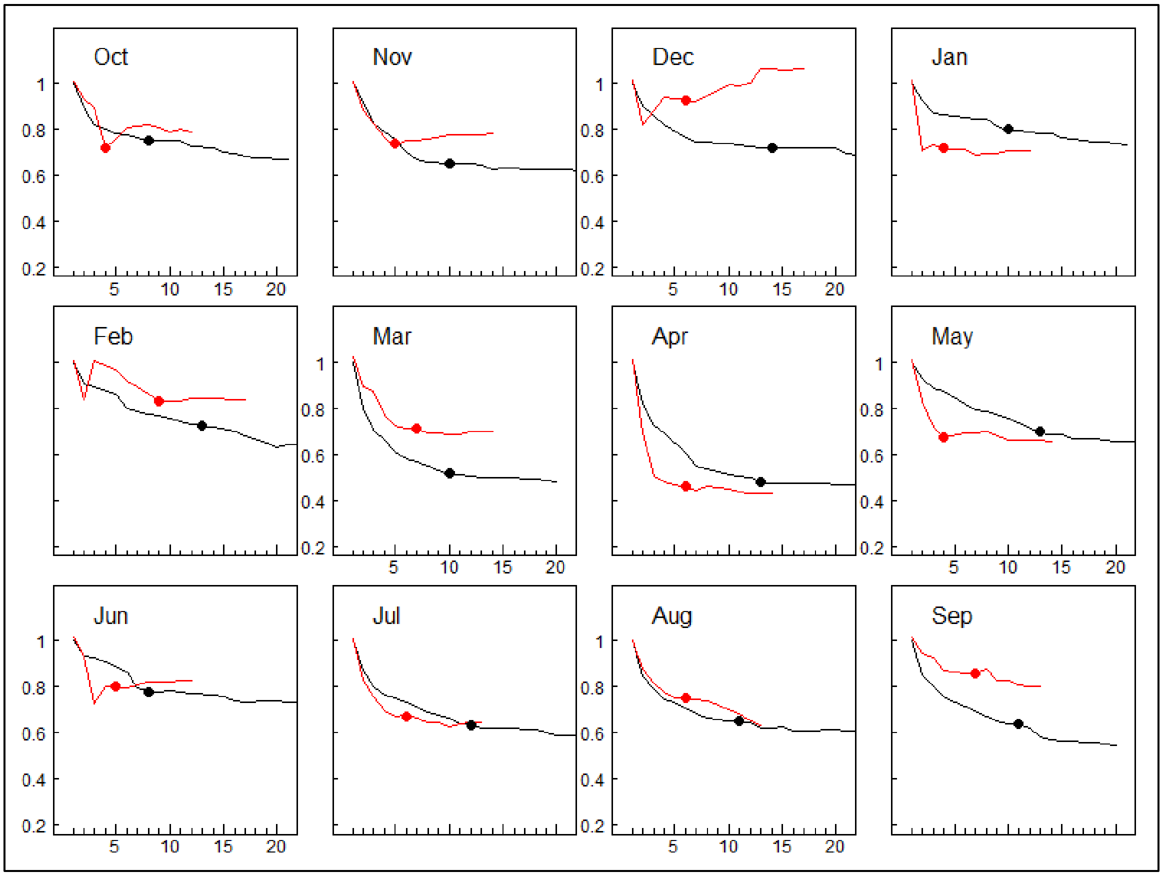

Figure 8: Cross-validation error (y-axis) versus number of clusters (x-axis) for monthly regression tree models. Black lines refer to models conditioned on MRR_i, while red lines refer to models developed with MRR_m. The dots indicate the point on the curve where increased clustering leads to a reduction in errors less than 0.01.

5.6 Model validation

Since the sample sizes of MRR_i (n = 1630) and MRR_m (n = 163) are so different, comparisons of relative error between the two temporal characterizations are not possible for purposes of model assessment. Consequently, the four models (multiple linear regression and regression tree, conditioned by both MRR_i and MRR_m) were used to predict monthly runoff in 62 validation watersheds. Data for the validation watersheds were also obtained from the GAGES-II dataset. None of the validation watersheds were among the 163 watersheds used to develop the models.

The Nash-Sutcliffe coefficient of efficiency (NSE; Nash and Sutcliffe, 1970), the coefficient of determination (R^2), mean absolute error (MAE), and deviation of runoff volumes (D_v) were computed to compare monthly predicted runoff (P) versus monthly observed runoff (O) in validation watersheds for all months *i* during WY 2001-2010 (n = 120). NSE (Equation 3) and R^2 (Equation 4) are goodness-of-fit statistics; MAE (Equation 5) quantifies error in units of mm of runoff; and D_v (Equation 6) assesses model bias in terms of total cumulative runoff.

$$NSE = 1 - \frac{\sum_{i=1}^{n}(O_i - P_i)^2}{\sum_{i=1}^{n}(O_i - \bar{O})^2} \qquad \text{(Equation 3)}$$

$$R^2 = \left[\frac{\sum_{i=1}^{n}(O_i - \bar{O})(P_i - \bar{P})}{\sqrt{\sum_{i=1}^{n}(O_i - \bar{O})^2}\sqrt{\sum_{i=1}^{n}(P_i - \bar{P})^2}}\right]^2 \qquad \text{(Equation 4)}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|O_i - P_i\right| \qquad \text{(Equation 5)}$$

$$D_v = \frac{\sum_{i=1}^{n}(P_i - O_i)}{\sum_{i=1}^{n}O_i} \times 100 \qquad \text{(Equation 6)}$$

For the NSE and R^2 statistics, values of one indicate a perfect model fit, where predicted runoff is equal to observed runoff. For D_v, a value of zero implies no model bias, where cumulative predicted and observed runoff (here, for WY 2001-2010) are equal. MAE quantifies the difference between observed and predicted values in actual units, in this case millimeters of runoff. Values closer to zero indicate a better model fit.

The performance ratings for NSE and D_v suggested by Moriasi et al. (2007) are shown in Table 6. Since R^2 is highly sensitive to outliers, Moriasi et al. (2007) do not provide performance ratings for this statistic, but consider a value greater than 0.50 to generally be acceptable.

Table 6: Performance ratings for model validation statistics from Moriasi et al. (2007).

Rating	NSE	D_v
Very good	$0.75 < NSE \leq 1.00$	$\lvert D_v \rvert < 10$
Good	$0.65 < NSE < 0.75$	$10 \leq \lvert D_v \rvert < 15$
Satisfactory	$0.50 < NSE < 0.65$	$15 \leq \lvert D_v \rvert < 25$
Unsatisfactory	$NSE \leq 0.50$	$\lvert D_v \rvert \geq 25$

6. Results

6.1 Spatial and temporal variability of hydrologic response

Figures 9 and 10 illustrate the spatial and temporal variability of monthly runoff ratio in the U.S. portion of the Great Lakes basin. Figure 9 depicts 30-year mean monthly runoff ratios (MRR_m) for April and October for the 163 gaged watersheds used to develop the regionalization models. Watersheds are shown as points graduated by drainage area, with the largest of any nested watersheds shown as polygons. Runoff ratios are symbolized by quartiles. As indicated in the legend, the quartiles for MRR_m are substantially different between the two months, reflecting the fact that April and October are typically high and low flow periods, respectively.

Spatial trends include very high April runoff ratios in northern Michigan and western New York due to snowpack ablation and very low October runoff ratios in the predominantly agricultural regions of eastern Michigan and northern Ohio. However, there is also evidence of highly dissimilar hydrologic response between spatially proximal watersheds, for example in central and northern Wisconsin.

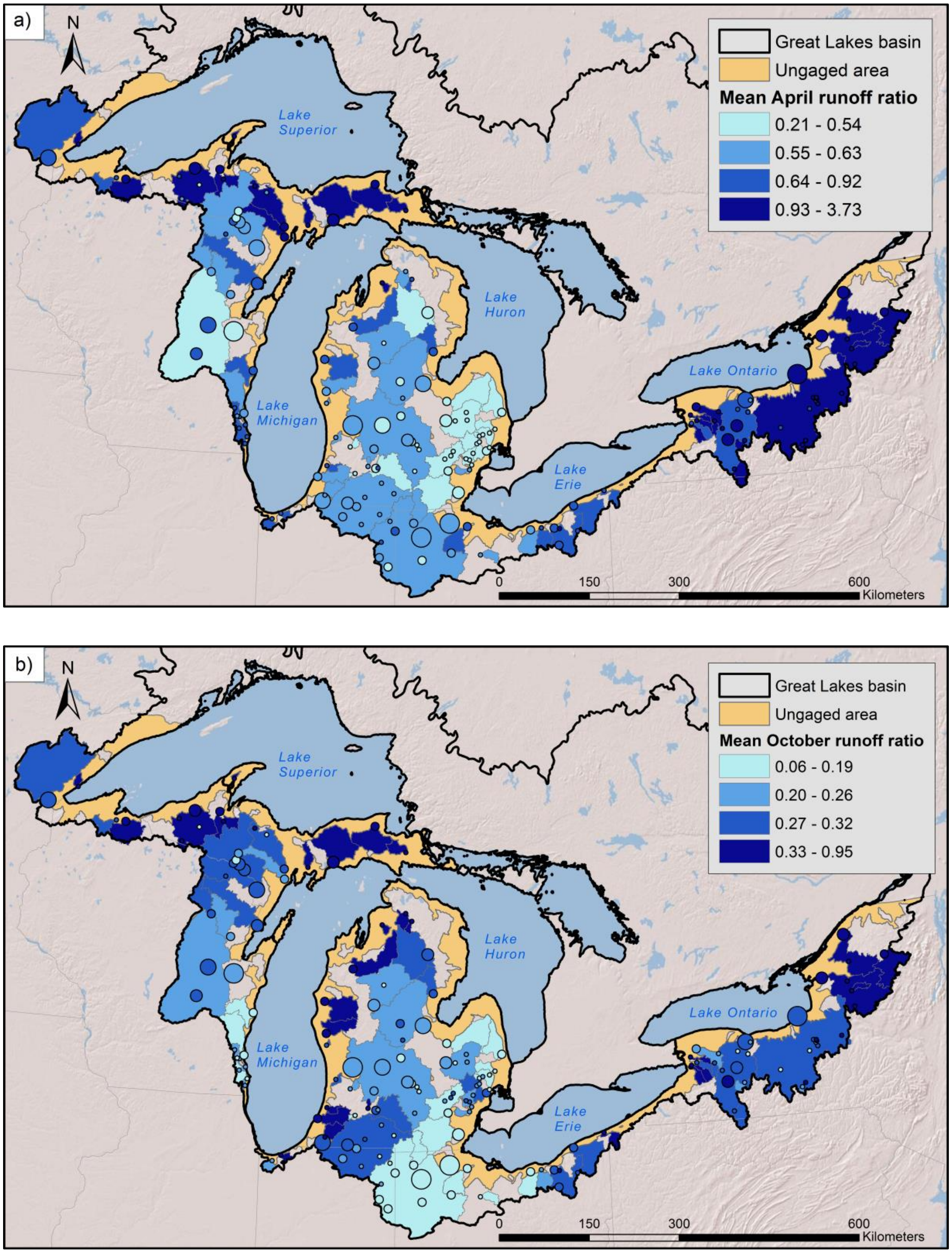

Figure 9: Seasonal and spatial variability of monthly runoff ratio in the Great Lakes basin. The 163 watersheds used to develop the regionalization models are shown as circles graduated according to drainage area. Solid-colored polygons show the largest of any nested watersheds. Ungaged areas are shaded orange. Quartiles of MRRm are mapped for a) April and b) October. Note the sizable difference in the range of values between the spring and autumn months.

Figure 10 presents the full range of seasonal and interannual variability in observed MRR_i and MRR_m for the same 163 watersheds. Seasonal trends are evident, with higher magnitudes and larger ranges for runoff ratio during winter and early spring compared to summer months. The left panel shows all individual monthly runoff ratios (MRR_i) over a ten year period. The right panel shows the means of these individual runoff ratios (MRR_m).

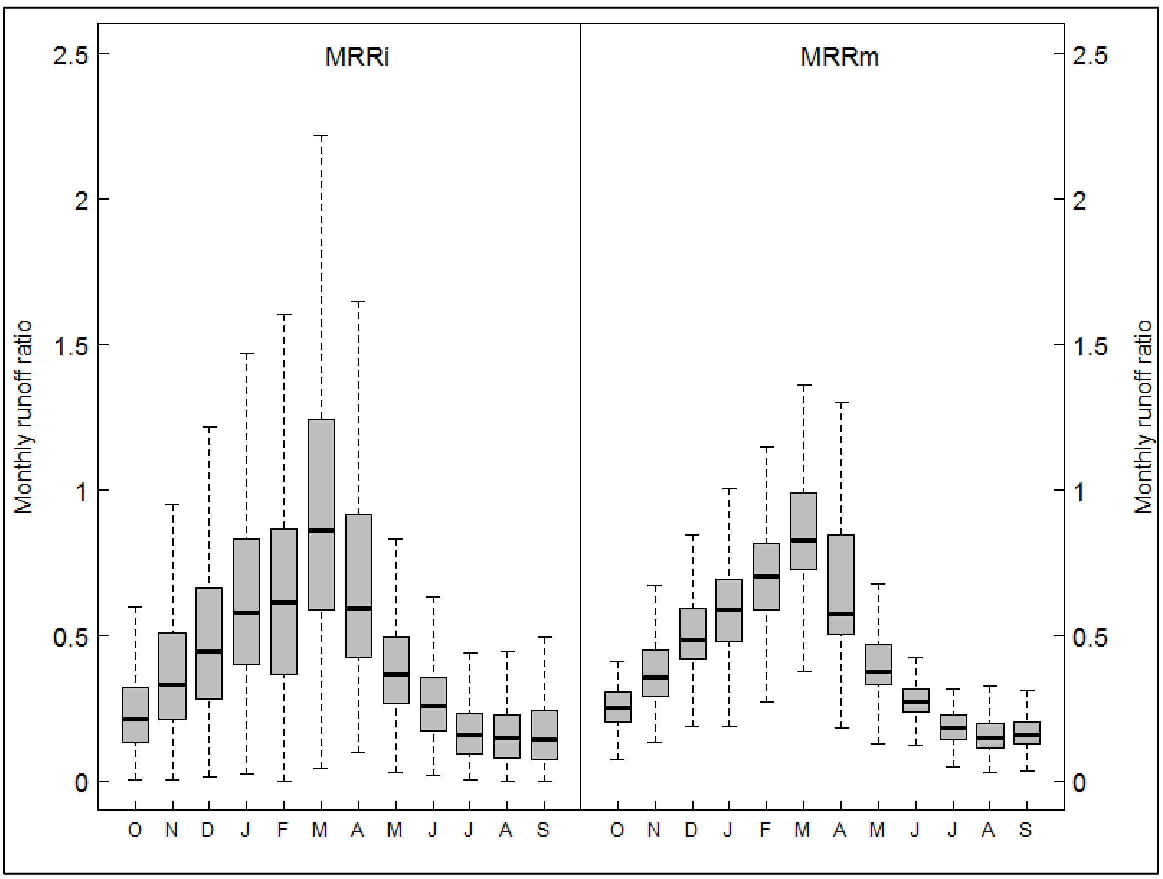

Figure 10: Seasonal and interannual variability of hydrologic response in the Great Lakes basin. The left panel shows all individual monthly runoff ratios (MRR_i) over a ten year period. The right panel shows the means of these individual runoff ratios (MRR_m). Runoff ratios greater than one indicate a net monthly watershed surplus.

The different distributions of MRR_i and MRR_m indicate the degree of interannual variability in hydrologic response among Great Lakes basin watersheds. While the median values for both temporal characterizations are similar, the interquartile ranges are very different, particularly during winter and spring months. As a result, for management objectives related to the magnitude and timing of high flow events (e.g. potential floods) in ungaged areas, regionalization schemes based on long-term or annual averages may not be suitable.

6.2 Model validation

The 62 validation watersheds are shown in Figure 11, symbolized according to the deviation of runoff volumes (D_v) for WY 2001-2010. Cumulative runoff was over-predicted in watersheds with a positive D_v and under-predicted in watersheds with a negative D_v. The distributions of D_v statistics are shown as boxplots. Runoff was generally over-predicted (median ~ 10%) with the MRR_m temporal characterization and under-predicted (median ~ -5%) with the MRR_i temporal characterization. However, in some regions, runoff is over- or under-predicted regardless of the model used, such as in western New York and central Michigan. In other regions, however, the bias depends on the model used, such as in northern Wisconsin and southern Michigan.

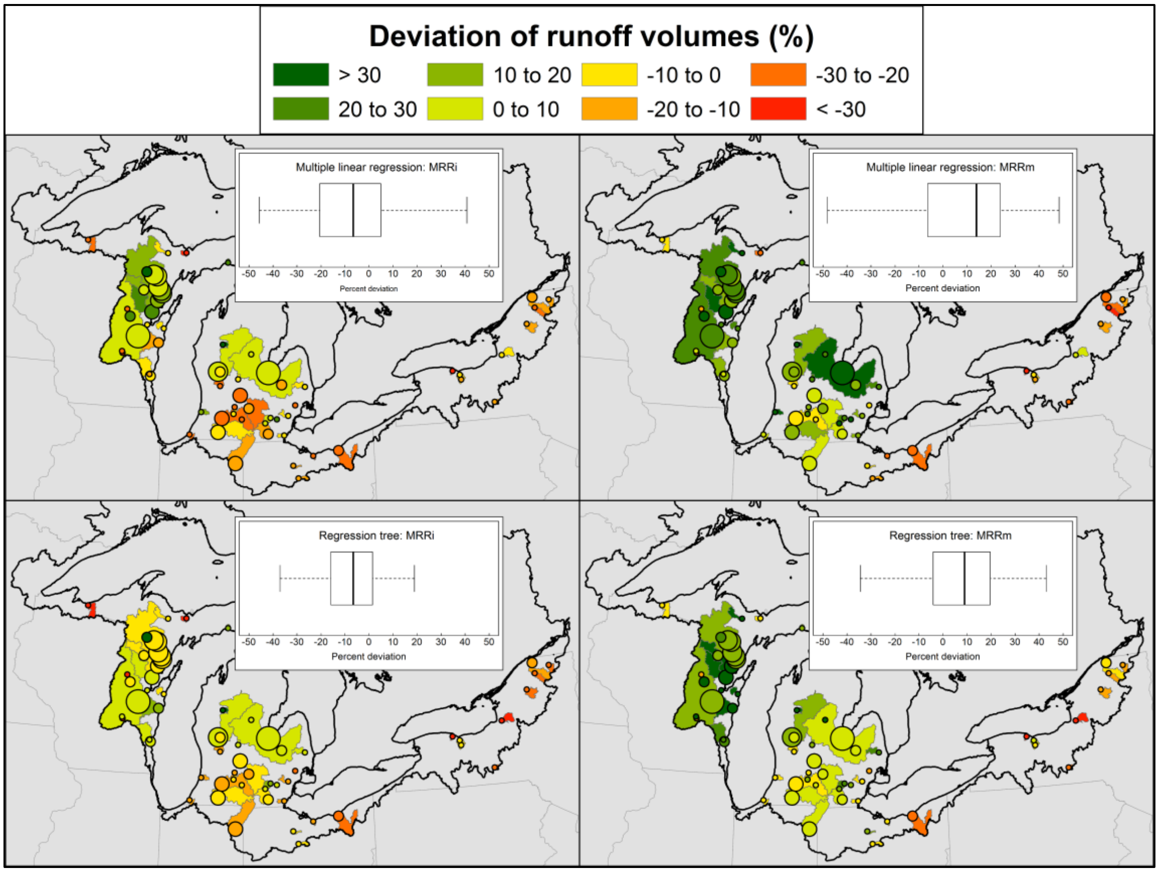

Figure 11: Deviation of runoff volumes (D_v) are shown for the 62 GAGES-II watersheds used to validate the linear and `rpart` models. Validation watersheds are shown as circles graduated according to drainage area. Solid-colored polygons show the largest of any nested watersheds. Positive Dv values indicate that cumulative runoff was over-predicted. Negative Dv values indicate that cumulative runoff was under-predicted. The distributions of D_v statistics for each model are shown as boxplots.

The NSE, R^2 and MAE statistics are given as boxplots in Figure 12. Multiple linear regression using mean runoff ratios performed poorly, while both regression approaches using MRR_i performed fairly well. Multiple linear regression using MRR_i resulted in the smallest interquartile range for both goodness-of-fit statistics, and was the only model with no NSE values less than zero (that is, higher variance in the model's residuals than in the observed data). The lowest mean absolute errors (in mm of runoff) were produced using the MRR_i temporal characterization of hydrologic response.

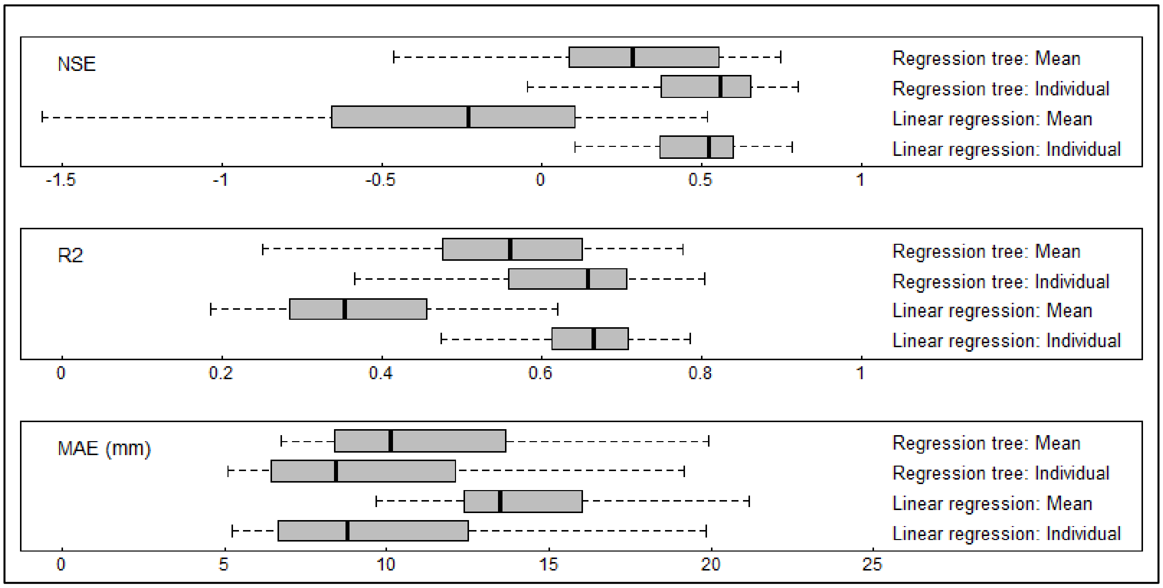

Figure 12: Nash-Sutcliffe coefficient of efficiency (NSE; top panel) and coefficient of determination (R^2; middle panel) goodness-of-fit statistics for the 62 validation watersheds. Mean absolute error (MAE) in mm of runoff is given in the bottom panel.

Hydrographs of model-predicted versus observed runoff are shown in Figure 13 for five contrasting validation watersheds. Summary descriptions of these watersheds are given in Table 7. In Figure 13, blue lines show observed runoff, while black and red lines show runoff predicted with the MRR_i and MRR_m temporal characterizations, respectively. Solid lines display predictions from the multiple linear regression approach, while dotted lines display predictions from the regression tree approach.

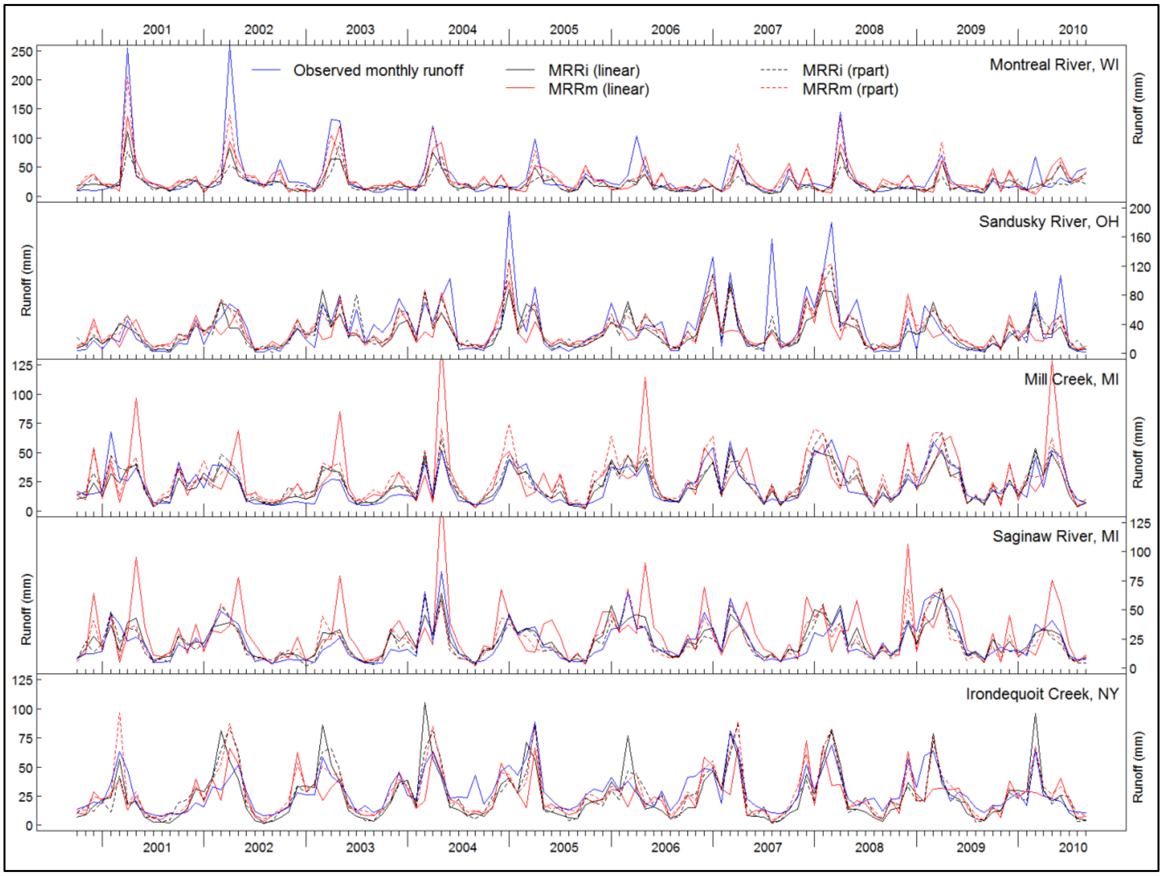

Figure 13: Model-simulated versus observed monthly runoff (in mm) for five validation watersheds during WY 2001-2010. The thick grey line represents observed runoff. Black and red lines represent the MRR_i and MRR_m temporal characterizations, respectively. Solid and dashed lines represent the linear and `rpart` models, respectively. January is indicated with the large tick marks on the x-axis.

Table 7: Characteristics of validation watersheds used for hydrograph comparison.

Name	Area (km^2)	Dominant land cover		Mean annual runoff (m^3/s)	Mean annual precip. (mm)	Average annual temp. (°C)
Montreal River, WI	684	Forest (59%)	Wetlands (23%)	8.9	852	4.8
Sandusky River, OH	231	Agriculture (70%)	Developed (15%)	2.6	1059	10.0
Mill Creek, MI	326	Agriculture (51%)	Forest (19%)	2.4	885	9.2
Saginaw River, MI	14,327	Agriculture (45%)	Forest (24%)	132.2	832	8.3
Irondequoit Creek, NY	380	Developed (38%)	Agriculture (33%)	1.1	884	9.2

Comparing the top two hydrographs in Figure 13, some basic relationships between streamflow regimes and watershed physical characteristics can be inferred. For example, while the Montreal River exhibits a regular annual cycle, the Sandusky River hydrograph appears more erratic, with a less apparent annual cycle. The regular annual cycle can be largely attributed to the predominance of forests and wetlands in the Montreal River watershed, while the irregular streamflow regime in the Sandusky River watershed likely reflects the prevalence of agriculture and high levels of urbanization and development in the region.

Runoff from the Montreal River consistently peaks in April as a result of spring snowpack ablation, while hydrograph peaks are observed throughout the year for the Sandusky River. In the latter case, warmer average annual temperatures imply less snowpack storage potential, and therefore runoff peaks occurring any time throughout the winter. In summer, hydrograph peaks for the Sandusky River can be attributed to fast runoff from agricultural and developed land cover.

Model bias varies considerably among the five watersheds in Figure 13. For all models, there is a recurring bias in late winter and early spring with runoff consistently under-predicted for Montreal River and over-predicted for Irondequoit Creek. For Sandusky River, numerous high runoff events in both winter and summer are under-predicted by all models. For Mill Creek and Saginaw River, the models conditioned on mean runoff ratio (MRR_m), particularly the linear model, greatly over-predicted monthly runoff, even in months not experiencing relatively high flows.

7. Discussion

Numerous water resource research and management objectives require knowledge of hydrological processes occurring in ungaged watersheds. Making predictions in ungaged basins through regionalization is inherently a geographical pursuit, addressing theoretical and practical means of (1) transferring knowledge of hydrological processes over space from gaged to ungaged watersheds; (2) determining similarities and differences among watersheds, including attempts to establish watershed classification systems; and (3) understanding and accounting for the temporal variability exhibited by hydrologic systems. A great deal of research has been directed towards the first two items. However, regionalization approaches involving hydrologic response indices have rarely accounted for the temporal variability of watershed behavior. Further advances in regionalization research involving hydrologic response indices require the consideration of their temporal as well as spatial variability.

In this research, four regionalization models (multiple linear regression and regression tree, conditioned by both MRR_i and MRR_m) were developed to predict runoff at a monthly time step based on watershed physical characteristics. Results from applications to validation watersheds indicate that model predictions are far more sensitive to the temporal characterization of runoff ratio than to the type of regression technique used to develop the relationships (see Figure 12). Specifically, the two regionalization schemes based on MRR_i performed comparably well alongside contemporary studies using response indices in conjunction with a rainfall-runoff model (e.g. Bulygina et al., 2009; Yadav et al., 2007). Moreover, predictions based on the MRR_i index were generally acceptable based on the performance ratings of Moriasi et al. (2007). However, mean monthly runoff ratio (MRR_m) does not appear to provide enough information about watershed behavior to be useful for making predictions in ungaged basins. This conclusion mirrors the opinion expressed by Olden and Poff (2003) that a single index of hydrologic response is insufficient for characterizing the seasonal and interannual variability of hydrologic systems. While MRR_m accounts for seasonal variations in hydrologic response (the monthly time step), the MRR_i characterization additionally accounts for interannual variability (the inclusion of all observations over a range of years). This additional level of temporal characterization likely explains the superior performance of MRR_i models compared to MRR_m models.

Compared to the contrasts exhibited by the temporal characterizations of runoff ratio, there were no substantial differences found between the multiple linear regression and regression tree techniques used to develop the models. In other words, predictions in ungaged watersheds were not sensitive to the watershed classification technique employed to determine hydrologic similarity. These results reflect the contemporary challenges described by Wagener and Montanari (2011) of determining hydrologic similarity among watersheds.

In this research, predictions of runoff in ungaged basins were based solely on empirical relationships between a watershed's physical characteristics and observed hydrologic response. This approach is distinct from the more commonly used regionalization approaches that rely on process-based rainfall-runoff models to make runoff predictions, for example the LBRM and MESH in the Great Lakes basin (see Section 4.2). Whereas rainfall-runoff models attempt to model specific hydrological processes occurring in a watershed (see Figure 2), the method presented in this study modeled the watershed as a system, without explicitly modeling constituent routing, storage and loss processes.

An important result of this study is that monthly runoff can be predicted with reasonable skill without recourse to a process-based rainfall-runoff model. This finding is particularly important considering the many regions of the world with sparse stream gage networks and limited resources for gathering the large amounts of field data required to calibrate a rainfall-runoff model. In such cases, the approach used in this study may be viable for understanding and predicting watershed behavior, particularly over large spatial domains.

The method used in this study is similar to the area ratio method (ARM; see section 4.2) in its empirical approach for predicting runoff in ungaged watersheds. The primary advantage of the ARM is its utilization of all available streamflow observations at a daily time step. The advantage of the method used in this study is its ability to account for spatial heterogeneity between gaged and ungaged watersheds. Comparisons between these two approaches would provide an opportunity to assess the significance of this spatial heterogeneity, while an integration of these two approaches could be developed as an improved alternative to process-based rainfall-runoff models.

8. Conclusion

In this research, regionalization models were developed to predict runoff at a monthly time step based on watershed physical characteristics. Results from this research suggest the following conclusions, each of which contributes to contemporary research involving hydrologic predictions in ungaged watersheds:

- Monthly runoff in ungaged watersheds can be predicted with reasonable skill using regionalization relationships between runoff ratio and watershed physical characteristics;
- Predictions in ungaged watersheds are highly influenced by the temporal scale used to condition the models; and
- Predictions in ungaged watersheds were not sensitive to the watershed classification technique employed: similar results were obtained using multiple linear regression and regression tree analysis.

The results from this research are important given the numerous applications of hydrologic response indices in contemporary research for making predictions in ungaged watersheds. These predictions are essential for water resource management in the Great Lakes basin and worldwide.

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Appendix A: Pearson correlation coefficients for watershed physical characteristics

In order to identify representative and non-redundant watershed physical characteristics, Pearson correlation coefficients were computed for variables from the GAGES-II dataset (see section 5.4). Correlation matrices are given below for three major classes of variables: climate, soils, and land cover.

Table A.1: Correlation matrix for climate variables.

Climate variables	Precip	Temp	PSI	Snow	Latitude	RH	First frost	Last frost
Mean annual precipitation	1.00							
Average annual temperature	0.26	1.00						
Precip. seasonality index	-0.69	-0.24	1.00					
Percent precip. as snow	0.01	-0.86	-0.21	1.00				
Latitude	-0.46	-0.95	0.36	0.80	1.00			
Relative humidity	-0.42	0.25	0.13	-0.20	-0.05	1.00		
Day of first frost	0.20	0.90	-0.19	-0.75	-0.80	0.30	1.00	
Day of last frost	-0.21	-0.92	0.16	0.81	0.84	-0.29	-0.97	1.00

Table A.2: Correlation matrix for soils variables.

Soils variables	AWC	Perm	BD	Clay	Sand	K factor	R factor	Sub Flow
Available water capacity	1.00							
Permeability	-0.37	1.00						
Bulk density	-0.40	-0.31	1.00					
Percent clay	0.19	-0.75	0.59	1.00				
Percent sand	-0.21	0.93	-0.42	-0.85	1.00			
Erodibility (K) factor	0.30	-0.86	0.39	0.80	-0.91	1.00		
Erosivity (R) factor	-0.02	-0.10	0.52	0.41	-0.22	0.30	1.00	
Subsurface flow index	0.05	-0.32	0.36	0.51	-0.37	0.38	0.37	1.00

Table A.3: Correlation matrix for land cover variables.

Percent land cover	Dev	For	Ag	Water	Shrub	Grass	Pasture	Crops	Wet	Rip dev	Rip for	Rip ag	Imperv
Developed	1.00												
Forest	-0.46	1.00											
Agriculture	-0.23	-0.67	1.00										
Water	-0.09	0.28	-0.36	1.00									
Shrubland	-0.24	0.37	-0.16	-0.05	1.00								
Grassland	-0.05	0.22	-0.31	-0.06	0.05	1.00							
Pasture	-0.20	-0.28	0.58	-0.25	0.25	-0.33	1.00						
Crops	-0.19	-0.68	0.94	-0.32	-0.30	-0.22	0.27	1.00					
Wetlands	-0.35	0.36	-0.46	0.25	-0.10	0.13	-0.39	-0.38	1.00				
Riparian developed	0.98	-0.45	-0.23	-0.12	-0.21	-0.04	-0.20	-0.19	-0.37	1.00			
Riparian forest	-0.35	0.86	-0.49	0.05	0.47	0.10	-0.02	-0.57	0.03	-0.33	1.00		
Riparian agriculture	-0.20	-0.65	0.97	-0.39	-0.15	-0.31	0.52	0.93	-0.50	-0.18	-0.47	1.00	
Impervious surfaces	0.97	-0.45	-0.23	-0.12	-0.20	-0.06	-0.21	-0.18	-0.33	0.96	-0.34	-0.19	1.00