2-2022

Effects of Climate, Basin Characteristics, and High-Capacity Wells on Baseflow in the State of Wisconsin, United States

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This is an Accepted Manuscript of an article published by Wiley in the Journal of American Water Resources Association *on 06/Feb/202, available online:* *https://doi.org/10.1111/1752-1688.12986*

Research Impact Statement: Understanding the factors that affect groundwater-surface water interactions will lead to policy decisions that will both protect stream habitats and provide for the needs of the agriculture industry.

ABSTRACT: When it comes to water resources management, it is critical to understand the factors that affect baseflow processes. Declines in baseflow due to increased use of the groundwater from unconfined aquifers is well documented, but that is not the case for confined aquifers. Furthermore, since the groundwater basin size and shape can be different than the surface water basin, the use of the surface basin to determine well withdrawal rates can affect baseflow and be problematic. This study used the variables determined to be related to baseflow variability (precipitation, temperature, drainage class, available storage, land use, and slope) and the withdrawal rates of wells located within the study basins to create regression models for the state of Wisconsin, United States. We find that: (1) precipitation and temperature variable are significant in explaining the temporal variability of baseflow whereas land cover variables are important when the temporal variability is not considered; (2) evaporation and soil drainage are important in basins over unconfined aquifers whereas precipitation the most significant over confined aquifers; (3) whether to use surface water or groundwater divides to delineate basins matters in particular conditions, and (4) groundwater withdrawal rates do not significantly affect baseflow when using statistical analysis. Therefore, analyzing baseflow should be supplemented by a process-based model for the effects of groundwater withdrawals.

(KEYWORDS: baseflow; aquifer; high-capacity wells; groundwater; regression model.)

INTRODUCTION

Understanding the factors that affect baseflow processes is critical to protecting both water quality and supply (Price 2011). Baseflow is important to streams because of its cooler temperature and better quality than stormflow, and its ability to maintain streamflow during dry periods. Baseflow decreases and stream temperature increases will lead to decreases in aquatic biodiversity (Brown and Krygier 1970). Because baseflow is groundwater that discharges to surface water, groundwater that normally would have discharged as baseflow to surface water can be diverted away from discharge points by the gradients created by high-capacity wells (Sophocleous 2002). High-capacity wells, used to irrigate agriculture, can significantly impact groundwater storage and the associated interaction of surface to groundwater systems (Sophocleous 2002, Wahl and Tororelli 1997). Several studies documented baseflow declines in the state of Wisconsin, United States due to the increased use of groundwater for agricultural irrigation from unconfined aquifers that are well connected to surface waters (e.g., Kraft et al. 2012, Weeks and Stangland 1971, Weeks et al. 1965 Wahl and Tororelli 1997, Barlow and Leake 2012, Fienen et al. 2018). Groundwater pumping affects surface waters (rivers, lakes, streams, and wetlands) by reducing baseflow that feeds into them. Extreme groundwater pumping has also been shown to extract surface water out of the stream bed and into the aquifer (Barlow and Leake 2012, Zipper et al. 2019, Li et al. 2020).

Baseflow can vary both spatially and temporally due not only to groundwater pumping but also to climate, topography, and human activities (Ayers et al. 2021, Price 2011, Santhi et al. 2008). Climate factors such as precipitation and temperature influence baseflow by controlling the availability of water (Ayers et al. 2021, Price 2011). Topographic factors then influence if the available water will infiltrate the land surface and recharge surface water over time or will flow across the surface and add to streamflow as surface runoff (Ayers et al. 2019, Zhang and Schilling 2006). In addition, land use also affects how and when available water reaches surface waters. Increases in urbanization will lead to increased stormflows and decreased baseflows as a result of increases in impervious surfaces, whereas increases in agricultural land use have produced mixed baseflow responses depending on management practices (Price 2011).

Baseflow increases have also been documented in basins in Wisconsin where the primary land use is agriculture (Gebert et al. 2007), but the mechanism and conditions of such increases are unclear. Two potential explanations are the increased use of soil conservation practices in southwestern Wisconsin (Potter 1991) and increased irrigation from confined aquifers that are not connected to the surface waters. Since the irrigation of agricultural land increases the soil moisture storage and increases in soil moisture storage have been found to be linked to increases in baseflow (Shaw et al. 2013, Price 2011), withdrawals from the confined aquifer may be related to baseflow increases. There are few if any studies on the effects of the withdrawal of groundwater on baseflow from confined aquifers that are disconnected from surface waters (Borchardt 2019). The lack of such understanding puts environmentalists and agricultural growers across the state at odds with each other on how best to preserve the state's freshwater resources. A better understanding of the factors that affect the groundwater-surface water system will help balance both the needs of the agricultural industry and conservation efforts in Wisconsin and elsewhere.

It is crucial to understand how both climate change and anthropogenic impacts affect the relationship between physical basin properties, such as soil texture and land use, and baseflow (Price 2011), but few studies address both climate and anthropogenic impacts. Currently, numerical models (e.g., MODFLOW) can simulate the impacts of multiple variables on baseflow, but they are site specific and require significant effort, time, and knowledge for calibration and validation (Li et al. 2020). Some studies examined how either anthropogenic (e.g., Borchardt 2019; Sophocleous 2002, Wahl and Tororelli 1997) or climate factors (e.g., Borchardt et al. 2016) affect baseflow. Some other studies have used analytical depletion functions to quite accurately predict which streams in a given basin would be affected by the groundwater withdrawal of an individual well (e.g., Zipper et al. 2019, Li et al. 2020), but climate factors were not considered. Ayers et al. (2021) combined the effects of climate factors, physical basin properties, and land-use factors to find the main drivers in baseflow variability using regression analysis, but the groundwater withdrawal variable was not included. In Wisconsin, annual precipitation and temperature have been trending upward over the last several decades (WICCI, 2011). Increases in precipitation will increase the water available for infiltration to the aquifer, whereas increases in temperature will decrease available water via increased evaporation. In consideration of the limitations in previous studies and climatic trends in Wisconsin, we find it necessary to study how these climate factors, along with the physical basin characteristics, affect baseflow in areas where there is extensive use of high-capacity wells.

The effects that land use, irrigation, and/or climate change have on baseflow could be amplified or mitigated by the subsurface topography (Dubé et al. 1995). The subsurface topography can have a strong influence on groundwater flow and baseflow (Price 2011). Price (2011) describes subsurface topography as the relief of the first confining layer, more specifically it is the subsurface strata that prompts the horizontal movement of groundwater. The groundwater basin size and shape can be different than the surface water basin and they can vary over time as well. During high moisture conditions, when the water table is high, the soil moisture surface is likely to follow that of the surface topography (Hutchinson and Moore 2000). On the other hand, when conditions are dry, and the water table is low, the soil moisture surface is likely to follow the topography of the confining layer (Price 2011). Fienen et al. (2018) also note that wells outside the surface basin can impact the baseflow by changing the local flow field. These changes in the water table elevation and groundwater flow will shift the peaks that define the basin area. Therefore, whether to use surface basins or groundwater basins as units of analysis may produce different results (Borchardt 2018). The discrepancy between surface water and groundwater divides makes a large difference in annual baseflow values (Gebert et al. 2007). The dynamic nature of the groundwater basin boundaries makes it difficult to determine which wells are potentially affecting baseflow at a given stream gauge. Several studies including Freer et al. (1997) and Hutchinson and Moore (2000) found that the topography of the confining layer (subsurface topography) and the properties of the soil overlaying the confining layer are better predictors of the water table than surface topography. On the other hand, Li et al. (2018) found several surface topographic variables that contribute to streamflow variability, but the effects were not consistent. Therefore, it is necessary to consider both surface and subsurface topography when examining the effect of high-capacity wells.

The aim of this study is to investigate how climate variables and human activities affect baseflow across Wisconsin. This study builds on a previous one (Borchardt 2019) that examined baseflow trends and related factors in Wisconsin, and utilizes a range of regression models to answer the following research questions: (1) How are the temporal and spatial variabilities of baseflow affected by climate and basin physical characteristics? (2) How are baseflow trends related to withdrawal rates of high-capacity wells and aquifer types? and (3) To what extent does the variability of groundwater basin boundaries influence baseflow? The study intends to sort out factors that could affect baseflow differently by time and space.

MATERIALS AND METHODS

Overview

In this study, we used precipitation, temperature, drainage class, available storage, land cover, slope, and the recorded well withdrawal rates to predict baseflow variability across basins. The variables were found to be related to baseflow in previous studies (Borchardt 2019, Santhi et al. 2008, Lorenz and Delin 2007). Thirty US Geological Survey (USGS) streamflow monitoring sites were selected for the analysis, and each site had continuous daily streamflow during the study period (2011-2017). The years 2011-2017 were chosen for their availability of wells withdrawal data. Annual baseflow was derived from the streamflow data, and regression analysis was used to determine which variables affected baseflow variability during the study years. The list of the USGS sites and associated variables can be found in Appendix A.

Baseflow

Annual baseflow was calculated from streamflow data collected for the years 2011-2017 at the 30 USGS sites using the USGS computer program Groundwater Toolbox (GWTB) (http://water.usgs.gov/ogw/gwtoolbox/, last accessed on 15 September 2018). GWTB contains six hydrograph-separation methods to calculate groundwater discharge, and one recession-curve displacement method (RORA) to estimate groundwater recharge (Barlow et al. 2015). The RORA method was chosen for this study to represent baseflow. The RORA recharge estimates have been found to be slightly greater than those estimated using the hydrograph-separation methods due to some loss of groundwater by riparian evapotranspiration versus discharge as baseflow to the stream (Barlow et al. 2015). These losses however are relatively small. The RORA program estimates net recharge. Net recharge is recharge minus leakage to deeper aquifers and losses caused by groundwater evapotranspiration (Rutledge 2000). It is assumed that groundwater discharged to streams is an episodic response to storms, unlike the hydrograph-separation methods which assume a continuous process (Rutledge 2007). The RORA method is a recession-curve displacement method based on a mathematical solution. A recession index (*K*) is specified for each basin based on the time required for groundwater to discharge to the surface water. *K* is estimated using a semilogarithmic plot of streamflow as a function of time. The index is then used to calculate the solution for the conditions related to the instantaneous rise in height of the water table over the basin, and the volume of water that drains from groundwater storage after each precipitation event (Barlow et al. 2015).

Explanatory variables for baseflow

Basin types. Basins with daily recorded streamflow during the study period (2011-2017) were filtered to include only unregulated streams with minimal wastewater discharge measurements. The selected basins were then delineated for both the surface contributing runoff to the stream and the area of groundwater contributing baseflow to the stream at the gauging station because groundwater basins do not always coincide with surface water basin boundaries (Borchardt et al. 2016). The gauging stations were used as pour points to delineate only the groundwater area that contributes water to each gauging station. The delineation of the groundwater basins followed the same process as the delineation of the surface water basins except that an interpolated groundwater elevation was used in lieu of the Digital Elevation Model (DEM) as described in Borchardt (2018).

The interpolated groundwater elevation was determined by subtracting from the DEM the "depth to groundwater" data obtained from well drilling reports.

Since groundwater basin divides generally follow surface topography in wet years and subsurface topography in dry years, we delineated the groundwater basin only for the dry years between 2011 and 2017. Data retrieved from the Wisconsin State Climatology Office website (http://www.aos.wisc.edu/~sco/clim-history/state/graphics/WI-precip-annual.gif) reveals that only 2012 was a dry year, and the drought of 2012 caused low groundwater levels from late 2011 until spring of 2013 (Han et al. 2018). Therefore, the static water level of wells drilled during this time period were used to create the groundwater DEM used to delineate the groundwater basin for 2012. We used the surface basin for the years 2011 and 2013-2017 since groundwater basins generally follow the size and shape of the surface water basins in wet years (Hutchinson and Moore 2000).

Climate variables. Growing Degree Days (GDD) was used as the temperature variable because it is a better measure of temperature during the growing season when irrigation is in use, and it eliminates the negative temperature recordings from the annual sum. The GDD is a measure of the mean temperature above the base temperature for each day (Equation 1).

$$GDD = T_m - T_b \text{ for } T_m > T_b$$

$$T_b \text{ otherwise} \qquad \text{Equation 1}$$

where T_m = daily mean temperature (°C)

T_b = base temperature (set at 10°C).

Annual GDD data (annual sum of daily GDD) was obtained for the weather station that was closest to each delineated basin from the Midwestern Regional Climate Center (Cli-MATE 2018). Because temperate data does not vary significantly over relatively short distances, the use of the nearest weather station is appropriate.

The precipitation data was obtained from the National Centers for Environmental Information for the state of Wisconsin (NCEI n.d.). Because weather stations are not necessarily located in the study basins and precipitation can vary across relatively short distances, precipitation data was interpolated using the kriging method. The weather stations with the most complete data set were selected (Appendix B). The data from the weather station closest to each selected weather station was used to replace any missing data. The data from NCEI contains precipitation totals for each month and a yearly total. Months with missing data for 1-9 days were indicated with an "X", and months with >9 days of missing data were left blank. For months containing missing data, if the monthly data from the adjacent weather station is greater than the data from the original station, the greater value was used in place of the missing data for that month at the original station. Sixty-eight stations were selected in Wisconsin, approximately one station per county. Two stations in Minnesota and one in Michigan were also selected to mitigate edge effects following the interpolation process. The yearly totals from 2011 through 2017 were recorded on a spreadsheet for each station along with each station's latitude and longitudinal co-ordinates. Using ArcGIS 10.4 from ESRI, the data from the spreadsheet was mapped. The interpolation tool kriging in ArcGIS was used to create a raster layer with a 2-km resolution. Kriging weights the surrounding measured values to estimate a value in an unmeasured location using a formula within the ArcGIS program. The weights are based on both the distance between the measured points and the prediction location and on the overall spatial arrangement of the measured points (ESRI 2016). The mean annual precipitation (in mm) for each study year in each basin was then calculated in ArcGIS and is denoted by Precip hereafter.

Basin physical characteristics. We used both available water storage (denoted by AS_150) and soil drainage class (denoted by DrainClass) to characterize the soil, and both were downloaded from the Soil Survey Geographic Database, part of the United States Department of Agriculture. The use of both is further explained in Borchardt (2019). However, we modified the use of the DrainClass from percent of well-drained soil to the mean value for the basin. Each drainage class was classified numerically 1–7, with 1 representing excessively drained and 7 representing very poorly drained, and the mean was calculated for each delineated basin. Both the AS_150 and DrainClass map layers were downloaded from ESRI (19 April 2019 and 5 June 2019, respectively). The topographical characteristics of the basin were represented by the average percent slope.

The landcover was downloaded from the Multi-Resolution Land Characteristics Consortium for years 2011, 2013, and 2016. The data for 2011 was used for study years 2011-2012, 2013 for 2013-2014, and 2016 for study years 2015-2017. The layers were created from the National Land Cover Database at a resolution of 30m and contain 16 classes of landcover. The layer was reclassified to reduce the number of classes to eight (water, developed, barren, forested, shrubland, herbaceous, agriculture, and wetland). The data was then clipped to the area of each delineated basin. The percentage of the three most prominent land covers (forested, agricultural, and urban) were calculated for each time in each basin, and it is denoted by PerFor, PerAg, and PerUrban, respectively.

Annual groundwater withdrawal rate. High-capacity well data for the state of Wisconsin was acquired from the Wisconsin Department of Natural Resources (WDNR) through email correspondence (Smail 2018) (see Figure 1 for the location). The state of Wisconsin has required owners of high-capacity wells to report annual groundwater withdrawal only since 2011, therefore actual reported values for years 2011–2017 were used in the regression analysis. It should be noted that the reporting of the annual withdrawal rate is on the honor system and is subject to some inconsistencies.

The extent to which a well affects the baseflow of a stream is in part related to the distance of the well from the stream. But when there are numerous wells within a single basin, it becomes difficult to determine this distance. Furthermore, wells can divert groundwater (by bending the groundwater flow path) from a tributary to the main stem of the stream (Fienen et al. 2018). To simplify the distance calculation, we measured the distance from the weighted mean center of all the wells within the basin to the stream gauge located at the basin outlet. Therefore, with the premise that wells closer to a stream have more effect on the baseflow to the stream than wells farther away, we used a modified annual withdrawal rate (MAWR) for the withdrawal variable.

The annual withdrawal rate is reported in gallons and was converted to $m^3 \times 10^{-5}$ for this analysis. Then we modified the annual withdrawal rate by multiplying by the relative distance of the wells from the basin outlet to account for the different effects of well locations to baseflow measured at the outlet. The MAWR was determined by combining the total annual rate of withdrawal from all the high-capacity wells within each basin and the relative distance of the weighted mean of those wells from the basin outlet. The first step was to determine which wells were in each basin, and the second was to determine the withdrawal rate from each, then the weighted mean center of the wells within the basins was determined using the withdrawal rate as the weight. This moved the mean center closer to the well with the highest withdrawal rate for any given year. Then the distance (d_{ij}) between basin i's weighted mean center for year j and the individual basin outlet was calculated in meters. The relative distance (RD_{ij}) between the weighted mean center for basin i in year j and the basin outlet is then calculated, and subsequently, the MAWR was calculated according to Equation 2.

$$\mathrm{MAWR}_{ij} = \frac{\mathrm{AWR}_{ij}}{\mathrm{RD}_{ij}} \qquad \text{Equation 2}$$

where AWR_{ij} denotes annual withdrawal rate, and $\mathrm{RD}_{ij} = \frac{\mathrm{d}_{ij}}{\sum \mathrm{d}_{ij}}$. $\sum$dij is the sum of distance for all the basins in all the study years. The MAWR is denoted by WxDd, and its unit is $m^3 \times 10^{-5}$.

Aquifer types. Because groundwater withdrawals from unconfined and confined aquifers can have different effects on baseflow, we determined the aquifer type for each well. We examined two data sources, well construction reports and a geological map, to determine the aquifer type. Well construction reports are filed with the WDNR after the completion of a well installation, and they record both the well depth and the depth of the confining layer. By comparing the two depth records, we could determine which wells are drawing from the confined aquifer and which are drawing from the unconfined aquifer. Well construction report data compiled by the Wisconsin Geological & Natural History Survey was received from the University of Wisconsin-Extension via email correspondence (Mavel 2018). Well construction reports are only available for a small portion of the wells within each basin. It is a common practice for well drillers to drill to the depth on a par with other wells in the general area with a reliable water source. Therefore, it is assumed that if all the wells with a construction report are pumping from the same aquifer, then the wells without a construction report are also withdrawing from that same aquifer in each basin. Well locations were also compared to a map layer titled "Aquifers of Alluvial and Glacial Origin". The aquifer types layer was delineated by the USGS from data in The Ground Water Atlas of The United States and was downloaded from ArcGIS online (AGOL 2002) (Figure 1). Per the aquifer map layer, 26 of the 30 basins were located over only one aquifer type. After comparing these two data sources, we determined if each basin's wells were drawing groundwater mainly from the confined or the unconfined aquifer. The determination was primarily based on the data derived from the aquifer map layer with the construction reports acting as a verification.

[Insert Figure 1]

Regression Analysis

We employed the panel data analysis (PDA) to build regression models. PDA is a statistical method used to analyze data simultaneously varying over time and space (or sector). The dependent variable Y (annual baseflow in cm) for the basin i at time t is modeled using explanatory variables X_k as follows:

$$Y_{it} = \beta_0 + \beta_1 X_{1it} + \beta_2 X_{2it} + \ldots \beta_k X_{kit} + u_{it} \qquad \text{Equation 3}$$

where β_0 is the constant term and u is the error term. It should be noted that some explanatory variables can be time-invariant.

PDA can be divided into four main categories: independently pooled panels, between estimation models, fixed effect models, and random effect models (Min and Choi, 2019). The pooled regression model is a method of applying to the ordinary least squared model incorporating different observations from different periods of time, ignoring temporal changes and the objects' difference in the panel data. Between estimation models use the variables averaged over time, using only cross-sectional information, and removing time variation in the data. Fixed effect models, also called within estimation models, replace time-invariant explanatory variables with a time-invariant term αi representing different intercepts by object (Equation 4):

$$Y_{it} = \beta_0 + \beta_1 X_{1it} + \beta_2 X_{2it} + \ldots \beta_k X_{kit} + \alpha_i + u_{it} \qquad \text{Equation 4}$$

where all the explanatory variables are time-variant. They examine the variability within each object. Random effect models assume that α_i in the model follow a probability model, independent of explanatory variables. In other words, α_i is very small or all factors are controlled for, which is a better assumption than that in fixed effect models.

We used the plm package of R (Croissant & Millo, 2008) using the between estimation and random effect models to focus on time-invariant and time-variant variables, respectively. We ran PDA for different combinations of aquifer types and basin types. It was first run on the entire data set, and then on the divided sets. The analysis was run two times for each aquifer type. The first run included variables from within the surface basin. The second run used the same variables but from within the groundwater basin (Table 1). We inserted all the explanatory variables, and the plm package automatically eliminated insignificant variables.

[Insert Table 1]

RESULTS AND DISCUSSION

Descriptive statistics of the variables

The descriptive statistics for the annual baseflow estimated using the RORA method is presented in Table 2. The mean is 26.7 cm, and the distribution is quite symmetrical between the first and third quartiles. The data stretches further to the maximum than to the minimum. We also present the descriptive statistics of baseflow predicted by Model 1 (random effect) for comparison. There are some discrepancies, but the magnitude of each statistic is generally comparable. The biggest discrepancy is found in the maximum. The predicted maximum is smaller than the observed by about 5.7 cm.

[Insert Table 2]

The distribution of each explanatory variable is presented in Figure 2. Most of the variables have quite symmetrical distributions. Notable exceptions are PerAg, PerUrban, and WxDd. Most of the basins have less than 40% agricultural land cover with the median of about 10%. PerUrban has a more skewed distribution than PerAg, with the median of about 5% and the maximum close to 100%. Highly urbanized basins are concentrated in the southeastern corner of the state. WxDd varied extremely widely, thus is shown as logarithm. The log WxDd has a quite symmetrical distribution with a few extreme outliers below zero.

[Insert Figure 2]

Model 1

[Insert Table 3]

The result for Model 1 where all the basins were considered is presented in Table 3. PerFor was found to be the only significant variable when we used the between estimator. When the time-variant variables were averaged over time, only PerFor was left to explain the variability of baseflow across basins. PerFor varied widely across the state, from 0.29% to 67.40% with the median of 29.48%, and basins with more forest cover tended to have more baseflow. The catchment 04025500 has the largest observed baseflow and the highest PerFor. R^2 is higher than with the random effect model even though there is only one explanatory variable that is statistically significant. It is likely because PerFor kept its large variability whereas other variables' variabilities were reduced in the model. In addition, PerFor is correlated with other variables regarding basin characteristics and land cover. Therefore, it makes sense that all the other ones were left out.

In the random effect model, both time-invariant (DrainClass) and time-variant (Precip and GDD_10) variables significantly explained the variability of baseflow (Table 3). Precip had a positive coefficient whereas DrainClass and GDD_10 had negative. Lower numbers in DrainClass indicate better drainage of the soil, thus the result indicates that baseflow increases with better drained soils. The negative coefficient of GDD_10 suggests the effect of higher evaporation with higher temperatures on baseflow. Model 1 suggests that precipitation and temperature variabilities play larger roles than basin characteristics in baseflow variability when time is considered.

Models 2 and 3

When only the basins over unconfined aquifers were considered (Model 2), Precip, DrainClass, and GDD_10 were found to be significant with the random effect model whereas none with the between estimator model (Table 4). The significant variables with the random effect are the same as in Model 1, suggesting both climate and drainage characteristics matter for baseflow. The magnitude of the DrainClass coefficient and the GDD_10 coefficient approximately doubled respectively compared to Model 1, suggesting stronger influences of evaporation and soil drainage on baseflow over unconfined aquifers than over confined ones. Because the surface water is more strongly connected to unconfined aquifers than to confined ones, evaporation and soil drainage have stronger effects on baseflow over unconfined aquifers. The non-significance of the between estimation model suggests that the interannual variability of baseflow is so large whereas the inter-basin variability is not so large. The large interannual variability was eliminated by the between estimator whereas the inter-basin variability was not large enough to be explained by any explanatory variables.

[Insert Table 4]

When the analysis was conducted for the basins over confined aquifers (Model 3), the variability of baseflow was explained by PerUrban with the between estimator and Precip and GDD_10 with the random effect. PerUrban is negatively correlated with PerFor, therefore the coefficient is negative unlike in Model 1. The result is essentially identical to that from Model 1. With the random effect model, only Precip and GDD_10 are statistically significant variables. Unlike over unconfined aquifers, drainage characteristics were not an important factor, and the Precip coefficient is larger. The non-significance of basin characteristics is likely because the aquifer is detached from surface water. In summary, for the basins over confined aquifers, baseflow is better explained with climate variables only compared to the basins over unconfined ones.

Models 4 and 5

Model 4 is the same as Model 2 except for that groundwater divides were used to delineate basins boundaries. The regression results (Table 5) are almost identical to those from Model 2 with minor differences in coefficients. R^2 with the random effect model increased marginally from 0.313 to 0.321. Therefore, whether to use surface water or groundwater divides did not affect baseflow in the basins over unconfined aquifers.

[Insert Table 5]

Noticeable effects of groundwater divides were found for the basins over confined aquifers (Model 5) when the between estimator was used. Precip, PerAg, and PerUrban were found to be significant variables and R^2 was >0.68. The time-averaged annual precipitation is a significant variable only in Model 5 with the between estimator. We think it is because the basins are spread across the state and the variability of precipitation is larger than for the basins over unconfined aquifers. In this set of basins, agricultural and urban land covers are more prevalent than forest. For example, the median of PerAg and PerUrban is 38% and 17% respectively whereas that of PerFor is 10%. The negative effect of agricultural and urban land covers on baseflow is not surprising by itself, but their significance is due to their prevalence and large variability.

The effects of groundwater divides seem to have disappeared with the random effect model. Precip and GDD_10 are significant variables like in Model 3, and their coefficients are similar. R^2 is slightly lower than Model 3. It indicates again the large interannual variability of baseflow and climate variables.

We examined the shape of surface water and groundwater basins in detail (Figure 3). It seems groundwater basin boundaries generally follow surface topography over unconfined aquifers. There was not much discrepancy between groundwater and surface water basin boundaries at higher bedrock elevations, and there was greater discrepancy at lower elevations. The groundwater basin areas decreased in size compared to the surface water basin boundaries at lower bedrock elevations (Figure 3a). The basin boundary discrepancy over confined aquifers appeared to be particularly large in the southeast where the percentage of urban land cover was high. On the other hand, the discrepancy is quite small in forest-dominated basins (Figure 3b). This is why land cover variables were significant in Model 5 with the between estimator.

[Insert Figures 3a & 3b]

The overall area within the basin boundaries varied less in the basins over the unconfined aquifer than those over the confined aquifer (Figure 4). Six out of the thirteen basins over the unconfined aquifer had a change in area from the groundwater basin to the surface water basin area of less than 10%. Only two of the remaining basins had a decrease in size over 10% (04066500, 04060993), five basins however had an increase in size greater than 10% ranging from approximately 18% (05435943) to greater than 95% (04080000) (Figure 4a). Seven out of the eighteen basins over the confined aquifer had a change in area from the groundwater basin area to the surface water basin area of less than 11%. Six of the remaining basins had groundwater basins that were larger in size than their surface water basin, and five had smaller groundwater basins than their surface water basin. The percent decrease of all the basins over the confined aquifer ranged between over 2400% (04087204) to less than 2% (05414000), and the percent increase in size ranged from less than 1% (05399500) to greater than 97% (04087240) (Figure 4b).

[Insert Figures 4a and 4b]

Effects of groundwater withdrawal

The groundwater withdrawal was not a significant variable in any model when it was modified with the relative distance to basin outlets. The data comes in volume, and because the same amount of withdrawal can have different effects on baseflow depending on the basin size, we first converted to depth by dividing by area. When we used the withdrawal depth in regression models, it was found to be insignificant. We then used the modified annual withdrawal rate (WxDd) for the regression models to find it insignificant again.

We speculate for reasons for the insignificance. A possible reason is that the distribution of WxDd is extremely skewed, like an exponential distribution with a sharp decline. It was very high in particular years in particular basins, with little to no correlations with other variables. When we examined the correlation between WxDd and observed baseflow each year, the correlation was always negative and statistically insignificant. We suspect the effect of groundwater withdrawal on baseflow, but the statistical approach we employed failed to demonstrate it. It could also be because the relationship between groundwater withdrawal and baseflow is not direct. The effect could occur with temporal and/or spatial lags or via another mechanism, and exploring them is beyond the scope of this study.

CONCLUSIONS

The study investigated the spatial and interannual variability of baseflow in Wisconsin using the panel data analysis method for the period 2011-2017. The findings are summarized as follows: (1) precipitation and temperature variable are significant in explaining the temporal variability of baseflow whereas land cover variables are important when the temporal variability is not considered; (2) the drainage condition is important for baseflow over unconfined aquifers; (3) evaporation and soil drainage are important in basins over unconfined aquifers whereas precipitation the most significant over confined aquifers; (4) whether to use surface water or groundwater divides to delineate basins matters in particular conditions, and (5) groundwater withdrawal rates do not significantly affect baseflow when using statistical analysis. Overall, we cautiously argue that groundwater basins should be considered when delineating basin boundaries for baseflow studies, and statistical analyses show limited too little success in revealing the effect of high-capacity wells on baseflow in Wisconsin at the annual scale. A process-based modeling approach would be necessary.

This research yielded knowledge of the role of hydrological stress, both natural and anthropogenic, on stream baseflow. The results will be useful for hydrologists and water resources managers interested in environmental change impacts and adaptations. Precipitation and temperature were significant variables in each of the models representing separate aquifers. Additionally, we expect that this research will lead to further research that investigates how the state's groundwater resource can be best used and how to balance that resource between the state's agricultural needs and environmental concerns.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request (Borchardt 2021).

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APPENDIX A

List of streamflow monitoring sites and associated basin characteristics.

ID	Name	Latitude	Longitude	Slope (%)	AS_150 (mm)	DrainClass	PerFor (%)	PerUrban (%)	PerAg (%)	Aquifer
04025500	BOIS BRULE RIVER AT BRULE, WI	46.53778	-91.5953	4.80	17.82	3.09	65.62	3.85	1.42	Unconfined
04060993	BRULE RIVER AT US HIGHWAY 2 NEAR FLORENCE, WI	45.96079	-88.316	5.41	19.79	4.02	61.48	4.21	2.33	Unconfined
04063700	POPPLE RIVER NEAR FENCE, WI	45.76357	-88.4632	3.23	19.02	4.55	45.81	1.85	0.55	Unconfined
04066500	PIKE RIVER AT AMBERG, WI	45.49997	-88.0001	4.06	16.66	3.20	55.13	3.66	2.00	Unconfined
04067958	PESHTIGO RIVER NEAR WABENO, WI	45.38774	-88.3051	4.01	23.23	4.16	54.90	2.67	2.11	Unconfined
04074950	WOLF RIVER AT LANGLADE, WI	45.18997	-88.7334	4.63	18.08	4.00	53.76	3.28	3.15	Unconfined
04077630	RED RIVER AT MORGAN ROAD NEAR MORGAN, WI	44.89803	-88.8443	4.40	20.41	3.78	43.01	3.58	20.69	Unconfined
04080000	LITTLE WOLF RIVER AT	44.41248	-88.8654	4.11	21.54	3.87	31.66	4.13	37.09	Unconfined

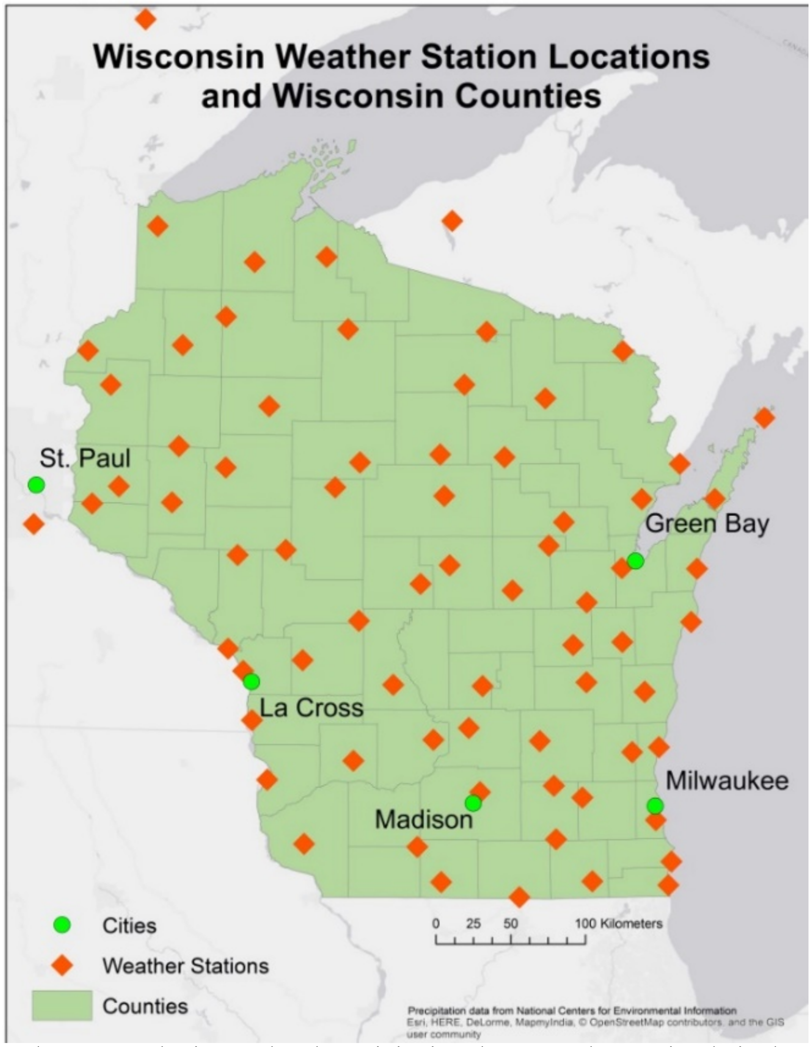
	ROYALTON, WI									
05357335	BEAR RIVER NEAR MANITOWISH WATERS, WI	46.04884	-89.9846	2.26	29.51	3.91	27.31	2.29	0.00	Unconfined
05393500	SPIRIT RIVER AT SPIRIT FALLS, WI	45.44913	-89.9793	3.99	19.47	4.73	59.32	2.67	4.81	Unconfined
05394500	PRAIRIE RIVER NEAR MERRILL, WI	45.2358	-89.6498	4.63	20.50	4.35	48.86	2.82	8.96	Unconfined
05397500	EAU CLAIRE RIVER AT KELLY, WI	44.91889	-89.5519	2.76	20.06	4.15	36.97	5.13	30.53	Unconfined
05435943	BADGER MILL CREEK AT VERONA, WI	42.97694	-89.5396	5.71	21.44	3.23	9.02	57.19	34.70	Unconfined
04024430	NEMADJI RIVER NEAR SOUTH SUPERIOR, WI	46.63327	-92.0941	4.76	21.62	4.14	51.24	2.50	10.53	Confined
04027000	BAD RIVER NEAR ODANAH, WI	46.48664	-90.6963	5.90	20.57	4.44	67.40	2.59	5.83	Confined
04087030	MENOMONEE RIVER AT MENOMONEE FALLS, WI	43.17279	-88.104	2.65	24.64	4.42	8.88	34.90	37.88	Confined
04087050	LITTLE MENOMONEE	43.20667	-88.0384	2.91	23.30	4.53	7.50	18.13	61.67	Confined

	RIVER NEAR FREISTADT, WI									
04087070	LITTLE MENOMONEE RIVER AT MILWAUKEE, WI	43.12362	-88.0437	3.27	21.77	4.45	9.61	41.74	35.75	Confined
04087088	UNDERWOOD CREEK AT WAUWATOSA, WI	43.05473	-88.0462	3.85	24.00	4.68	2.34	90.22	1.19	Confined
04087119	HONEY CREEK AT WAUWATOSA, WI	43.0439	-88.0029	3.60	22.38	4.57	0.29	98.31	0.54	Confined
04087204	OAK CREEK AT SOUTH MILWAUKEE, WI	42.92502	-87.8701	3.27	21.36	4.66	12.32	62.58	10.79	Confined
04087220	ROOT RIVER NEAR FRANKLIN, WI	42.87363	-87.9959	3.49	21.28	4.56	9.22	72.81	7.51	Confined
04087240	ROOT RIVER AT RACINE, WI	42.75141	-87.8237	2.53	22.33	4.57	9.63	30.84	49.19	Confined
04087257	PIKE RIVER NEAR RACINE, WI	42.64696	-87.8606	2.08	24.09	4.26	5.25	35.66	51.78	Confined

05362000	JUMP RIVER AT SHELDON, WI	45.30803	-90.9565	2.51	25.61	5.19	48.81	2.64	9.15	Confined
05399500	BIG EAU PLEINE RIVER AT STRATFORD, WI	44.8219	-90.0796	3.40	19.71	4.80	15.54	4.89	71.07	Confined
05408000	KICKAPOO RIVER AT LA FARGE, WI	43.57414	-90.6432	18.53	21.50	3.24	50.09	4.68	43.94	Confined
05413500	GRANT RIVER AT BURTON, WI	42.72027	-90.8193	10.86	23.22	3.08	17.97	5.15	76.45	Confined
05414000	PLATTE RIVER NEAR ROCKVILLE, WI	42.7311	-90.6404	11.81	22.72	3.07	18.64	3.81	77.09	Confined
05427718	YAHARA RIVER AT WINDSOR, WI	43.20888	-89.3526	2.94	25.98	3.46	1.80	13.12	81.11	Confined

Page Break

APPENDIX B



Weather stations locations used to create the interpolated precipitation data. Weather station latitude and longitude data obtained from the National Centers for Environmental Information (NCEI n.d.).

TABLES

Table 1 Regression Models

Model	Aquifer type	Basin type	Number of basins
1	Confined and Unconfined	Surface	30
2	Unconfined	Surface	13
3	Confined	Surface	17
4	Unconfined	Groundwater	13
5	Confined	Groundwater	17

Table 2 Descriptive statistics for observed and Model 1-predicted annual baseflow during 2011-2017 for the 30 basins selected for the study.

Baseflow	Minimum	1st quartile	Median	Mean	3rd quartile	Maximum
Observed	7.95	19.13	25.77	26.70	32.12	57.66
Model 1-Predicted	6.85	22.27	27.04	26.70	30.36	51.92

Table 3 Panel data analysis results for Model 1 using between estimation and random effect models.

	Between estimator	Random effect
Coefficients for significant variables ($p < 0.05$)	0.221PerFor	0.029Precip –4.786DrainClass –0.015GDD_10
R^2	0.38272	0.35691
p-value for F statistic	0.00026842	< 2.22e-16

Table 4 Panel data analysis results for Models 2 and 3 using between estimation and random effect models.

		Between estimator	Random effect
Model 2	Coefficients for significant variable ($p < 0.05$)	None	0.028Precip –9.236DrainClass –0.028GDD_10
	R^2	0.10856	0.31343
	p-value for F statistic	0.27161	3.386e-07
Model 3	Coefficients for significant variables ($p < 0.05$)	–0.088PerUrban	0.035Precip –0.007GDD_10
	R^2	0.25306	0.43828
	p-value for F statistic	0.039558	2.9667e-15

Table 5 Panel data analysis results for Models 4 and 5 using between estimation and random effect models.

		Between estimator	Random effect
Model 4	Coefficients for significant variables ($p < 0.05$)	None	0.026Precip –7.649DrainClass –0.026GDD_10
	R^2	0.085701	0.3208
	p-value for F statistic	0.33172	2.1399e-07
Model 5	Coefficients for significant variables ($p < 0.05$)	0.2096Precip –0.5272PerAg –0.5113PerUrban	0.024Precip –0.008GDD_10
	R^2	0.68695	0.35795
	p-value for F statistic	0.01398	4.5044e-11

FIGURE LEGENDS

Figure 1 Location of high-capacity wells and aquifer types delineated by the USGS from data in The Ground Water Atlas of The United States.

Figure 2. Box and whisker plots of explanatory variables.

Figure 3. (a) Groundwater and surface water basin boundaries over unconfined aquifers and bedrock elevation downloaded from ESRI ArcGIS online, and (b) Groundwater and surface water basin boundaries over confined aquifers and land cover data downloaded from the Multi-Resolution Land Characteristics Consortium for the year 2011.

Figure 4. Areas of groundwater basins and surface water basins in the year 2012 over (a) unconfined aquifers and (b) confined aquifers.