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Research papers

On the statistical attribution of changes in monthly baseflow across the U. S. Midwest

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ABSTRACT

Baseflow, or the groundwater component of streamflow, is an important source of water for several applications, from increasing demands on freshwater resources to ecosystem health. Despite its relevance, our understanding of the processes driving baseflow and its interannual variability is limited. In this study, we focus on 458 U.S. Geological Survey streamflow gauges that have at least 50 years of daily data. We use a statistical modeling framework to select a set of predictors that represent the role of climate (i.e., precipitation, temperature and antecedent wetness) and land use (harvested acres of corn and soybeans). The models are able to describe well the variability in monthly baseflow across the region, with an average correlation coefficient between the observational records and the median of the fitted distribution of 0.70 among all months. Our results indicate that precipitation and antecedent wetness are the strongest predictors, where the latter was selected the most often. Temperature is an important predictor during the spring when snow-related processes are the most relevant. Agriculture was frequently selected in the Cornbelt region during the growing season (from March to July). The results of this study can inform future watershed management that sustains low flows and improves water quality.

1. Introduction

Baseflow is the portion of streamflow discharged from groundwater or other delayed sources. It is an important water resource because it sustains streamflow between precipitation events or periods of drought, and it has potential consequences for water quality (Kang et al., 2008; Schilling and Lutz, 2004; Schilling and Zhang, 2004). Although we have progressed significantly in our understanding of the changes in streamflow, we still do not fully understand what factors influence baseflow. Baseflow varies regionally and spatially because it is affected by differences in climate, topography, surface water, groundwater and human activities (Price, 2011; Santhi et al., 2008). Watershed characteristics, such as geology and topography, that promote infiltration and recharge have been shown to be important for sustaining baseflow (Price et al., 2011; Zimmer and Gannon, 2018). On the other hand, climate factors (e.g., precipitation and temperature) influence baseflow through water availability, evapotranspiration rates, and the timing of snowmelt runoff (Ahiablame et al., 2017a; Cadol et al., 2012; Gupta et al., 2018; Mishra et al., 2010; Slater and Villarini, 2017). Although climate controls the availability and timing of discharge, previous research has shown that climate alone cannot explain observed changes in baseflow (Raymond et al., 2008; Schilling and Libra, 2003; Tomer and Schilling, 2009). Often, land use and land cover influence soil and topographic characteristics that dictate whether precipitation is distributed as either runoff or recharge. While previous studies identified changes in baseflow across large areas of the Midwest (Ahiablame et al., 2017a; Ayers et al., 2019; Ficklin et al., 2016; Zhang and Schilling, 2006), it is still unclear what factors are driving these changes.

In the Midwest, natural vegetation of grasslands, wetlands and prairies have been converted to maize and soybean row crops (e.g., Frans et al., 2013). This area, also known as the Cornbelt region, is one of the highest yielding global agricultural areas for corn (Nikiel and Eltahir, 2019). Studies have identified agricultural land use as an important driver for increases in baseflow across the region (Ahiablame et al., 2017a; Ayers et al., 2019; Schilling, 2005; Schilling and Libra, 2003). For a watershed in Iowa, Schilling and Libra (2003) argued that improved agricultural management practices in the second half of the 20th century contributed to increasing baseflow. In addition, tile

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drainage has been a crucial part of agricultural systems. Tiles remove excess water from traditional wetlands which provides a nutrient rich environment for corn and soybean production (e.g., Kelly et al., 2016). While artificial drainage has changed the hydrologic regime across agricultural landscapes and contributes to baseflow (Arenas Amado et al., 2017; Basu et al., 2012; Blann et al., 2009; Schilling et al., 2019), the extent of its control remains unknown. Another component of land use change has been groundwater pumping for irrigation, which has been shown to decrease baseflow (e.g., Bhaskar et al., 2016; Wen and Chen, 2006); however, reliable records for groundwater storage are not available because they are not complete or long enough to analyze changes in water resources (Brutsaert, 2008).

Large-scale landscape modifications have likely affected atmospheric processes such as temperature, precipitation, evapotranspiration, humidity and soil moisture (Alter et al., 2018; Bonan, 1997; DeAngelis et al., 2010; Germer et al., 2010; Huntington, 2006; Twine et al., 2004). Agricultural land use can intensify the effect of climate change because it transforms the surface energy balance and influences temperature at the regional scale (Mueller et al., 2016); For example, Bonan (1997) showed large differences in precipitation due to land use across the Midwest and documented wetter conditions during the summer that were likely a result of increased latent heat flux where crops had replaced forest vegetation. Agricultural intensification has added moisture to the global atmosphere through evapotranspiration, and a large percentage of the vapor actualizes directly over irrigated lands (Ferguson and Maxwell, 2011; Nocco et al., 2019; Sacks et al., 2009). These studies highlight how difficult it can be to determine the impact of climate and land use changes because human activities influence watershed characteristics and near surface climate dynamics.

To date, there are no studies that disentangled the effects of interdependent controlling variables on baseflow. Previous climate and land use change research has tended to focus on streamflow (Ahiablame et al., 2017b; Chien et al., 2013; Gupta et al., 2018; Juckem et al., 2008; Kibria et al., 2016; Norton et al., 2019; Slater and Villarini, 2017); however, baseflow is a distinct streamflow component because it includes subsurface water from different flow paths (i.e. deep regional groundwater storage and shallow near streamflow paths) (Miller et al., 2014; Price, 2011). More detailed analysis is needed to understand how climate and land use have affected this nuanced water resource. Previous studies that have determined the influence of forcing factors on baseflow have been limited in their scope where they have either examined baseflow on a small scale (e.g., Kibria et al., 2016; Mishra et al., 2010; Price et al., 2011) or on an annual basis (e.g., Brutsaert, 2008) and/or their methods focused on individual drivers (Ayers et al., 2019). For instance, Ayers et al. (2019) reported the correlation coefficients between baseflow and different forcing factors, including precipitation, temperature and agricultural intensity; however, they did not account for the potential concurrent role of different drivers nor did they develop a statistical model to capture the influence of different drivers. Therefore, considering the gap in our attribution of the detected changes in baseflow, the crucial objective of this study is to determine the main drivers responsible for the historical changes in monthly baseflow at 458 U.S. Geological Survey (USGS) stream gauges in the U.S. Midwest. In term of drivers, we focus on the role of climate (precipitation, temperature, and antecedent wetness) and land use/land cover changes (agriculture) using regression models.

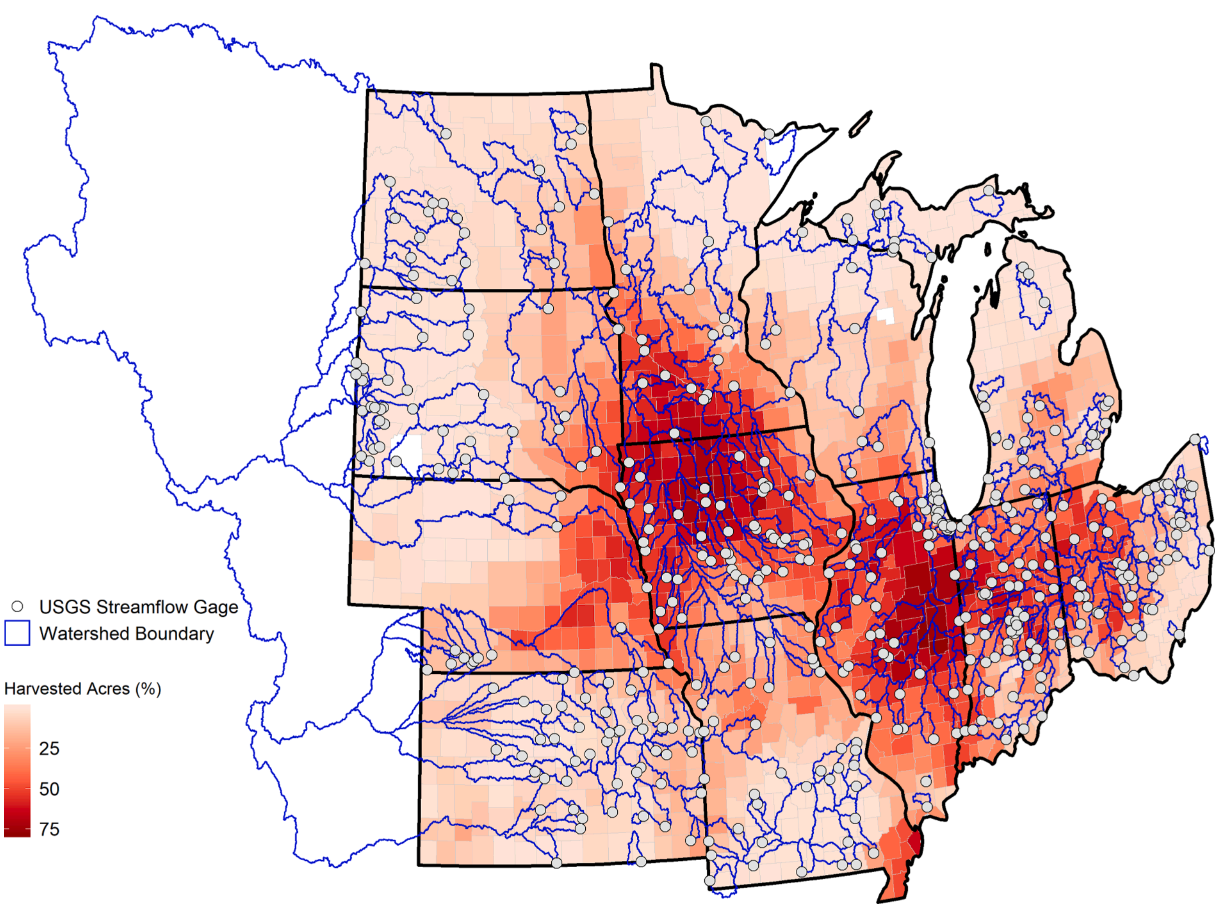

Fig. 1. Map showing the study area with the location of the 458 streamflow gages and the percentage of harvested acres of corn and soybeans within each county. The map shows data for agricultural intensity from 2018.

2. Materials and methods

2.1. Data

We selected 458 USGS stream gauges located within 12 different U.S. Midwest states, which include: Illinois, Indiana, Iowa, Kansas, Michigan, Minnesota, Missouri, Nebraska, North Dakota, Ohio, South Dakota, and Wisconsin (Fig. 1). While the gauges themselves are located within these 12 different states, their watershed boundaries extend outside of the region. The stations were chosen based on long-term gauging records where each record had at least 50 years of data. The record length was extended as far back as 1940 in some cases because of data availability; however, the oldest common year among the gauges is 1966. Mean daily streamflow data for these sites were downloaded from the USGS NWIS website (U.S. Geological Survey, 2016). Drainage areas of the catchments range from 19.63 km^2 to 1,074,586 km^2 with a median basin size of approximately 1525 km^2. Across all basins the range of mean annual baseflow ranges from 0.02428 to 1192 m^3/s with an average of 25.51 m^3/s.

To model historical monthly baseflow, basin-averaged precipitation, antecedent wetness (i.e., the previous three month's precipitation), temperature and agricultural land use were used as predictors in the model formulations (Table 1). Both monthly precipitation and monthly average temperature data were based on the Parameter-elevation Regression on Independent Slopes Model (PRISM) climate group (Daly et al., 2002). These data are freely available on a ~4-km grid resolution for the conterminous United States. PRISM data extend back to 1895 and thus cover the study period (1940–2019). For every USGS gauge, the monthly time series of mean monthly basin-average precipitation (and temperature) were calculated with the basin boundaries from the USGS Streamgage NHDPlus Version 1 (Stewart et al., 2006). We define antecedent wetness by using the previous month's precipitation as an approximation for basin wetness. Because there is insufficient soil moisture data for the last 50 years, defining it from precipitation observations is valuable for understanding water availability in the subsurface. The sum of the previous three months was used for modeling baseflow in the Midwest, but we also performed sensitivity analysis to examine the role of different weighting schemes (see Section 3.4).

To analyze land use changes, we considered the effects of agricultural intensity on baseflow. We used harvested acreage of corn and soybeans because they are the main crops that are grown in the study domain, and have been shown to be a significant predictor in similar studies (Neri et al., 2019; Schilling, 2005; Schilling et al., 2008; Slater and Villarini, 2017; Villarini and Strong, 2014). County-level data are obtained from the U.S. Department of Agriculture (USDA)'s National Agricultural Statistics Service (NASS) QuickStats database (USDA and NASS, 2020). Total annual corn and soybean harvested acres were computed as a weighted average for each watershed based on the percentage of each county within an individual watershed, assuming that the crops were evenly distributed throughout the county (e.g., Neri et al., 2019; Villarini and Strong, 2014). Annual agricultural intensity values were used in model selection because crops are typically grown on an annual cycle. Similar to Slater and Villarini (2017), we only considered agriculture in watersheds that had at least 30% of the area covered by corn and soybeans at any given point in the historical time series. This threshold limits the inclusion of agriculture as a predictor to those watersheds that experienced substantial land use change (in corn and soybeans) over the study record, and excludes those that would have a false signal (i.e., watersheds that change from 0.005 to 0.1%). Few observations were missing from each dataset, so when missing data were present in the record (in either baseflow, precipitation, temperature, or antecedent wetness), the data for that year were excluded from the analysis.

Table 1
Formulation of the four most common statistical models "Percent selected" includes the number of models selected out of all models for every month and site.

Model	Model Formulation	Percent Selected
Pr + Aw *Precipitation + Antecedent Wetness*	$log(\mu_1) = \alpha_1 + \beta_1 \cdot x_p + \gamma_1 \cdot x_m$	41%
Pr + Aw + Ag *Precipitation + Antecedent Wetness + Agriculture*	$log(\mu_3) = \alpha_3 + \beta_3 \cdot x_p + \gamma_3 \cdot x_m + \delta_3 \cdot x_{ag}$	20%
Pr + Aw + Te *Precipitation + Antecedent Wetness + Temperature*	$log(\mu_4) = \alpha_4 + \beta_4 \cdot x_p + \gamma_4 \cdot x_m + \delta_4 \cdot x_t$	13%
Aw *Antecedent Wetness*	$log(\mu_1) = \alpha_1 + \beta_1 \cdot x_m$	11%

2.2. Baseflow separation

Many different analytical methods have been developed to separate baseflow from streamflow (Arnold and Allen, 1999; Eckhardt, 2008; Lyne and Hollick, 1979; Nathan and McMahon, 1990; Sloto and Crouse, 1996). In this study, we used a hydrograph separation method, the one-parameter digital filter technique that was first proposed by Lyne and Hollick (1979). The recursive digital filter used for baseflow separation is mathematically expressed as (Arnold and Allen, 1999; Lyne and Hollick, 1979; Nathan and McMahon, 1990):

$$q_t = \alpha \times q_{t-1} + \frac{(1+\alpha)}{2} \times (Q_t - Q_{t-1}) \tag{1}$$

where q_t is the filtered direct runoff at the t time step; q_{t-1} is the filtered direct runoff at the t-1 time step; α is the recession constant; Q_t is the total streamflow at the t time step; and Q_{t-1} is the streamflow at the t-1 time step.

The recession constant, α, is the parameter that describes the rate at which streamflow decreases following a rainfall event. We used $\alpha = 0.925$ in our study because it has been shown to be an accurate value for watersheds in the U.S. Midwest, and studies have reported consistent results (Arnold and Allen, 1999; Nathan and McMahon, 1990). In addition, this method provides a quick and easy way to obtain a time series of baseflow which would otherwise be difficult to obtain for the 458 stream gauges analyzed in this study. Other methods would require more information about the bedrock and stream type which is not realistic across a large region such as the Midwest (i.e., the Eckhardt method; Eckhardt, 2005). Figure S1 shows an example (USGS station 05440000) of the streamflow hydrograph with the baseflow time series separated out. All baseflow separation calculations were performed in R using the EcoHydRology package (Fuka et al., 2018).

2.3. Statistical modeling

To describe variability in baseflow, we fit statistical models using precipitation (x_p), antecedent wetness (x_m), temperature (x_t), and agricultural intensity (x_a) as covariates. Our statistical modeling builds on the methodology described in Villarini and Strong (2014).

We selected the gamma distribution for modeling monthly baseflow because it has worked well for modeling streamflow and low flows across the study area (Slater and Villarini, 2017; Villarini and Strong, 2014). The gamma distribution has two parameters, which include the location, μ, and scale, σ, and they depend linearly on the predictors via a logarithmic link function. The variability of the μ parameter over time was described by one of 16 possible regression models that relate baseflow to the four covariates in our model. Four regression models are shown in Table 1 as examples for the most common model formulations. On the other hand, the σ parameter was held constant similar to previous studies (Slater and Villarini, 2017; Villarini and Strong, 2014). We modeled baseflow based on the parameterization in the Generalized, Additive Models for Location, Scale and Shape (GAMLSS; Rigby and

Stasinopoulos, 2005). The monthly models are probabilistic and provide a probability distribution for every year.

Model selection is based on the Bayesian Information Criterion (BIC; Schwarz, 1978), which balances statistical fit with model parsimony. It utilizes a larger penalty function than other criteria such as the Akaike Information Criterion (Akaike, 1978), and it generally suggests a model with fewer parameters. At each of the 458 sites and for every month, the best fit GAMLSS model (one out of 16 potential models) was chosen in terms of the predictors and their functional relation to the parameters of the probability distribution. We ran model selection only on those months that contributed greater than 5% of total annual baseflow. We also performed leave-one-out cross validation where for each year and month we removed the observation and predicted it using the remainder of the observations in the record; this process was repeated for every year until we obtained a complete time series. The cross-validation results were compared with the observed data using Pearson's correlation coefficient R.

2.4. Trend analysis

The Mann-Kendall (MK) nonparametric trend test (Kendall, 1948; Mann, 1945) was used to determine the presence of temporal trends in monthly baseflow. It is a rank-based statistical method that determines monotonic patterns in the central part of the distribution. Trend detection was run over the 1966–2018 record period because it is the common year for all stream gauges considered in this study. The MK statistic, Z, has the same interpretation as other trend-analysis statistics where a positive (negative) value indicates an increase (decrease) over time. To offset the potential impact of autocorrelation on the trend results, a variation of the MK test (i.e., prewhitening based on the approach described by Yue et al. (2002)) was used and the results are reported here. In this study, we set the significance level to 5%. We use this metric to assess how successful our models are at reproducing the observed trends in monthly baseflow.

3. Results and discussion

3.1. Statistical model fits

For each month's best fit model, the correlation coefficient was used as an assessment of the degree that the model simulations matched the observed baseflow records (Fig. 2). We also performed leave-one-out cross validation to evaluate the robustness of our model's predictive ability. Overall, the correlation coefficients were high with a mean $R = 0.70$ and median $R = 0.73$ for all months. This indicates the good prediction skills of these statistical models. Goodness-of-fit varies based on regional differences in climatic differences, antecedent conditions and the presence of agricultural land use. The model fit distributions are best fit during the summer months where average R values are 0.69, 0.72, and 0.71 in May, June, and July, respectively. We are still able to capture baseflow during periods of little to no precipitation which suggests that antecedent conditions play a large role in baseflow discharge.

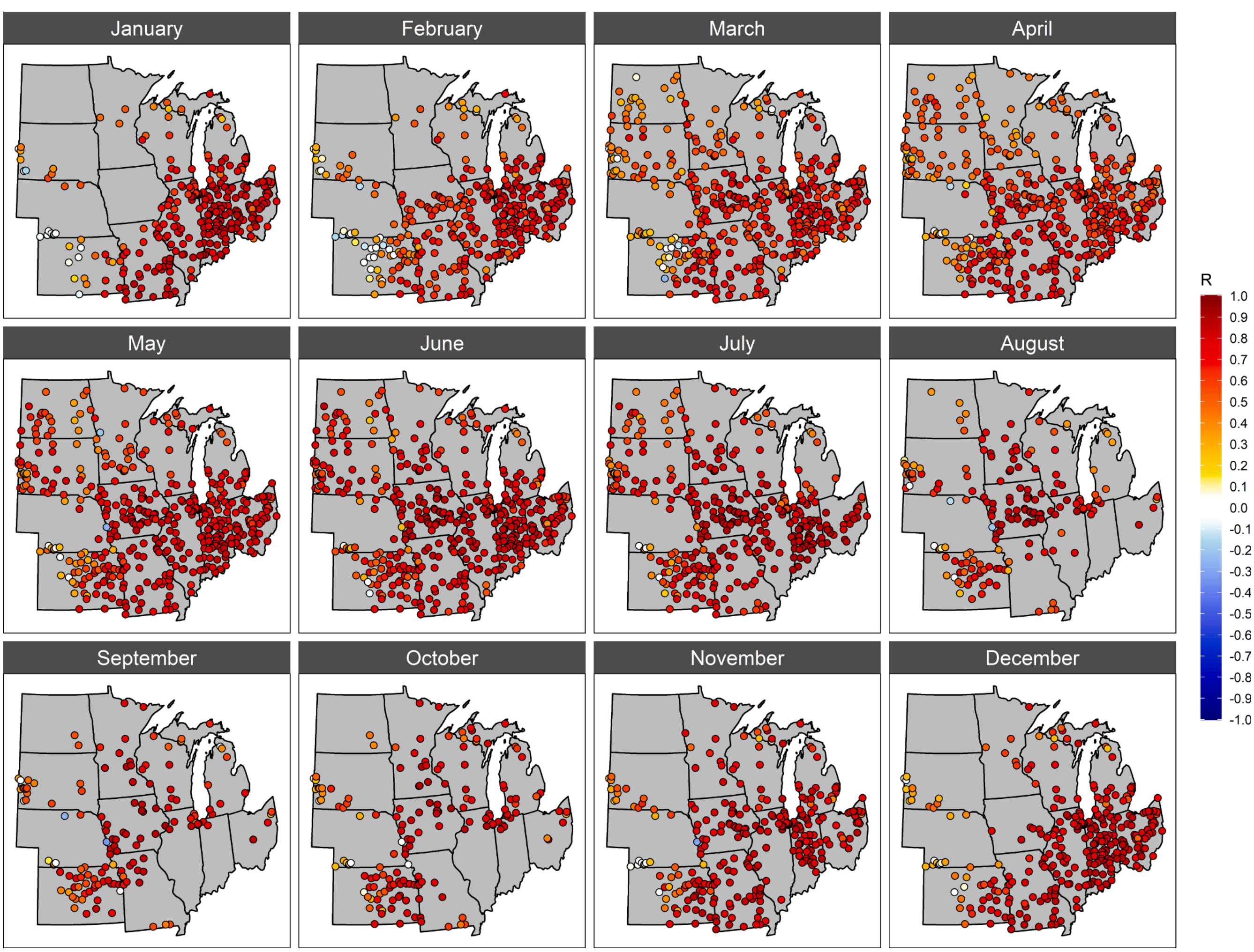

Fig. 2. Map of the Pearson correlation coefficient between the baseflow observations and the median of the best fitted model based on BIC for every month. For each site and month, model selection was only run if that month's baseflow contributed more than 5% of total annual baseflow.

Correlation coefficients have an average value of 0.71, 0.68, and 0.59 during December, January, and February, respectively. Models performed the worst in April (mean $R = 0.57$), and while it is comparatively low, it still indicates good correlation. These results show how monthly baseflow follows large-scale weather patterns in the study region (Andresen et al., 2012; Villarini, 2016).

Models exhibit the poorest skill in the western part of the domain (Nebraska, Kansas, South Dakota, North Dakota and northern Minnesota) where there is a difference in climate compared with the rest of the Midwest, and hydrologic response occurs later in the year because of snowmelt and rain on frozen ground in the spring (Neri et al., 2019; Villarini, 2016). Lower correlation is observed in Kansas and Nebraska which is a region where groundwater pumping is prevalent; a lowered water table from groundwater abstraction can alter lateral flow and decrease discharge from groundwater systems (Condon and Maxwell, 2019). While groundwater pumping for agricultural purposes may be correlated with one another, previous studies have shown that while pumping alone has caused decreases in streamflow, irrigation for agriculture may cancel out decreases on an annual basis (Brutsaert, 2008; Wang and Cai, 2010). Although we were not able to examine the relationship between baseflow and groundwater pumping in this study, it may be of interest for future research.

To further examine how well our models perform, leave-one-out cross validation was conducted for the best-fitting model at every site and month. The correlation coefficients for cross-validation were high (mean $R = 0.62$, median $R = 0.66$) which supports previous findings that our models exhibit good skills. These results highlight the potential applicability of these models for monthly baseflow forecasting (Neri et al., 2019; Slater and Villarini, 2018).

3.2. Forcing factors

The uniqueness of our statistical modeling framework is that it selects the best set of covariates to describe the response variable (baseflow); Fig. 3 shows which drivers were chosen in the model formulations (Table 1) at every streamflow gauge and for selected months. Supplemental material S2–S5 show the results for all months while Fig. 3 shows one month for each season (i.e., March, June, September, and December) for simplicity. We found that precipitation was a major driver across the region: 79% of the best-fitting models include it in the

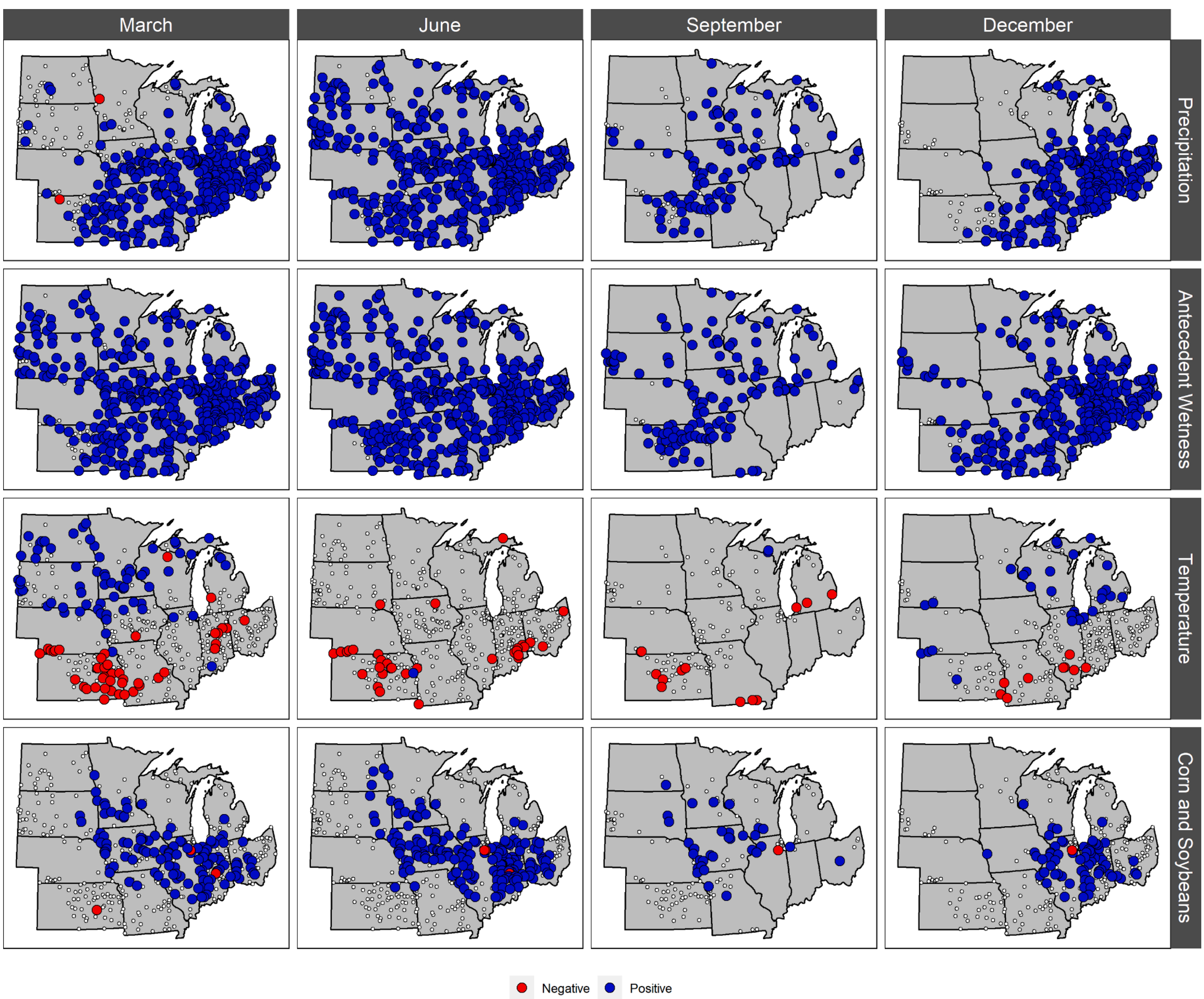

Fig. 3. The maps illustrate the relationship between monthly baseflow and monthly precipitation, monthly antecedent wetness, monthly temperature and annual corn and soybean harvested acres. Selected months (March, June, September and December) are shown here for simplicity. A colored circle indicates that each driver was selected in the model formulation where blue (red) indicates a positive (negative) relationship. A white circle indicates that model selection was run, but the driver was not selected at that site.

model formulation. As expected, increasing baseflow is positively related to precipitation because it is the major source of recharge to groundwater systems (Memon, 1995). From April to July, precipitation is chosen more often than other months of the year (between 77% and 93%). During the spring, the U.S. Midwest often receives large amounts of rainfall, which are often associated with extratropical storms and atmospheric rivers (Nayak and Villarini, 2017; Villarini, 2016).

Model selection for precipitation is different in the east compared to the northwest region. The precipitation-baseflow relationship is detected more often in the east during the winter. There are differences in weather patterns which have a strong control over water resources. It is wetter and warmer in the central and eastern Midwest than the west, and these patterns can be observed in the variability of the relationship between baseflow and precipitation. Precipitation is selected as a driver during the winter months mostly in the east (Missouri, Illinois, Indiana and Ohio). It is considered a major driver given that precipitation inputs determine water availability for soil moisture conditions which is relevant to baseflow. These results support the notion that increasing regional precipitation is the dominant driver of positive streamflow trends across the area (Frans et al., 2013; Hodgkins et al., 2007; Slater and Villarini, 2016; Tomer and Schilling, 2009).

Antecedent wetness was the most important driver in the U.S. Midwest because it was selected most often (i.e. 93% of the best-fitting models included x_m as a significant predictor). Similar to precipitation, a positive relationship between the two variables indicates that more moisture in the soil (from the previous three months precipitation) will lead to an increase in baseflow response. The model that was selected most often for all sites and months was the model that only considered antecedent wetness, x_m, and precipitation, x_p, in its model formulation (about 41% of sites; Table 1). It is well-established that basin wetness plays a major role in controlling the flow distribution, and it is especially important for low flows (Berghuijs et al., 2016; Slater and Villarini, 2017). Although baseflow is directly related to groundwater storage in a catchment, it also changes in response to precipitation events (Brutsaert, 2008). The ability of our models to capture baseflow during periods of little to no rainfall (from September-February) is largely dependent upon soil moisture. In the winter, wetter antecedent conditions paired with lower evapotranspiration rates could contribute to increased groundwater recharge and groundwater contribution to streamflow (Bosch et al., 2016).

The inclusion of temperature as a predictor in the model produced a better fit for certain subregions and specific months. About 21% of all the best fit models (for every site and month) identify temperature as a significant predictor. These results show how monthly baseflow follows a strong seasonal pattern of winter precipitation and spring snowmelt. In colder months (January-March) there is a notable positive relationship between baseflow and temperature. As temperature warms in the spring, the relationship between temperature and baseflow flips from positive to negative. The negative relationship is first observed in March in the south and east (Nebraska, Missouri, Indiana and Ohio) where temperatures get higher earlier in the year. Watersheds in higher latitudes hold snow for a longer time because temperatures are colder, and larger flows are not observed until later in the season when snow melts and the ground thaws (Byun et al., 2019). This phenomenon is observed with baseflow response in the northwest; continuing later into the spring the negative relationship gradually moves north (Iowa, Minnesota, the Dakotas) and from April to May most sites identify temperature as a significant, negative predictor. The inverse relationship between temperature and baseflow is expected because warmer temperatures increase evaporation and thus reduce soil moisture.

Temperature changes in the U.S. have trended towards warming over the past century. Trends in seasonality have been documented where a greater proportion of the regional warming has occurred in the winter and spring (Andresen et al., 2012; Kibria et al., 2016; Zhang et al., 2000) which have caused higher flows to occur in the winter and spring. There is also evidence that mean summer temperatures have decreased in sections of the U.S. Midwest (Andresen et al., 2012; Mueller et al., 2016) which could explain the inverse relationship between temperature and baseflow from April to July because increasing trends in baseflow have been documented throughout the region during these months (Ayers et al., 2019). In addition, cooling in the U.S. Midwest is often associated with agricultural intensity and evapotranspiration which could magnify this effect (Pan et al., 2004; Zhang et al., 2000).

The influence of agricultural land use on baseflow is prominent in the Cornbelt region of the study area. Corn and soybean harvested acres are selected more often in the growing season (in watersheds with more 30% of agricultural land cover, where x_a was included as a potential predictor). Beginning in March and continuing into the summer is when models selected agriculture most often (i.e. 24% in March, 34% in May, 41% in June, and 34% in July). For these months, the Cornbelt region is clearly highlighted in an arc from eastern North Dakota and into Iowa, Illinois, Indiana and western Ohio. Most sites show a positive relationship between annual harvested acres and monthly baseflow. These results indicated that increases in agricultural land use have increased baseflow for watersheds with greater than 30% agricultural land use. While we can identify that agricultural intensity has influenced baseflow in the U.S. Midwest, we can only speculate about the specific mechanisms that are related to baseflow; for example, Schilling and Libra (2003) theorized that land use conservation practices, such as terraces, conservation tillage and contour cropping have contributed to increasing baseflow by slowing runoff and increasing infiltration in sloping agricultural fields. No-tillage practices can prevent early season soil evaporation and conserve water in the soil (Gallaher, 1977). On the other hand, tile drainage is one of the major changes in agricultural landscapes, and it has significantly altered the hydrologic regime across the region. Both tile drainage density and incision depth affect baseflow where increasing density and depth can increase tile contribution to baseflow (Schilling et al., 2012; 2019). To understand the exact mechanisms of agricultural land practices and their influence on baseflow, we would need a different modeling framework than what is considered in this study.

3.3. Monthly trend detection

To validate our model predictions, trend analysis was conducted on the monthly baseflow record from 1966 to 2019. We compared the trend results from the observed baseflow record to the results from the median value of the fitted gamma distribution. Fig. 4 illustrates the spatial variability of the prewhitened Mann-Kendall observed and predicted (using the 50th percentile of the fitted gamma distribution) time series. Fig. 4 shows a side by side comparison using only four months, but the analysis was conducted for every month. The observed trends were described in detail in Ayers et al. (2019), and the goal here is not to analyze these trends. Rather we want to evaluate if our models can recreate the observed trends in monthly baseflow in terms of the drivers we have identified. Overall, the model predictions are good at reproducing monthly trends in baseflow. From May to August the two results agree the most when increasing trends are detected more often. On the other hand, the differences in trend analyses are the largest in both the southwest (Kansas, Nebraska and southern Missouri) and in the Great Lakes Region (northern Wisconsin and Michigan). Interestingly, these are both areas where decreases in baseflow have been identified in the baseflow record. The areas in Kansas and Nebraska are where groundwater abstraction has led to declining water tables (Brikowski, 2008; Sophocleous, 2005; Wen and Chen, 2006). In the Great Lakes region decreases in precipitation have been documented which may result in decreases in baseflow (Mallakpour and Villarini, 2015; Norton et al., 2019).

To evaluate the model results further, we compared the MK tau values between the observed and leave-one-out-cross validation trend results. Fig. 5 illustrates the how well the values match via the one-to-one line where each point is color coordinated by the correlation

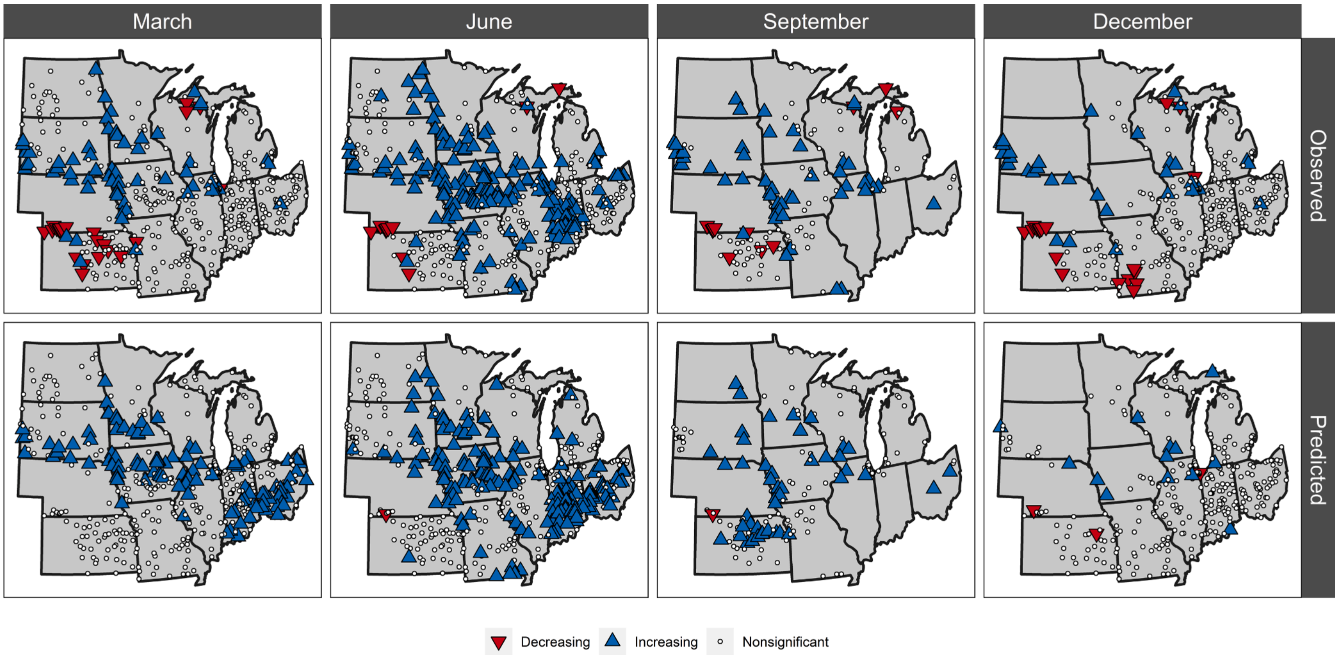

Fig. 4. Results of the Mann-Kendall trend test applied to prewhitened time series data in the presence of serial correlation using the approach described by Yue et al. (2002). Observed and predicted (median of the probabilistic model fit) trends were analyzed from 1966 to 2019 with a 5% significance level. A blue upward (red downward) arrow shows an increasing (decreasing) trend, but a white circle indicates a site that documented no statistically significant trend. The observed trend results modified from Ayers et al. (2019).

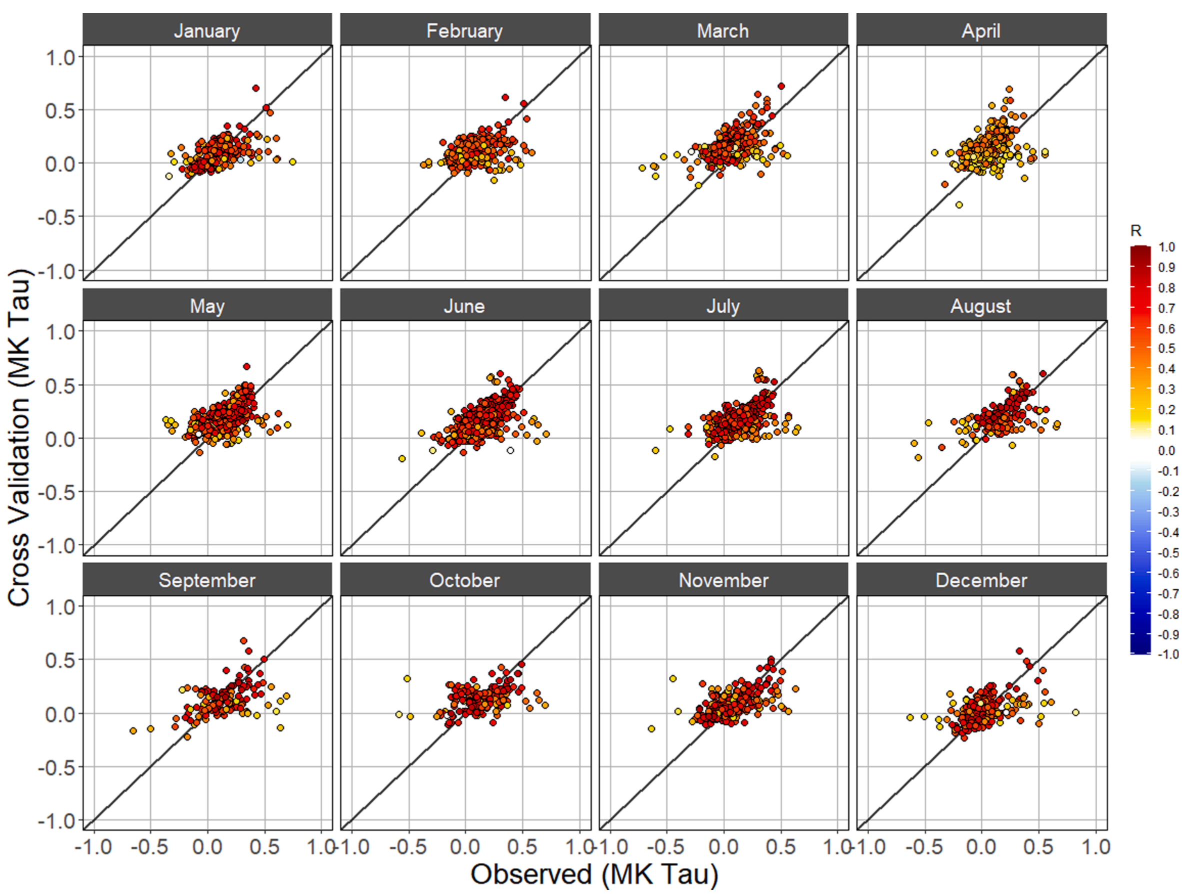

Fig. 5. Figure showing the agreement of the MK's tau values between the observed and the leave-one-out-cross validation trend results over the 1966–2019 period. Each point is color coded based on the correlation coefficient between the observed and leave-one-out-cross validation time series.

coefficient between the two baseflow time series. For all months, most values are clustered around the one-to-one line indicating good model fit with little to no bias. The correlation coefficients of the leave-one-out-cross validation have high R values (mean $R = 0.62$, median $R = 0.66$). Values that deviate from the one-to-one line for MK tau are generally those that have lower correlation coefficients, as expected.

3.4. Sensitivity analysis of antecedent wetness

We performed a sensitivity analysis to determine which definition of antecedent conditions was most relevant to baseflow. The sum of the previous three months precipitation described above was compared with different ways of weighing them, including: 0.90 and 0.70 given to the previous month, 0.10 and 0.20 given to the second month, and 0 and 0.10 given to the third month, respectively (Supplemental Materials S6 and S7). As an example, for June, antecedent wetness was defined as 90% of May's precipitation, 10% of April's precipitation, and no consideration for March. To determine which metric was most suitable, we ran our GAMLSS model for each definition and compared the results. The sensitivity analysis showed that the sum of the previous three months was the best metric for modeling baseflow in the U.S. Midwest. We concluded that the sum of the previous three month's precipitation captures subsurface water availability better than the different weighted values analyzed here.

4. Conclusions and future directions

Our study described a method for evaluating the drivers of monthly baseflow in the U.S. Midwest. We focused on 458 long-term USGS stream gauges and developed statistical models that describe the inter-annual variability in monthly baseflow with different combinations of predictors (precipitation, antecedent wetness, temperature and agriculture). We used leave-one-out cross validation and the Mann-Kendall trend test to verify our results. The outcomes of this study can be summarized as follows:

1. Despite the simplicity of these statistical models, they are able to capture well the monthly variations in baseflow throughout the U.S. Midwest (mean $R = 0.70$); however, there were differences in model fits across the region and for different months. Generally, the models fit better during warm months (May-July) and in the central and eastern part of the U.S. Midwest. The robustness of these results was also supported by the leave-one-out cross validation (mean $R = 0.62$).
2. Most models included both precipitation and antecedent wetness, and the model formulation that was selected most often included only these two predictors (41% of the best fit models for all months). Antecedent wetness was the most important predictor (92% included x_m) followed by precipitation which was selected 79% of the time.
3. Temperature was not a strong predictor (21%) but its inclusion from March to May produced a better fit in some areas like in the west and northwest. In the spring it is evident that temperature, likely through the effect of snowmelt, significantly influences monthly baseflow.
4. Agriculture was selected as a relevant predictor most often during the growing season (from March to July). There was a positive relationship between agriculture and baseflow in the Cornbelt region which indicates that corn and soybean production promote baseflow discharge to streams.
5. To further evaluate the performance of the modeling framework, we used the model formulations to identify monthly trends in baseflow. We compared the prewhitened MK trend analysis results from the observed monthly baseflow record to the median of the fitted distribution. We found the same trends for most stations within the U.S. Midwest; however, our models were unable to capture the decreasing trends in Kansas, Nebraska, southern Missouri, and in northern Wisconsin and Michigan which is likely due to the role of other drivers not included as predictors (e.g., groundwater withdrawal).
6. Overall, these results paint a different picture due to the role of agriculture compared with similar studies that focused on flooding and the frequency of flood events (e.g., Neri et al., 2019; Slater and Villarini, 2017), in which agriculture was not selected as an important predictor; it appears that agricultural intensity plays a more dominant role at the lower end of the discharge spectrum.

Building on this study, there are a number of future research directions that this work could be taken. For instance, it could be of interest to evaluate the influence of specific mechanisms behind land use or climate change (e.g., tile drainage, conservation practices, evapotranspiration or groundwater pumping), assess the interaction between baseflow drivers (e.g., land use on soil moisture conditions), examine future changes in baseflow based on projections of predictors, and quantify the relationship between baseflow and indicators of water quality. Although future research is needed to determine the influence of forcing factors in other regions of the world, our work provides a clear framework to understand and describe baseflow in the context of climate and land use change. Ultimately, these models show the potential applicability for monthly baseflow predictions and projections.

CRediT authorship contribution statement

Jessica R. Ayers: Conceptualization, Formal analysis, Methodology, Software, Formal analysis, Writing - original draft. **Gabriele Villarini:** Conceptualization, Methodology, Writing - review & editing, Funding acquisition. **Keith Schilling:** Validation, Writing - review & editing. **Christopher Jones:** Validation, Writing - review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jhydrol.2020.125551.

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