Projected changes in monthly baseflow across the U.S. Midwest

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Abstract

Baseflow is an essential water resource because it is the groundwater discharged to streams and represents long-term storage. Understanding its future changes is a major concern for water supply and ecosystem health. This study examines the impacts of climate and agriculture on monthly baseflow in the U.S. Midwest through the end of the 21st century. We use a statistical approach to evaluate three scenarios. The first scenario is based on downscaled and bias corrected Global Climate Model (GCM) outputs and the Representative Concentration Pathway (RCP) 8.5, and agriculture is held constant (and equal to the mean from 2013-2019). In the next two scenarios, climate is held constant (2010-2019) to isolate the impact of agriculture on baseflow. In terms of agricultural changes, we consider scenarios representative of either increases or decreases with respect to the production of corn and soybeans. Changes in the climate system point to increases in baseflow that are likely a result of increased precipitation and antecedent wetness. Seasonally, warmer temperature in the winter and spring (i.e., February to July) is expected to cause increasing trends in baseflow. Changes in land use showed that agriculture would either mitigate the impact of climate change or possibly amplify it. Expanding corn and soybean areas would increase baseflow in the Corn Belt region. On the other hand, converting land back to perennial vegetation would decrease baseflow throughout the entire year. Despite its simplicity, this study can provide basic information to understand where to expect adverse effects on baseflow and thus improve land management practices in those areas.

Introduction

In the U.S. Midwest, climate change is expected to cause more intense precipitation with longer, drier periods between events (e.g., Ukkola et al., 2020; USGCRP, 2018). There is evidence that drought-induced stress on water supply and crop production will increase reliance on groundwater (e.g., Jin et al., 2017; Phung et al., 2019). Groundwater that is discharged to streams is referred to as baseflow, and it is what sustains flow between precipitation events (Brutsaert, 2008). Baseflow also represents minimum streamflow conditions needed to sustain ecological health, farming and drinking water supply. Given that baseflow can stabilize streamflow and water supply during droughts, it is important that we analyze how future climate and land use changes are expected to influence it.

Baseflow in the U.S. Midwest has changed over the last half century because of climate and agriculture (Ahiablame et al., 2017a; Ayers et al., 2019; Buttle, 2018; Xu et al., 2013). Specifically, increases in baseflow have been linked to increases in precipitation, soil moisture and corn and soybean areas, while decreases have been attributed to increasing temperature and decreasing precipitation (Ayers et al., 2020; Ficklin et al., 2016; Schilling and Libra, 2003). Temperature influences baseflow differently depending on the time of year where warmer temperature is associated with increases (decreases) in winter (summer) (Hellwig et al., 2020; Ayers et al., 2020). Increasing greenhouse gas emissions have already been documented and are expected to intensify hydrologic regimes in the future (IPCC, 2007; Wuebbles and Hayhoe, 2004). Winter warming will likely continue to influence the timing and type of precipitation which influences groundwater recharge and seasonal baseflow (Barnett et al., 2008; Carroll et al., 2019). Previous studies have found a tendency towards increasing trends in precipitation, especially in the extremes (e.g., Byun et al., 2019; Southworth et al., 2000; Villarini et al., 2013). These projected changes can have differing effects on baseflow trends, and we need to understand their influence in combination with land use change.

There is evidence that increasing baseflow in the U.S. Midwest is partly related to historical changes in agriculture (Ayers et al., 2020; Schilling, 2005; Schilling et al., 2008). Since the 1940s small grains and diverse perennial cropping systems have been converted to annual corn and soybean row crops which altered the water balance of these watersheds (Zhang and Schilling, 2006). Agricultural land management practices associated with corn and soybean production can have differing effects on baseflow. Tillage changes infiltration and runoff processes, which affect recharge to groundwater and delivery of water and sediment to surface water (Winter et al., 1998). In the Midwest, corn and soybeans are related to subsurface drainage that drains soils and lowers the water table. Tile drains predominantly affect the baseflow portion of streamflow, and are a contributing factor to increasing baseflow trends (Arenas Amado et al., 2017; Schilling and Helmers, 2008; Schilling and Libra, 2003). On the other hand, groundwater pumping has been shown to reduce baseflow because pumping removes aquifer storage available for discharge (Kundzewicz and Doll, 2009; Wen and Chen, 2006). Although agriculture and associated land management practices significantly altered baseflow in the past, we do not know how these patterns will continue to impact baseflow, especially given the projected changes in the climate system.

Previous studies usually focused on the effect of climate and land use to streamflow (e.g., Ahiablame et al., 2017b; Byun et al., 2019; Cherkauer and Sinha, 2010; Chien et al., 2013; Koirala et al., 2014; Kundzewicz et al., 2008; Villarini et al., 2015); however, it is difficult to know how subsurface water will respond to changes since the relationship is more complicated (Green et al., 2011). Numerical groundwater flow models are useful because they can incorporate complexities associated with linking climate change to groundwater recharge, discharge, and withdrawal (e.g., Hanson et al., 2012; Peterson et al., 2020). Because physical models are computationally demanding, their application is limited over large regions; however, previous studies can provide useful insight into factors driving the direction and magnitude of future baseflow trends. Some studies have indicated baseflow will increase, but the results tend to be more difficult to discern than streamflow (e.g., Cherkauer and Sinha, 2010; Demaria et al., 2016; Ghafouri-Azar et al., 2021; Kahsay et al., 2018; Maurer et al., 2010). Baseflow in mountainous regions has been studied extensively because of shifts in snowmelt timing that may cause baseflow discharge earlier in the year (e.g., Barnett et al., 2005; Huntington and Niswonger, 2012; Stewart et al., 2005). Other studies have analyzed the impact of projected climate change on baseflow, but in other parts of the world (e.g., Eckhardt and Ulbrich, 2003; Hellwig and Stahl, 2018; Kahsay et al., 2018; Li and Zhang, 2018; Nyenje and Batelaan, 2009; Peterson et al., 2020; Samuel et al., 2012) or on a larger, global scale (e.g., Koirala et al., 2014). Because statistical models are less computationally intensive and are easier to implement over large regions, they can help fill in the gap to project changes in baseflow.

To date, no studies have sought to examine how future climate and land use changes will affect baseflow in the U.S. Midwest through the end of the 21st century, which is what this study addresses. We use a statistical modeling framework to relate changes in baseflow to changes in precipitation, temperature, antecedent wetness and harvested acres of corn and soybeans (i.e., agriculture in the region) on a monthly scale. The statistical models are driven by downscaled and bias corrected climate projections from two ensembles of Global Climate Models (GCMs) under the Representative Concentration Pathway (RCP) 8.5. To account for changes in agriculture we assess three difference scenarios where harvested acres of corn and soybeans remain constant, increase or revert back to perennial vegetation.

2. Methods

2.1 Data

In this study, we focus on the U.S. Midwest, which includes 10 states: Illinois, Indiana, Iowa, Michigan, Minnesota, Missouri, North Dakota, Ohio, South Dakota, and Wisconsin (Fig. 1). We considered 393 U.S. Geological Survey (USGS) streamflow gages that had a record of at least 50 years of data (dating back to a common year of 1966). Daily mean discharge was downloaded from the USGS NWIS website (U.S. Geological Survey, 2016). These data were used to obtain a time series of monthly mean baseflow via a hydrograph separation method. The one-parameter digital filter method first proposed by Lyne and Hollick (1979) was used because it is consistent with what was used in Ayers et al. (2020) and was validated in other studies (Arnold and Allen, 1999; Ladson et al., 2013; Xie et al., 2020; Zhang et al., 2017). This method uses a single baseflow filter parameter, the recession constant (α), and represents the rate that streamflow declines after a precipitation event. We used $\alpha = 0.925$ because it has been shown to be an accurate value for catchments in the Midwest (Arnold and Allen, 1999; Nathan and McMahon, 1990). Digital filter methods also provide a quick and easy way to create a time series for baseflow. All baseflow separation calculations were performed in R using the EcoHydRology package (Fuka et al., 2018).

The historical meteorological data were obtained from the Parameter-elevation Regression on Independent Slopes Model (PRISM) climate group (Daly et al., 2002). Temperature and precipitation are available on a ~4-km grid resolution for the conterminous United States, and extend back to 1895. For every USGS gage, the monthly mean precipitation and temperature were calculated as basin average values using the boundaries from the USGS Streamgage NHDPlus Version 1 (Stewart et al., 2006). As an approximation for basin wetness, antecedent wetness was calculated as the sum of precipitation from the three months prior to the current month (Neri et al., 2019; Slater and Villarini, 2017). Antecedent wetness defined using the sum of the previous three months' precipitation has been found to capture subsurface water availability for baseflow conditions (e.g., Ayers et al., 2020). In addition, soil moisture data are insufficient for analyzing baseflow response over the last 50 years, and precipitation data are easily obtained from the GCM outputs used in this analysis. These data were used as input to our modeling framework and then for comparison with climate projections, consistent with Ayers et al. (2020).

To simulate baseflow through the end of the 21st century, projections of monthly precipitation and temperature were obtained from two different datasets: the North American Coordinated Regional Downscaling Experiment (NA-CORDEX; Mearns, 2017) and the Localized Constructed Analogs (LOCA; Pierce et al., 2014). The NA-CORDEX is a data archive that provides output from regional climate models (RCMs) run over most of North America. It uses boundary conditions from GCM simulations in the Coupled Model Intercomparison Project 5 archive (CMIP5; Taylor et al., 2012). These simulations run on a monthly scale from 1950-2100 at a spatial resolution of 0.22º (about 25 km). We considered ten members of the NA-CORDEX which were generated using five GCMs that provided initial boundary conditions to five RCMs, although not every RCM was used for each GCM. LOCA is a statistical downscaling technique that simulates daily precipitation, and daily minimum and maximum temperature. Here we used the mean of the minimum and maximum temperature to calculate an average monthly time series. These data use outputs from GCMs part of the CMIP5 archive, and have a $1/16^{th}$ degree spatial resolution. We used all 32 members from downscaling 32 GCMs.

We considered the historical period from 1950 to 2005 and compared the simulations to observational data. The projection period spans from 2006 to 2100, and we focused on the RCP 8.5 for both NA-CORDEX and LOCA. We focused on the RCP 8.5 because that is what is currently available in the NA-CORDEX dataset for their higher-resolution (0.22□) RCM simulations. Within the NA-CORDEX dataset, other RCPs were only available on a resolution of 0.44□. Thus, they were not included because of uncertainties related to coarser data at the regional scale (e.g., Qian and Zubair, 2010). RCP 8.5 also provides the most extreme scenario in terms of radiative forcing which is expected to increase to 8.5 W m^{-2} from continued greenhouse gas emissions (Taylor et al., 2012). However, we acknowledge that our results do not capture the uncertainties associated with the response of the regional climate to different scenarios.

GCM projections were used to compute a basin-averaged time series of monthly average temperature, total precipitation, and antecedent wetness. To mitigate issues related to inter-model variability, we calculated the ensemble mean for each basin where each GCM member had equal weight (Meehl et al., 2009). The delta-change method was used to bias correct the ensemble mean of the NA-CORDEX and LOCA (Maraun, 2016). This approach was selected because it is simple, and it allows the structure of the projected time series to closely follow the observed one (Räty et al., 2014). We used a modification of the delta-change method that corrects the variance in the projected time series according to the observations, similar to what was done in Neri et al. (2020). The correction of the mean involved shifting the time series by the average difference between the simulated and observed data over the historical time period (1950-2005). The standard deviation of the shifted GCM time series was normalized so that it matched the standard deviation of the observations over the historical period. Fig. 2 shows an example (USGS site 03091500 at Mahoning River near Princetown, OH) of the monthly time series for the NA-CORDEX and LOCA projections.

For land use and land cover change we only considered agriculture defined as the fraction of land dedicated to corn and soybeans within a basin. Total harvested acres for each crop are reported at the county level from the U.S. Department of Agriculture (USDA)'s National Agriculture Statistics Services (NASS) database (USDA; NASS, 2020). Following previous studies (e.g., Ayers et al., 2019; Neri et al., 2019; Slater and Villarini, 2017; Slater et al., 2017), we obtained a time series for the annual harvested acres of combined corn and soybeans reported as a percent of the total watershed area. We calculated it as the fraction of the county within each basin multiplied by the total agricultural acreage of that county. We assumed that the agricultural area is uniformly distributed within each county, and then summed the values for all counties. Agriculture was only considered in model selection if the percentage of land dedicated to corn and soybeans was greater than 30% at any point in the time series.

To consider future changes in agriculture, we used a simple approach that did not require outputs from GCMs. We used the observed basin averaged harvested area to consider two potential agricultural scenarios (i.e., increases or decreases). Since the 1940s there has been an increase in the percent of corn and soybean across the Corn Belt region. For each watershed, we fit a logistic function to the USDA annual time series over the historical period, which allowed us to compute projections in agriculture through the end of the 21st century using time as a variable. The increased agricultural scenario assumed that corn and soybean areas will continue to increase at approximately the same rate as over the recent past. The decreasing agriculture scenario accounts for decreases by assuming that the fraction of land cultivated in corn and soybeans is reverted back to pre-1940s production by 2100.

2.2 Statistical modeling framework

The models build on the methodology described by Ayers et al. (2020) who showed how baseflow, Q_i, can be modeled using a gamma distribution where the parameters depend on covariates. The parameterization was based on the Generalized Additive Models for Location, Scale and Shape (GAMLSS; Rigby and Stasinopoulos, 2005), and has two parameters, μ and σ. The location parameter, μ, for each month and each watershed was described by one of 16 possible models that related baseflow to the four covariates (predictors): precipitation (x_p), antecedent wetness (x_m), temperature (x_t), and agricultural intensity (x_a). Table 1 shows the results of the five most commonly selected models. Model selection was based on the Bayesian Information Criterion (BIC; Schwarz, 1978). For every month, the analysis was only run if that month contributed more than 5% of total annual baseflow.

We fit the models to each station and month from 1940-2019 (start date depends on data availability). The parameters were estimated for each of the best-fit models and a time series for predicted monthly baseflow was obtained using observations as inputs to the models. Model performance was evaluated by calculating the correlation coefficient between observed and predicted (median of the probabilistic model fit) baseflow (see also Ayers et al. (2020)). To obtain a future time series of monthly baseflow, we used the model created over the historical time period but with inputs from climate and agriculture projections. For each scenario, we did not combine the effect of climate and agriculture together. Rather, to differentiate the role of each driver, either climate or agriculture was held constant in the model formulation. We examined baseflow response to climate change by using NA-CORDEX and LOCA projections (i.e., precipitation, temperature and antecedent wetness) while agriculture was held constant by calculating the mean of the percent total harvested area from the previous six years (2013-2019). These years were selected because they are the most recent and exclude the 2012 drought as an outlier. To isolate the effects of agricultural changes, climate was held constant by computing the average over the most recent decade (2010-2019). For the agricultural scenarios, the analysis was only performed for watersheds and months that historically selected agriculture as a predictor in the model formulation.

To identify statistically significant baseflow trends in both the historical and projection periods, the Mann-Kendall (MK) trend test was used (Kendall, 1948; Mann, 1945). It is a nonparametric, rank-based test that determines monotonic trends in a time series. To be consistent with Ayers et al. (2019), we used a modification of the MK test, the pre-whitened MK statistical test (Yue et al., 2002) that removes a lag-one autoregressive (AR(1)) process from the time series (consult Serinaldi and Kilsby (2016) for a discussion of the limitation of using this type of test and correction). We set the significance level to 5%. Statistical analyses were performed on the baseflow time series for each streamflow gage and for every month over the historical and projection periods. For trend analysis, we focused on the historic period of 1950-2005 because that is the common period for the GCM historic projections. The MK test was run using the longest period of record possible for each watershed, dating as far back as 1950, but no later than 1966 which is the common year for discharge data.

3. Results and Discussion

3.1 Model performance and comparison of historical trends

Before we examine future changes in monthly baseflow, we need to understand how well our models and the GCM simulations reproduce baseflow trends. First we compared observed trends to those predicted using the PRISM dataset over the historical period (1950-2005). Then the results of the NA-CORDEX and LOCA were examined for the same period. The climate data varied for each historical run, but the observed USDA harvested acres of corn and soybeans were used as inputs for agricultural watersheds. Fig. 3 illustrates the trend results using each climate dataset, and Fig. 4 highlights differences between the observed trends and the respective datasets (i.e., PRISM, NA-CORDEX and LOCA). Figs. 3-4 show one month for each season (i.e., March, June, September, and December) for simplicity while supplemental material S1-S2 show the results for all months.

The comparison between the observation and the median of the models using the observed predictors showed uncertainties inherent in the statistical models (Figs. 3-4, column 2). The statistical models captured the increasing trends in monthly baseflow well. While there are many similarities, especially in the central and eastern parts of the U.S. Midwest, the observations detected more increasing trends overall. Trends are reproduced better from May to August, which coincides with when the models performed best (Ayers et al., 2020). In the Corn Belt region, there were more matches likely as a result of an additional parameter (i.e., corn and soybeans) selected in the models during the growing season (Fig. 4). The model predictions differed in statistical significance the most during the winter. In December and January, mismatches were observed in the Ohio River basin and in Missouri. In May, the models had difficulty capturing trends in North and South Dakota, likely as a result of snowmelt processes. The models also failed to detect significant decreasing trends in the Great Lakes Region which points to their inability to capture the relationship of baseflow with decreasing precipitation and increasing minimum temperature in this area (Norton et al., 2019). Although the models have limitations for some months and areas, they perform well overall. This simple modeling framework captures tendencies in baseflow response across the region, demonstrating that it is suitable to project trends in monthly baseflow.

Trend analysis using NA-CORDEX and LOCA ensemble means yielded errors due to the GCMs' skill to reproduce the historical regional climate. The models were run with monthly climate projections and observed annual corn and soybean harvested area (Fig. 3, columns 3-4). Although differences in observations and model predictions were carried over into the projected trend results, there was strong agreement between observations and projected trends (Fig. 4). For NA-CORDEX and LOCA there was strong agreement in terms of increasing trends. The location of the trends followed a similar pattern from March to June (in Iowa, Illinois, Indiana), but there were noticeable differences between the two datasets. Overall, the trends by the NA-CORDEX reproduces those by the observations more closely than LOCA. For simplicity and to avoid redundancy, we will only report trend results from NA-CORDEX in the following sections. We recognize that the performance of projections over the historical period does not demonstrate their ability to capture future trends; however, NA-CORDEX has higher-resolution simulations that may be better suited to capture local climate trends because of its more realistic representation of topography and mesoscale processes (e.g., Gao and Schlosser, 2019; Karmalkar, 2018; Martynov et al., 2013; Qian and Zubair, 2010; Wang and Kotamarthi, 2015; Zhu and Liang, 2007). While the models and data have limitations, this approach allows us to assess changes in baseflow response.

3.2 Climate and land use change impacts to baseflow

Here we examine three different scenarios to analyze how predictors (i.e., precipitation, temperature, antecedent wetness and agriculture) will impact baseflow through the 21st century. Fig. 5 displays the trend results for all three different scenarios (climate change, increases to agriculture and decreases to agriculture, with respect to corn and soybeans). We start with the simplest, baseline scenario because only changes in climate were accounted for (Fig. 5, column 1). We only show the results for one month from each season (i.e., March, June, September, and December), but trend detection was run for every month (see Figs. S3-S4 for all months for both NA-CORDEX and LOCA). First, we used projections of monthly precipitation, temperature, and antecedent wetness, and annual combined corn and soybean crop area was kept constant (set to the mean from 2013-2019) in the models. Overall, more increasing than decreasing trends were present from January to July. Positive baseflow trends will likely be the result of increases in precipitation and subsequent increases in soil moisture which are the two main drivers of baseflow in the U.S. Midwest (Ayers et al., 2020). GCMs have shown that the frequency and intensity of precipitation are expected to increase across the region, especially in the spring and winter (e.g., Byun and Hamlet, 2018; Easterling et al., 2017; Jha et al., 2006; Villarini et al., 2013; Wuebbles and Hayhoe, 2004).

Projected baseflow trends displayed potential changes to the seasonality of discharge. Beginning in January, increasing trends were present in the eastern part of the study region (i.e., Ohio, Indiana and southern Michigan), and moving into February increasing trends were located further west. As temperatures increase in March, increasing trends were detected across the entire domain and increases persisted into the summer. By August, few increasing trends were concentrated in the central part of the domain (i.e., Minnesota, Iowa, Wisconsin, and Illinois), but increases were no longer present in the southeast where they occurred earlier in the year (January and February). There were few increases in baseflow from September to December. This shift in baseflow timing suggests temperature will be a driving factor in the future. Warmer temperatures in the winter and spring have been associated with an earlier onset of snowmelt and more precipitation falling as rain particularly in the Missouri River Basin (Rosenberg et al., 2003; Woodhouse and Wise, 2020). By the end of the summer and in the fall, baseflow trends showed little to no change possibly from decreases (or no change) in precipitation or because the influence of precipitation will be outweighed by warmer temperature and higher evapotranspiration. Interestingly, the results using LOCA had a more pronounced shift in seasonality than NA-CORDEX where increases were no longer present by July (Fig. S4). These findings agree with other regional analysis that have shown a shift in precipitation earlier in the spring and decreases in the summer by the end of the century (e.g., Cherkauer and Sinha, 2010; Winkler et al., 2012; Wuebbles and Hayhoe, 2004). Although precipitation in the late summer may decrease, the results of this study suggest that the absence of rain paired with warmer temperatures will not change baseflow, indicating the importance of antecedent conditions.

Baseflow is projected to decrease in the Dakotas for some months (i.e., April, May and July). In this area of the upper Missouri River basin, streamflow decreases have already been reported because of spring and summer temperatures that have increased the amount of precipitation falling as snow, leading to drier conditions later in the year (Wise et al., 2018; Woodhouse and Wise, 2020). Decreases to snowpack will likely persist in a warmer future, and be a driving factor for baseflow trends. In April, there are widespread decreasing trends in baseflow across the region for both NA-CORDEX and LOCA (Fig. S3 and S4). Temperature may be a significant factor for trends, potentially as a result of increased temperature outweighing the influence of precipitation and antecedent wetness. However, our model also performs poorly during April (Ayers et al., 2020), so there is some uncertainty in interpreting decreasing trends reported for this month.

To understand the influence of agriculture, baseflow simulations were run based on increases in corn and soybeans with the climate projections previously analyzed (Fig. 5, column 2 and Fig. S5). In this scenario, climate change was not accounted for in combination with agriculture (i.e., it was held constant to the average of the 2010-2019 period) in the model formulation). Increases to agricultural watersheds assumed that the fraction of total cropped area would increase at the same rate since the 1940s. Increasing crop area indicated increasing trends in baseflow in the Corn Belt Region (i.e., Iowa, Illinois and Indiana). Increasing trends were detected for nearly all months that agriculture was selected as a predictor in the model formulation, which highlights the direct relationship between the two variables, and shows the control that land use has on baseflow throughout the year. These results suggest that if we continue to expand the land area dedicated to corn and soybeans there will be more baseflow discharged to streams. There is also a potential for land use to intensify climate change and amplify increases to baseflow (Ahiablame et al., 2017b).

Compared to the native land covers of prairie, wetland and forest, corn and soybeans have caused the baseflow portion of streamflow to increase because of decreased evapotranspiration, artificial drainage and land management practices (e.g., Brye et al., 2000; Schilling and Drobney, 2014; Schilling et al., 2008; Zhang and Schilling, 2006). For example, Ayers et al. (2020) found that corn and soybeans had a direct impact on increases to baseflow during the growing season. Trends documented later in the summer could be a result of a prolonged growing season. Studies have shown that over the last 30 years crops have been planted increasingly earlier in the spring with an extended season, and this trend is expected to continue with climate change (e.g., Kucharik, 2006; Walthall et al., 2013). Increasing trends in baseflow also indicate that subsurface drainage will continue to alter the water balance. While artificial drainage has influenced the hydrology of agricultural watersheds, changes typically occur in conjunction with land management practices that play a significant role (Blann et al., 2009). These practices (e.g., conservation tillage, terraces, and contour cropping) were put in place to decrease erosion and increase infiltration which sustains higher baseflow (Schilling and Libra, 2003). Overall, it is difficult to separate out the influence of corn and soybeans from subsurface drainage and management practices because they are strongly related to one another.

In the U.S. Midwest, agricultural watersheds have changed from the untilled perennial cover of wetlands and prairie to cultivated annual row crops (Knox, 2001; Smith, 1998). The decreasing scenario infers that land use gradually returns to perennial systems by the end of the 21st century. In this case, perennial systems could include the integration of perennial bioenergy crops into the traditional corn-soybean rotation (Gassman et al., 2017), or possibly increasing crop rotations (Davis et al., 2012) or prairie strips (Hernandez-Santana et al., 2013). Decreasing row crop intensity would result in decreases to baseflow (Fig. 5, column 3 and Fig. S6). Decreasing baseflow trends were present throughout the entire year, and more often than in the increasing scenario. These results show how a more diverse system with native vegetation would decrease discharge, likely because the organic matter in soils beneath native perennials would sequester more precipitation (Brye et al., 2000). For example, Schilling and Drobney (2014) found that for a watershed in Iowa, prairie reconstruction increased evapotranspiration and reduced drainage from the soil profile, thus lowering baseflow.

It is important to note that caution is merited when interpreting these results. Decreasing the harvested area of row crops does not necessarily require removal of constructed drainage, and it is likely impractical in most circumstances. Decreasing trends in baseflow associated with agriculture will also depend on land management practices that alter infiltration (Ahiablame et al., 2017a; Price, 2011; Schilling and Libra, 2003). Overall, this study showed that agriculture has a more sustained impact than climate on the direction of changes to baseflow in the Corn Belt Region. These results are consistent with Phung et al. (2019) and Xu et al. (2013) who showed that for watersheds in the U.S. Midwest, streamflow was impacted by climate more than land use change which had a greater impact on changes in baseflow.

3. Conclusions and future implications

The main objective of this study was to evaluate the influence of climate and agriculture on projected changes in monthly baseflow. We used a statistical modeling approach to examine trends at 393 USGS streamflow gages across the U.S. Midwest. Projected changes were based on downscaled and bias corrected GCM outputs using the RCP 8.5 scenario, and predicted corn and soybean harvested acres. We analyzed changes through the 21st century based on three different climate and agricultural scenarios. The main findings of this study are:

- Historical trends (1950-2005) based of the statistical models forced with observations captured observed monthly trends well, although the models reproduced increasing trends better than decreasing ones. Both NA-CORDEX and LOCA recreated historical trends closely with observations, but NA-CORDEX captured trends better.
- Climate projections indicated that monthly baseflow will mostly increase, and these increases will likely be driven by increases in precipitation and antecedent wetness. Temperature is expected to change the timing of baseflow. Most of the increasing trends were detected from January to July, indicating that there will be more discharge earlier in the year. By the fall (September), not many increasing trends were present. For some months (April, May and July), decreasing trends were concentrated in the Dakota, potentially related to temperature and snowmelt processes.
- Results showed that the expansion of the area dedicated to corn and soybeans will increase baseflow for agricultural watersheds in the Corn Belt Region. On the other hand, decreasing the cultivated area caused decreases in baseflow. Both scenarios result in baseflow trends that will persist throughout the year, which highlights the potential control of land use on infiltration. The decreasing scenario assumes restoration of native covers in

agricultural watersheds, which could help mitigate the effects of climate change by storing more water in the basin.

This approach provides a clear and simple way to assess projected changes in monthly baseflow. The statistical models assumed that the relationship between the response variable (i.e., baseflow) and the predictors (i.e., precipitation, antecedent wetness, temperature and agriculture) was stationary. While this assumption is an approximation, it is useful in the modeling framework in that it can be applied in other regions of the world. In addition, we assumed that the performance of the GCMs in the historical period represented their future performance. To reduce the uncertainty and prediction error, we used bias correction and compared the historical trend results. In the future, these findings can be updated and improved with recent and higher resolution GCMs.

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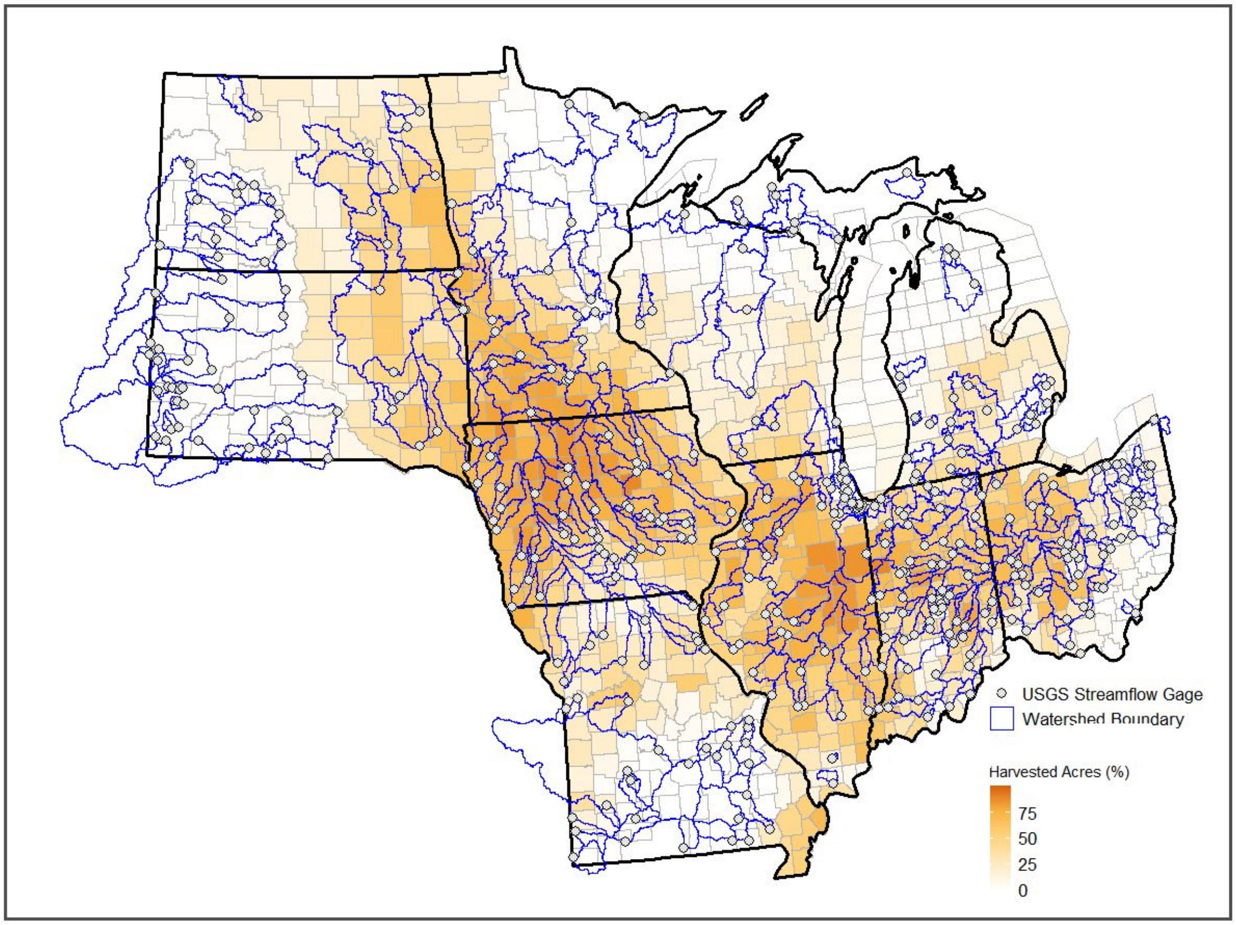

Fig. 1. Location of the 393 USGS gaging stations and mean annual (from 2013-2019) county level corn and soybean harvested acres as a fraction of the total county land area.

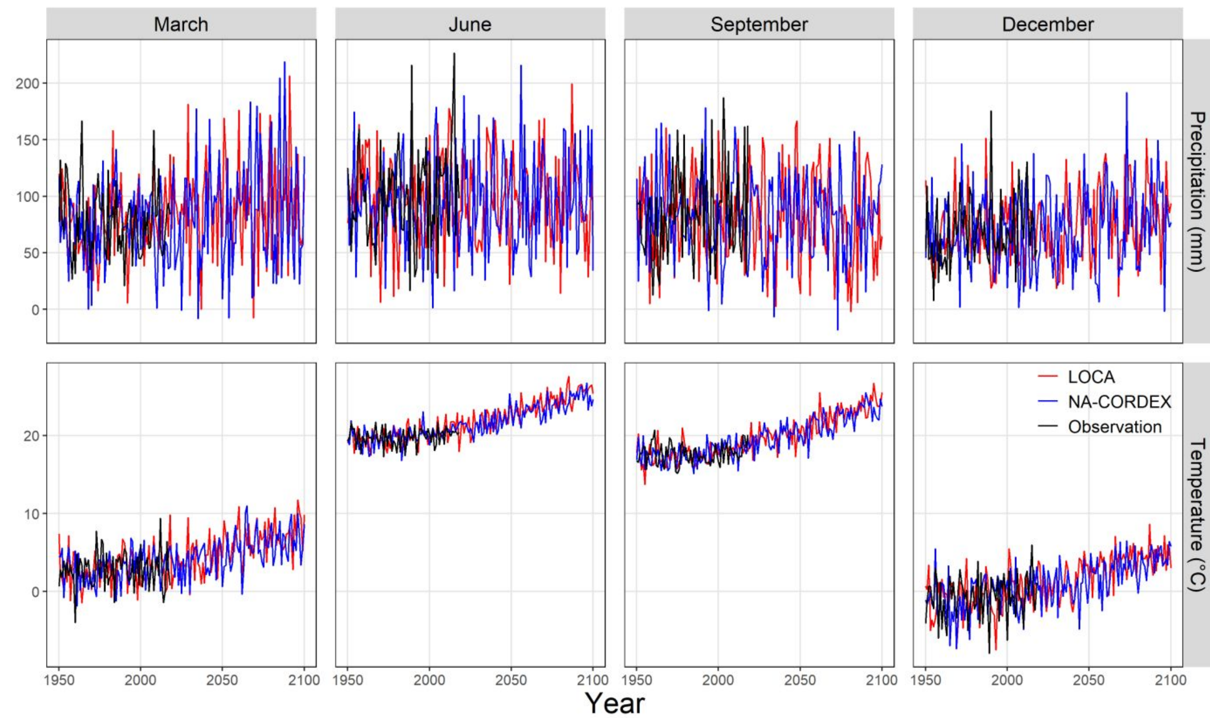

Fig. 2. The observed and projected bias-corrected monthly precipitation time series for USGS streamflow gage 03091500 (Mahoning River at Princetown, OH). The black line represents the observed values over the historical period (1950-2005), while LOCA and NA-CORDEX are run for the same period and for the projection period (2006-2100). The projections are run for every month, but in this figure we included only four months for reference. Projections are bias corrected using the delta change method.

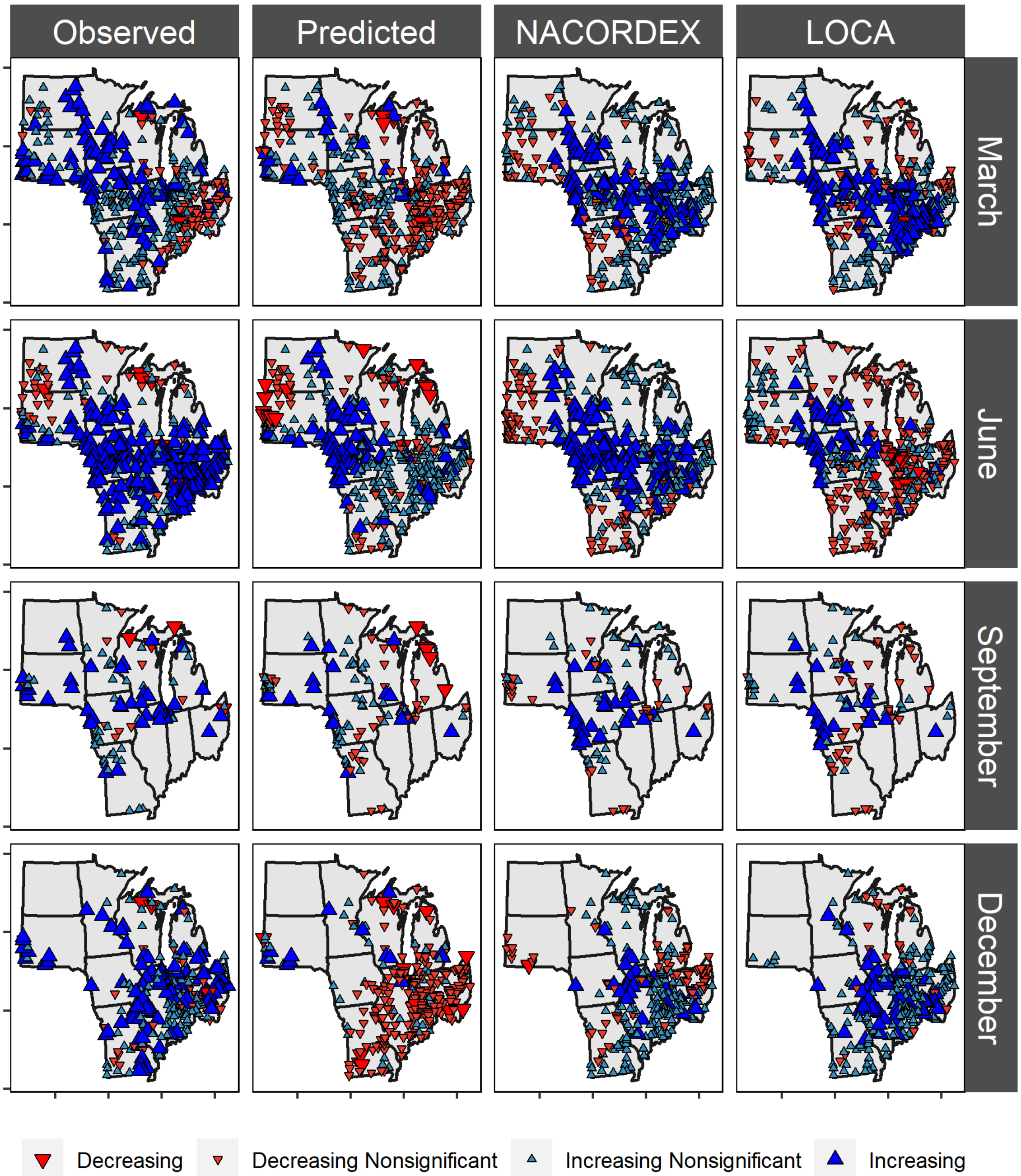

Fig. 3. Maps illustrating monthly baseflow trends over the historical period (1950-2005). Each column shows the results for four different datasets: the observations, the median of the models using the PRISM dataset (i.e., predicted), and the model run with NA-CORDEX or LOCA datasets. Each month's results are displayed in a row where a large blue upward arrow (red downward) indicates an increasing (decreasing) trend significant at the 5% level. Smaller arrow correspond to nonsignificant trends where the colors correspond to the trend direction.

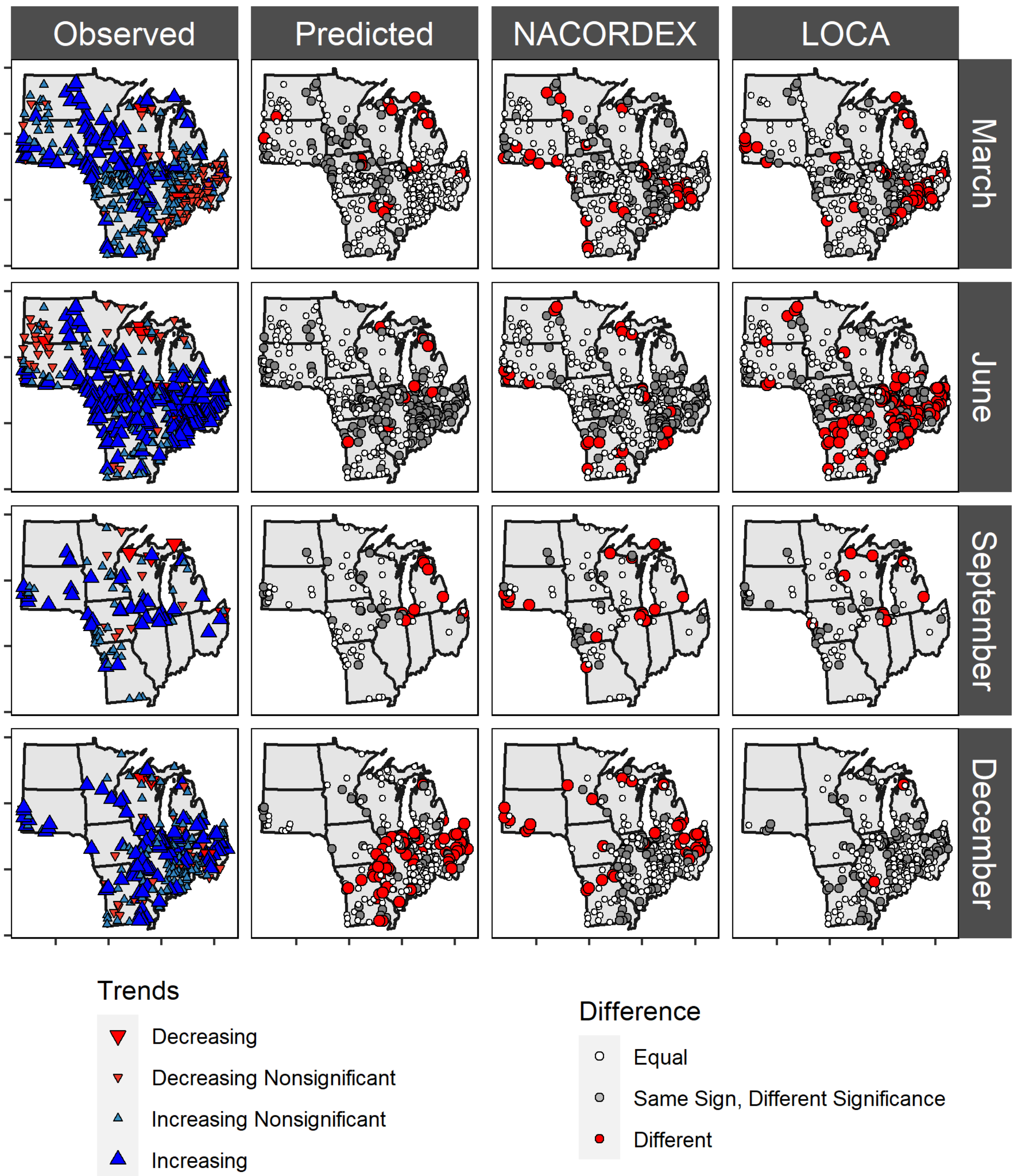

Fig. 4. Maps illustrating the difference in each dataset compared to the observed historical baseflow trends (column one, consistent with Fig. 3). Columns two to four illustrate the difference in trend detection between the observations and each dataset (i.e., PRISM, NA-CORDEX, and LOCA). "Equal" indicates that the significance of the trend was the same, which is shown as white dot. A grey circle shows that the sign of the trends was consistent but the significance was detected differently. Finally, a red circle indicates that the trends were different in significance and sign. Trend significance was set at the 5% level.

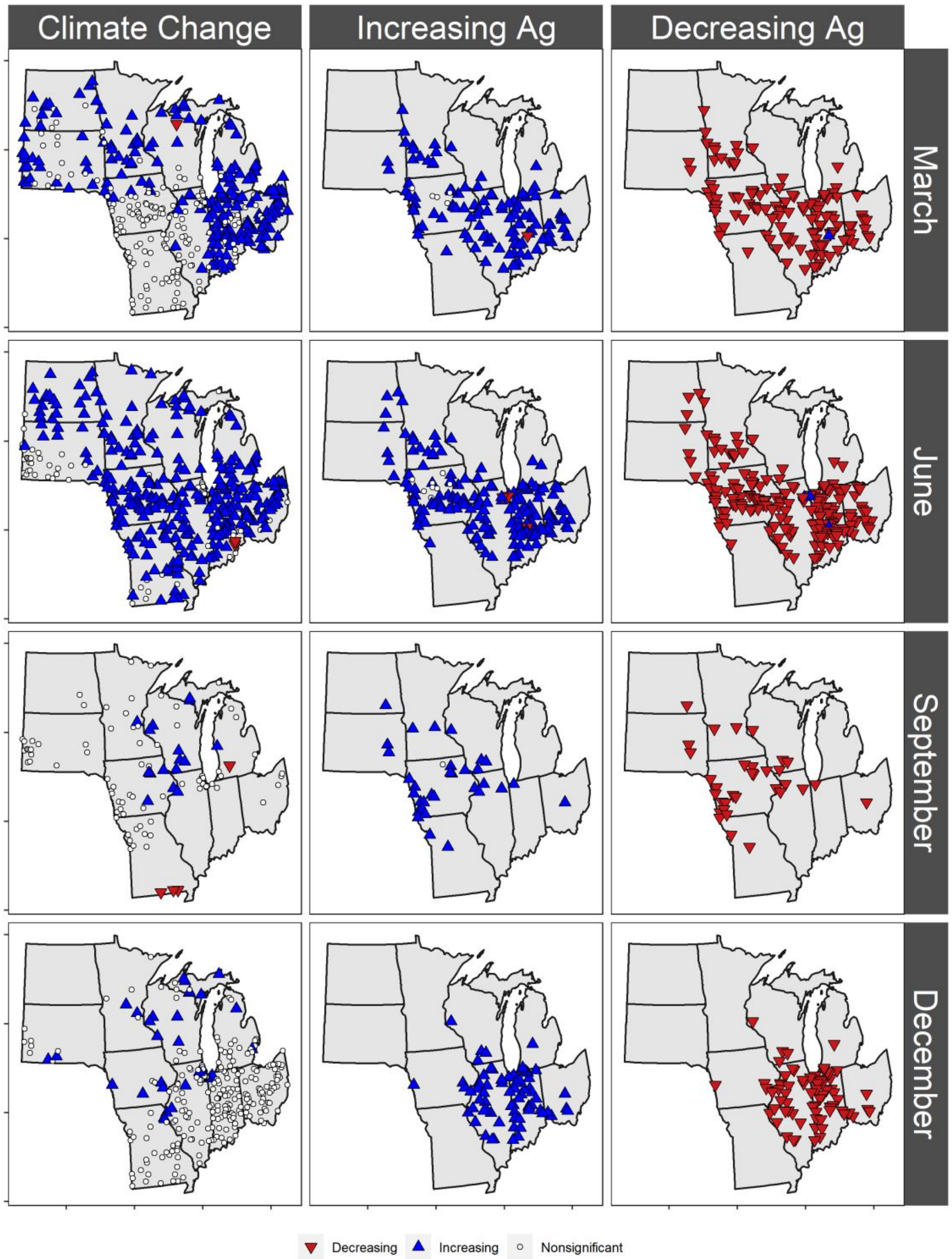

Fig. 5. Projected baseflow trend results (2006-2100) using the NA-CORDX dataset for the three scenarios representative of climate change, and increases and decreases with respect to the production of corn and soybeans. Results are shown for selected months; one from each season (i.e., March, June, September and December). See supplemental material (Figs. S3-S6) for results of every month for both NA-CORDEX and LOCA. A blue upward arrow (red downward) indicates an increasing (decreasing) trend significant at the 5% level. The white dots signifies that no significant trend was detected.

Table 1. The five most commonly selected statistical models to model monthly baseflow as a function of the four predictors: precipitation (x_p), antecedent wetness (x_m), temperature (x_t), and agricultural intensity (x_a). The σ parameter does not depend on predictors.

Model Name	Model Formulation
Precipitation + Antecedent Wetness	$log\,(\mu_1) = \alpha_1 + \beta_1 \cdot x_p + \gamma_1 \cdot x_m$
Precipitation + Antecedent Wetness + Agriculture	$log\,(\mu_2) = \alpha_2 + \beta_2 \cdot x_p + \gamma_2 \cdot x_m + \delta_2 \cdot x_a$
Precipitation + Antecedent Wetness + Temperature	$log\,(\mu_3) = \alpha_3 + \beta_3 \cdot x_p + \gamma_3 \cdot x_m + \delta_3 \cdot x_t$
Antecedent Wetness	$log\,(\mu_4) = \alpha_4 + \beta_4 \cdot x_m$
Temperature + Antecedent Wetness	$log\,(\mu_5) = \alpha_5 + \beta_5 \cdot x_t + \gamma_5 \cdot x_m$

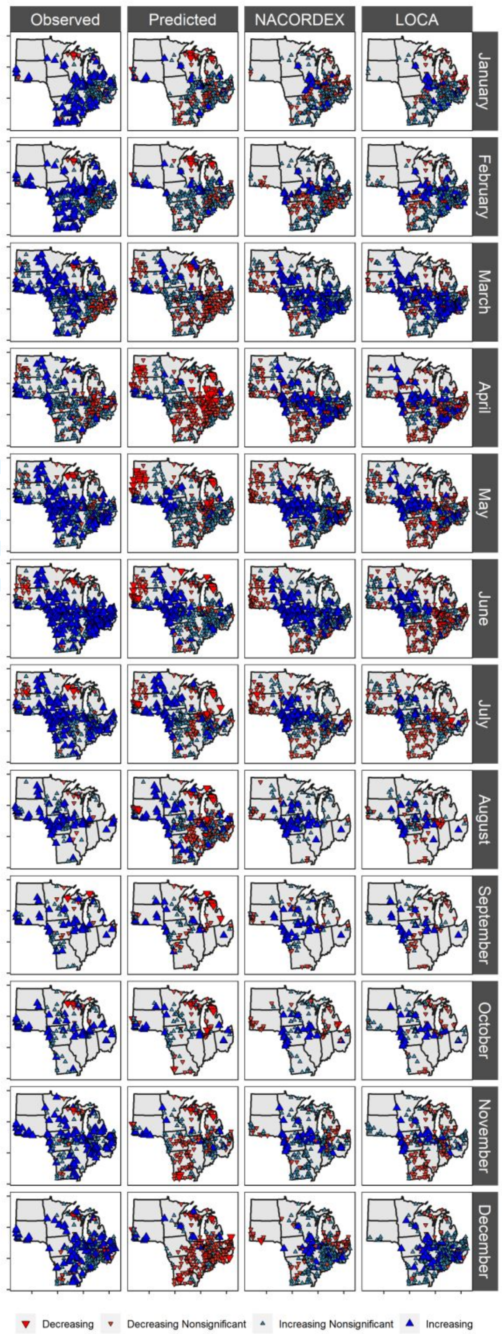

Fig. S1. Maps illustrating monthly baseflow trends over the historical period (1950-2005; same as Fig. 3). Trend results are shown in their respective columns for the observations, the median of the model fit using PRISM, and the model run with NA-CORDEX or LOCA datasets. Each month's results are displayed in a row where a large blue upward arrow (red downward) indicates an increasing (decreasing) trend significant at the 5% level. Smaller arrow correspond to nonsignificant trends where the colors correspond to the trend direction.

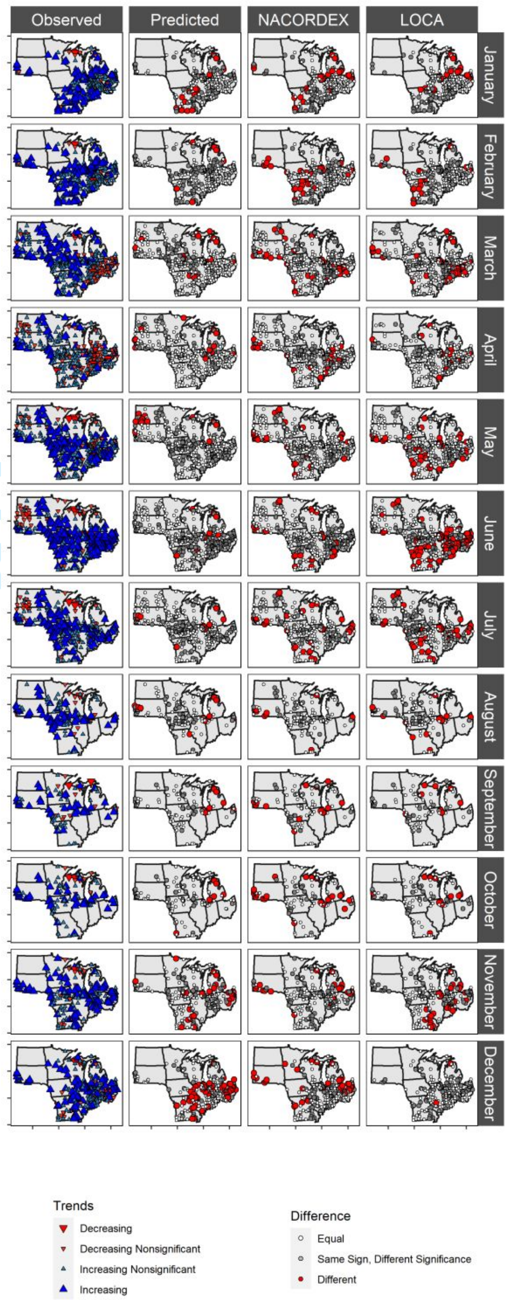

Fig. S2 Same as Fig. 4 illustrating the difference beween the observed baseflow trend results (1950-2005). Trend results for the observations are shown in column one where a large blue upward arrow (red downward) indicates an increasing (decreasing) trend significant at the 5% level. Columns two to four compare trend results to the observations as differences in detection for each dataset (i.e., PRISM, NA-CORDEX and LOCA). Equal indicates that the significance was the same, and is shown as white dot. A grey dot illustrates that the sign of the trends was consistent but the significance was detected differently. Finally, a red dot indicates that the trends were different in significance and sign. The MK trend test was used at the 5% significance level.

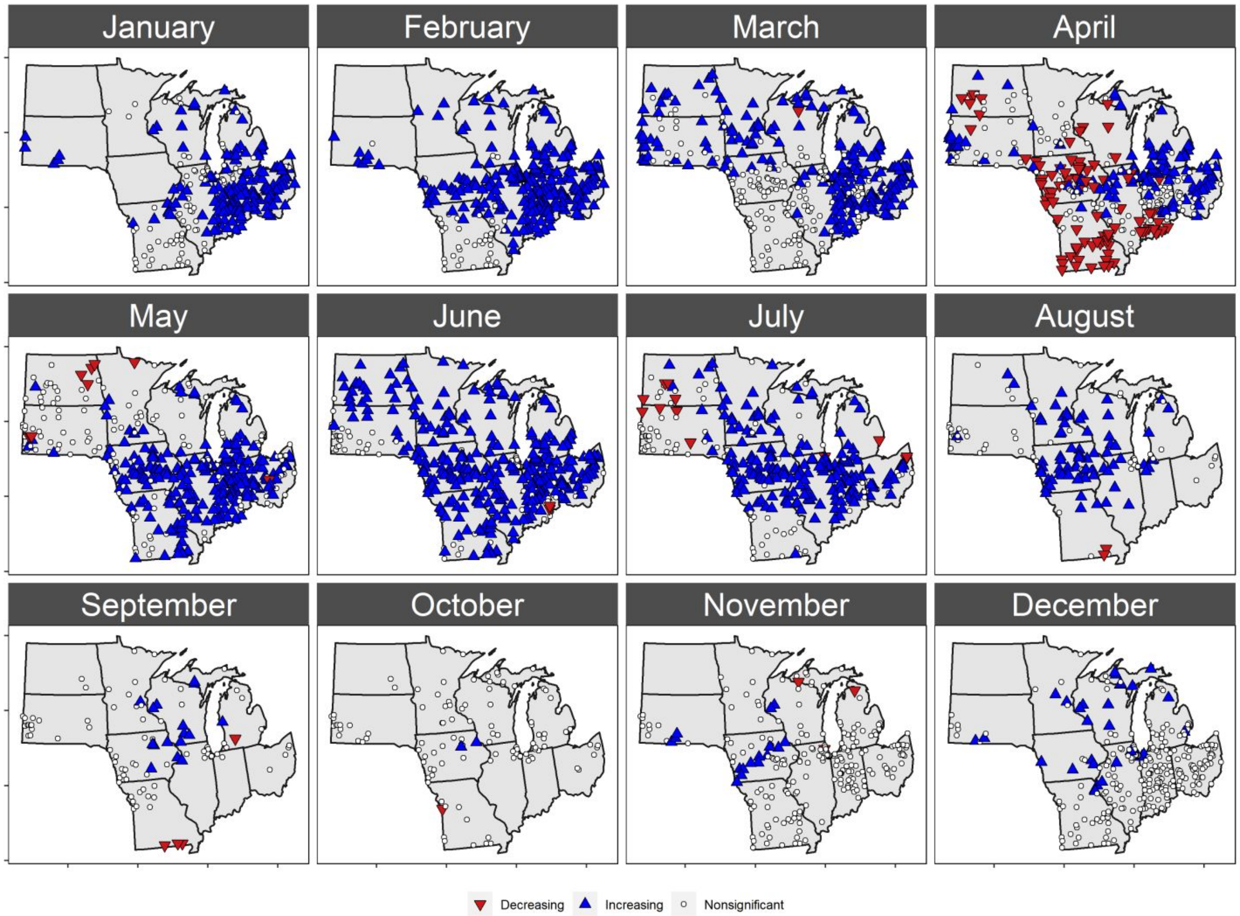

Fig. S3. Projected trends (2006-2100) in monthly baseflow based on projections from NA-CORDEX. Agriculture was held constant in the statistical models to account for climate change. A blue (red) upward arrow indicates an increasing (decreasing) statistically significant trend at the 5% level. A white point indicates a non-significant trend result.

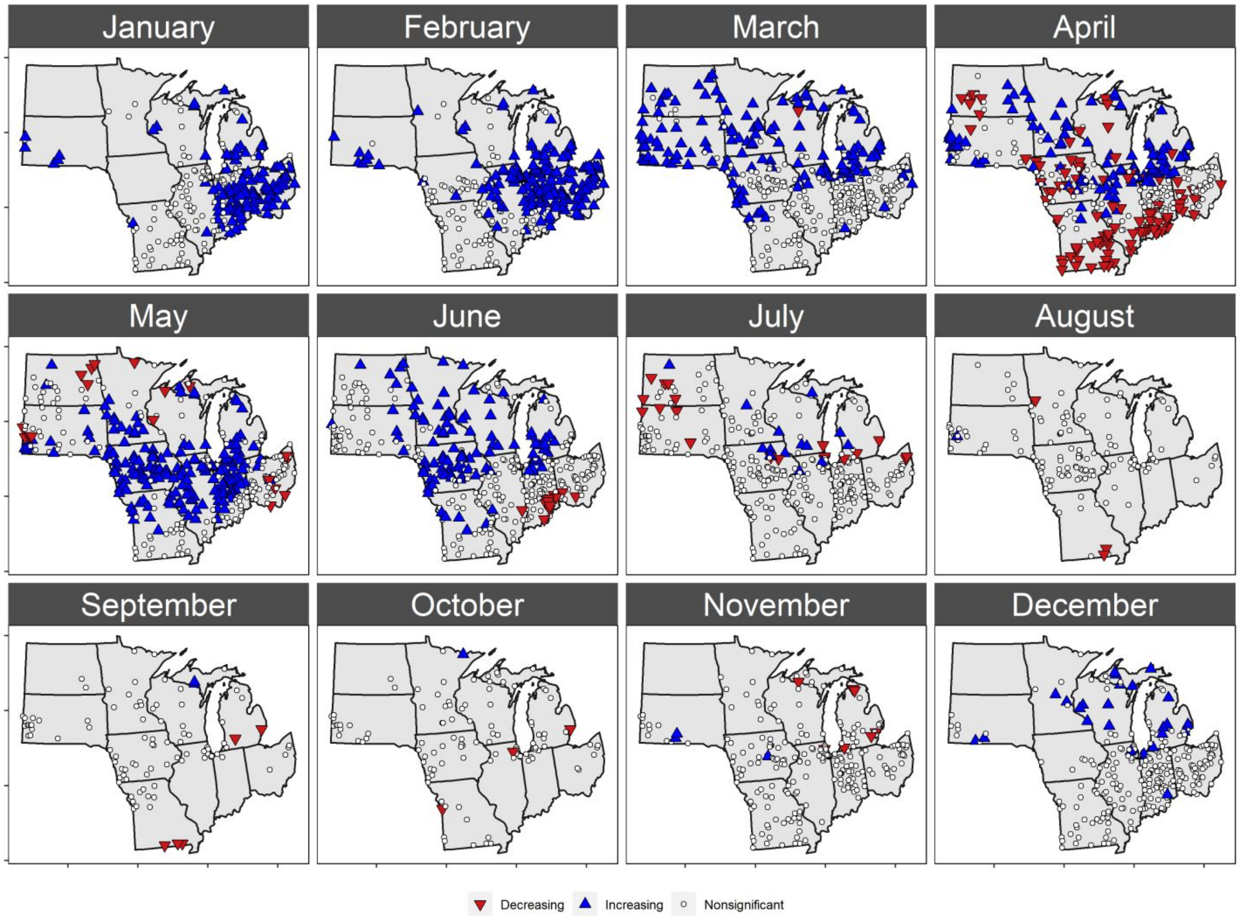

Fig. S4. Same as in Fig. S3 but using climate projections from LOCA. A blue (red) upward arrow indicates an increasing (decreasing) statistically significant trend at the 5% level. A white point indicates a non-significant trend result.

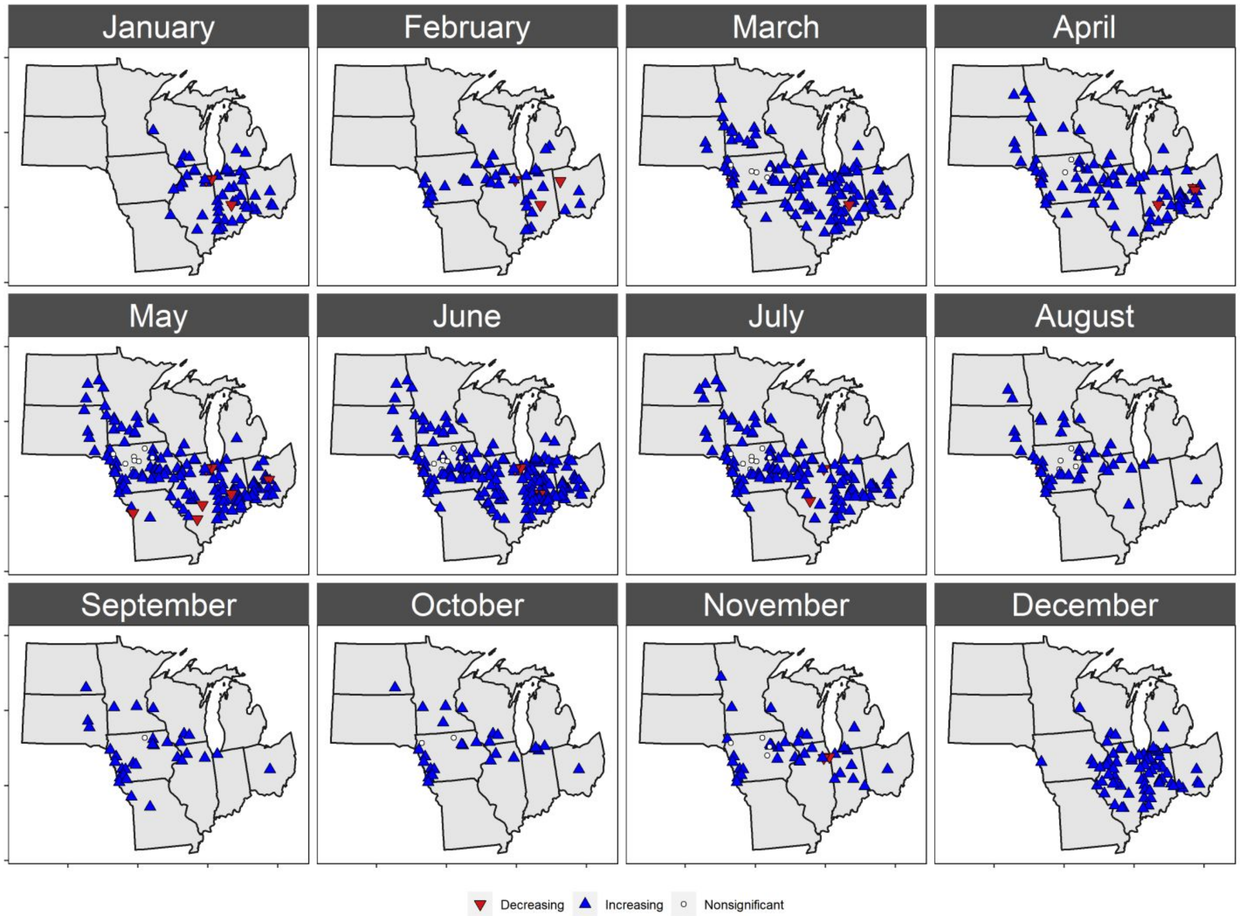

Fig. S5. Projected trends (2006-2100) in monthly baseflow accounting for increases in agriculture without the influence of climate. In this experiment agriculture is projected to increase at the same rate that it has over the recent past and with a limit of the watershed having 100% of the land allocated to corn and soybeans. A blue (red) upward arrow indicates an increasing (decreasing) statistically significant trend at the 5% level. A white point indicates a non-significant trend result.

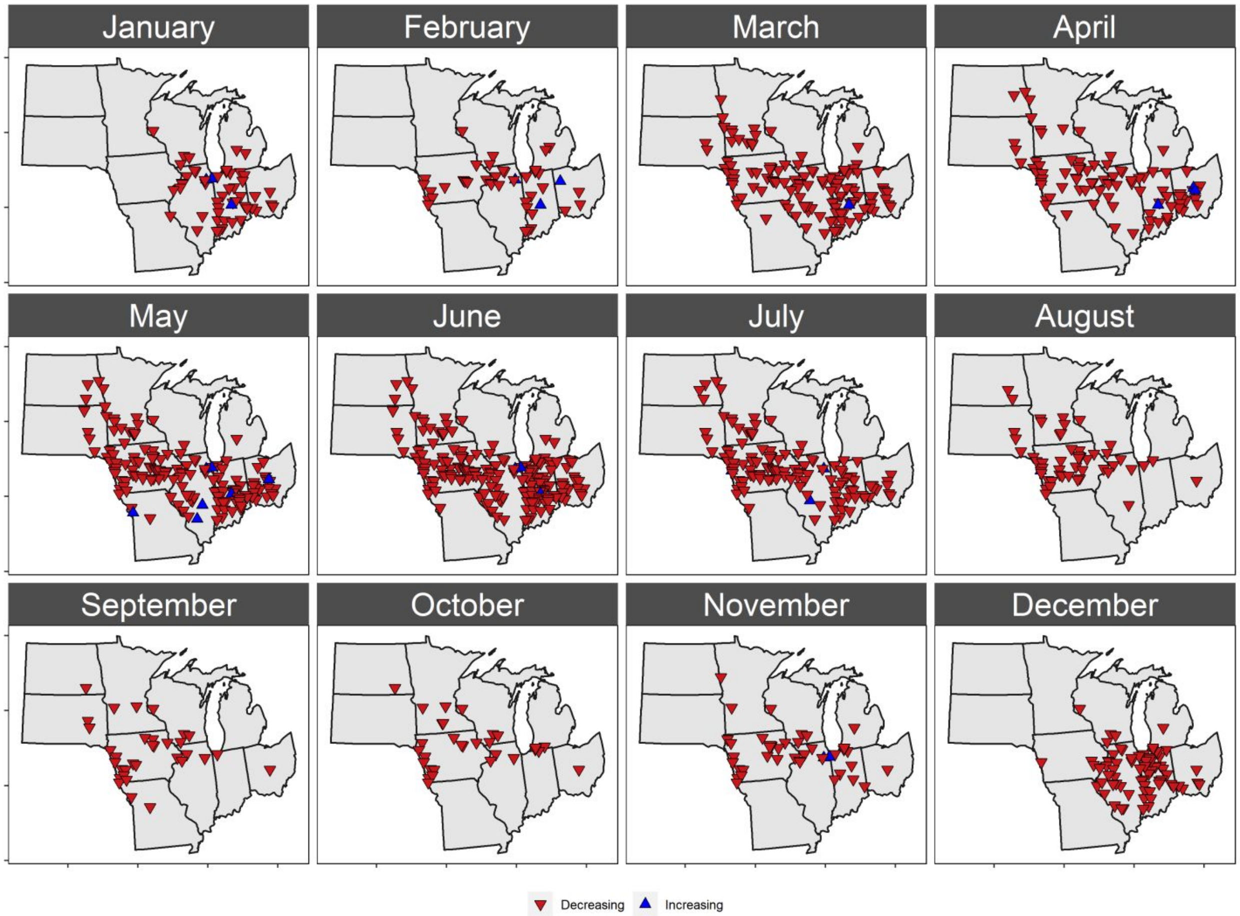

Fig. S6. Same as Fig. S3 but for the decreases in agriculture outside of climate change. The model inputs assume that harvested acres of corn and soybeans will revert back to pre-1940s conditions by the end of the 21st century. A blue (red) upward arrow indicates an increasing (decreasing) statistically significant trend at the 5% level. A white point indicates a non-significant trend result.