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Weather whiplash in agricultural regions drives deterioration of water quality

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Abstract Excess nitrogen (N) impairs inland water quality and creates hypoxia in coastal ecosystems. Agriculture is the primary source of N; agricultural management and hydrology together control aquatic ecosystem N loading. Future N loading will be determined by how agriculture and hydrology intersect with climate change, yet the interactions between changing climate and water quality remain poorly understood. Here, we show that changing precipitation patterns, resulting from climate change, interact with agricultural land use to deteriorate water quality. We focus on the 2012–2013 Midwestern U.S. drought as a "natural experiment". The transition from drought conditions in 2012 to a wet spring in 2013 was abrupt; the media dubbed this "weather whiplash". We use recent (2010–2015) and historical data (1950–2015) to connect weather whiplash (drought-to-flood transitions) to increases in riverine N loads and concentrations. The drought likely created highly N-enriched soils; this excess N mobilized during heavy spring rains (2013), resulting in a 34% increase (10.5 vs. 7.8 mg N L^{-1}) in the flow-weighted mean annual

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nitrate concentration compared to recent years. Furthermore, we show that climate change will likely intensify weather whiplash. Increased weather whiplash will, in part, increase the frequency of riverine N exceeding E.P.A. drinking water standards. Thus, our observations suggest increased climatic variation will amplify negative trends in water quality in a region already grappling with severe impairments.

Keywords Agriculture · Nitrate · Climate variability · Water quality

Introduction

Modern agriculture is inextricably linked to declining surface water quality (Verhoeven et al. 2006; Broussard and Turner 2009), creating ecological and economic problems spanning local (Bernot and Dodds 2005) to continental (Diaz and Rosenberg 2008) scales. Agriculture is a major source of reactive nitrogen (N) (Sobota et al. 2013) and interacts with hydrology to control N loading to aquatic ecosystems (McIsaac et al. 2001; Donner and Scavia 2007). How future hydrological changes associated with climate will alter N loading to freshwater ecosystems is an emerging concern that remains largely unexplored. Given the implications for water quality, it is critical to understand how agricultural management and a changing climate will interact in contemporary and future agroecosystems.

Understanding interactions between climate change and agriculture is critical to the continued compatibility of agricultural activity and local municipalities that use adjacent rivers as drinking water sources. The U.S.E.P.A. regulates nitrate in drinking water through standards established in the Safe Drinking Water Act (U.S.C. 1986); nitrate is costly to remove, which creates tension between downstream drinking water users and upstream agricultural activity (Des Moines Water Works 2016a). In the Midwestern U.S., tensions heightened recently when the City of Des Moines (Iowa) Water Works filed a lawsuit against county drainage districts in their supply watershed for contaminating water with nitrate (Des Moines Water Works 2015). In addition to local drinking water concerns, known interactions between climate and agriculture will significantly improve the ability of regional models to predict impacts to more distant downstream ecosystems, such as the Gulf of Mexico, where N loading from the Mississippi River creates extensive coastal hypoxia (Donner and Scavia 2007; Broussard and Turner 2009).

Herein, we describe how climate change may drive further deterioration of water quality in the agricultural belt of the North American Midwest. Climate change is predicted to increase the frequency and severity of growing-season drought (Dai 2012; Hatfield et al. 2013) and produce more extreme precipitation in the spring (Kunkel et al. 1999; Hatfield et al. 2013) (defined as > 30 mm in 24 h). Drought reduces agricultural crop yield (e.g., a 24% reduction of the U.S. maize harvest in 2012, Al-Kaisi et al. 2013) and enriches soil nitrate concentrations (Balkcom et al. 2003). We focus on the 2012–2013 Midwestern U.S. drought as a "natural experiment" to understand how changing climate may alter N loading to streams and rivers. We hypothesized that normal spring 2012 fertilization followed by drought-induced decreased crop yields would create a large, readily leached N pool in agricultural soils, setting the stage for excessive N losses the following spring (2013). We quantify drought-to-flood transitions, referred to as "weather whiplash," and show that weather whiplash is likely to increase under projected future climate. Finally, we connect changes in weather whiplash, driven by changing climate, to increases in riverine nitrate concentration and the probability of surface water exceeding U.S. Environmental Protection Agency (U.S.E.P.A.) drinking water standard maximum (10 mg L^{-1}).

Data and methods

Data sets

The data used in this manuscript are all publically available. The precipitation data were obtained from the Applied Climate Information System (ACIS 2016). These data are retrieved as an interpolated grid (Northeast Regional Climate Center Interpolated grid) of daily precipitation summed across the time period (1 Jan 1950–31 Dec 2015) at a 30 arc sec spatial resolution. Full documentation of these data is available online (ACIS 2016).

The projected future monthly precipitation data are from the NASA Earth Exchange Downscaled Climate Projections (NEX-DCP30; CMDS 2016). The downscaled products are at a 30 arc second spatial resolution and derived from the from the General Circulation Model runs conducted under the Coupled Model Intercomparison Project Phase 5 (CMIP5) (Taylor et al. 2012). We used the emission scenario 8.5 of Representative Concentration Pathways developed for the Fifth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC AR5). We accessed these data through the NCCS THREDDS data service (NCCS THREDDS 2016).

Stream nitrate and discharge data are available from the United State Geologic Survey's National Water Information System (NWIS 2016b). The high frequency stream nitrate data are recorded as nitrate + nitrite as N (mg N L^{-1}) using a Hach Nitratax plus sc Sensor (2 mm path length; Loveland, CO, USA), which has a measurement range of 0.1–50 mg NO_3^--N L^{-1} and a 0.1 mg NO_3^--N L^{-1} resolution (measuring error: ± 3% of the mean MW ± 0.5). Stream nitrate concentration, discharge (Q), and nitrate flux data from the USGS station (USGS 05465500) on the Iowa River near Wapello, IA, USA (41.180°N, 91.182°W; Fig. 1) were cumulative starting on the earliest DOY were data were available (DOY 105) for all years (2010–2015). This watershed is 32,375 km^2 of which 91% is classified as agricultural use, mostly maize and soy production (Broxton et al. 2014). We used the zoo R package to linearly interpolate across missing Q data (Moatar and Meybeck 2005). Cumulative Q for both the historical data (1970–2009) and the high frequency (2010–2015) data were calculated by summing the product of Q and time interval (daily for historical and 900 s for high frequency data) for each measurement. Similarly, cumulative nitrate flux for the high frequency (2010–2015) data were calculated by summing the product of Q, nitrate concentration, and time interval (900 s) for each measurement. Flow-weighted mean concentration was estimated as the total flux divided by the total stream Q during each year (DOY 105–300).

The Upper Mississippi River Basin (UMRB) wide grab sample nitrate data were collected by the USGS and are available online (NWIS 2016a). Only surface water samples were used in this analysis (n = 71,547)

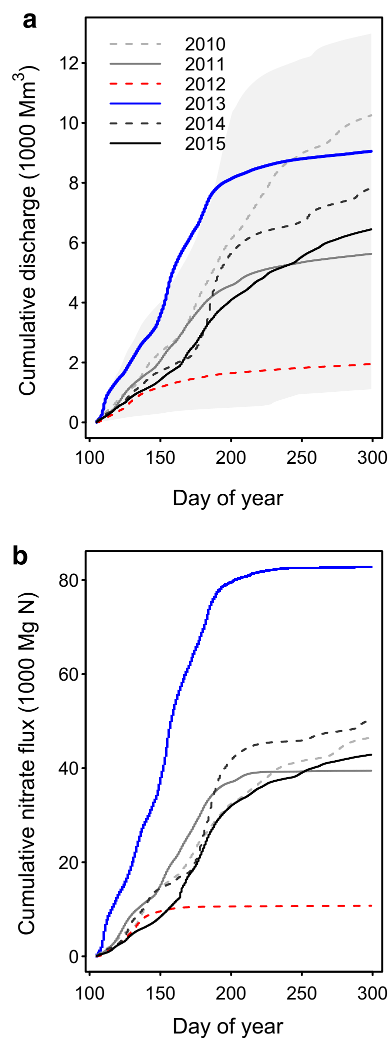

Fig. 1 Cumulative discharge (**a**) and nitrate flux (**b**) for the six years with continuous nitrate monitoring data in the Iowa River (at Wapello, Iowa, 25 km upstream of the confluence with the Mississippi River). *Grey background* in *panel a* indicates 95% interval of historical cumulative discharge; similar historical data are not available for nitrate, which has only been monitored from 2010 to 2015

i.e. all groundwater sample data were removed. Monitoring site details are presented in SM table S1. Samples below the detection limit (~0.2% of surface water samples) were assigned a value between the method detection limit and zero using an exponential model (Helsel 2006). From this data set we calculated spring surface water nitrate concentration (MJNOx) as the average nitrate concentration of grab samples during May and June of each monitoring site-year.

May and June are the months with highest average nitrate concentrations and fluxes in the UMRB (Donner et al. 2002). Sites with less than three years of spring nitrate concentration data were removed from further analysis to avoid over-fitting of parameters. Following these filters, 165 monitoring sites containing 2645 site-years were included in subsequent analyses.

Statistical analysis

Weather whiplash index

The weather whiplash index was calculated as the total precipitation from January to June of each year (1951–2099) minus the total precipitation from July to December of the previous year (1950–2098), divided by the total precipitation over that entire period. Watershed area specific WWI were extracted from the WWI annual grids (above) for the 163 watersheds upstream of the monitoring sites using the USGS Watershed Boundary Dataset (http://nhd.usgs.gov/wbd.html) and the sp R package (Bivand et al. 2013). Trends and cyclic patterns in projected and observed Iowa River Basin WWI were evaluated by least squares linear regression after checking for autocorrelation in R.

WWI relationship to spring nitrate historically and in the future

To understand the relationship between observed WWI and May–June nitrate (MJNOx), we constructed mixed effects models using the R package lme4 (Bates et al. 2015). MJNOx for each station-year was the response variable and the corresponding watershed WWI for each year was the fixed effect. Random slope and intercept of MJNOx vs. WWI for each sites were also included. We provide a conditional R^2 (Nakagawa and Schielzeth 2013) as an indicator of the total variance in MJNOx explained with the hierarchical model. However, because our model contains multiple variance components (i.e. hierarchical) its usage differs from a traditional R^2 as the conditional R^2 has a lower maximum (<1) and thus its interpretation is conservative relative to transitional R^2. (Nakagawa and Schielzeth 2013). To fully propagate the errors this hierarchical model was fit using the Markov chain Monte Carlo sampler No-U-Turn in the R package rstan (Hoffman and Gelman 2014) with four chains each with 10,000 iterations. The first 1000 iterations of each chain were discarded as warmup. Convergence was accepted when Rhat < 1.01. For the hierarchical Bayesian model uninformed priors were used for all parameters. Posterior probability distributions were obtained for the slope and intercept parameters of all 163 monitoring sites. Bayesian credible intervals of 2.5 and 97.5% were calculated for the Iowa River Basin posterior distributions.

Projecting effect of future WWI on spring nitrate concentration for the Iowa River Basin

To project MJNOx and its uncertainty in the future, a random subset ($n = 1000$) of the Iowa River Basin posterior distribution of slope and intercept parameters were multiplied by the Iowa River Basin watershed WWI realizations from each of the climate models ($n = 30$) for each year (1950–2099), resulting 4470,000 possible combinations. Linear trends in the mean and upper and lower credible intervals of the projected MJNOx were determined by regression and compared using analysis of variance. Significance was accepted at an alpha of 0.05. The projected probability of MJNOx exceeding the E.P.A. drinking water standard in the Iowa River Basin was calculated as the proportion of realizations that exceed 10 mg NO_3^--N L^{-1}.

Results and discussion

Near-record dissolved N fluxes combined with high cumulative discharge (i.e. the volume of water moving through the river; Fig. 1) provide overwhelming support for our hypothesis (droughts store reactive N in soil and floods flush reactive N into streams) and provide a unique insight into how climate variability creates extremes in N loading. The source of high 2013 N loads can be discerned by comparing the cumulative discharge (Fig. 1a) and cumulative nitrate load (Fig. 1b). Beginning at day of year (doy) 105 in 2013 (Fig. 1a), cumulative discharge climbed steeply, driven by precipitation including two storms that raised mean daily discharge above the 99th percentile (Fig. S1). Despite periods of intense precipitation, the 2013 cumulative discharge remained largely within the 95th percentile of the 40 year record (1970–2009,

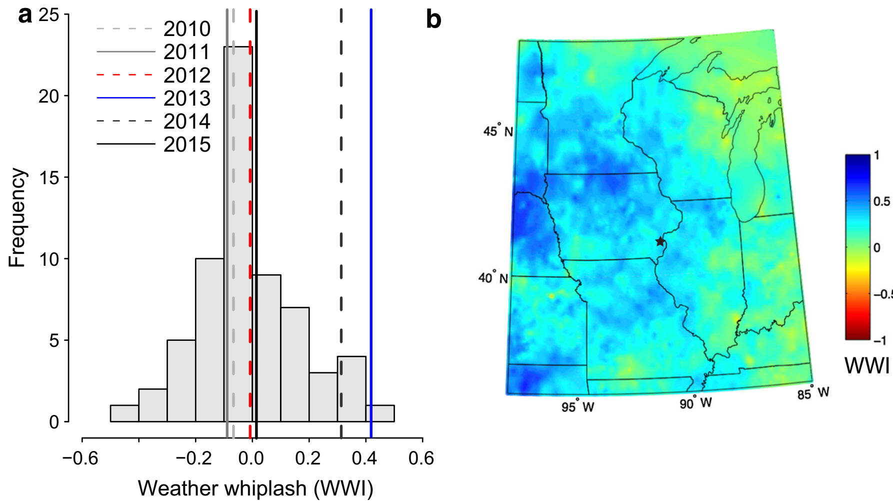

Fig. 2 Weather whiplash in the Upper Mississippi River Basin was historically (**a**) and spatially (**b**) extreme, as indicated by the *Weather Whiplash Index* (WWI). A *positive WWI* indicates shifts from dry to wet conditions; a *negative WWI*, a shift from wet to dry. **a** A histogram of the 113 year record of Weather Whiplash Index for Iowa River Basin, Iowa. 2010–2015 are highlighted as the period for which continuous stream nitrate concentration data are available. **b** A map of the UMRB indicating the spatial extent of the 2012–2013 weather whiplash. The *black star* on **b** references the location of Wapello, Iowa, where the continuous monitoring data were collected in the Iowa River (Fig. 1)

grey shading, Fig. 1a). However, discharge alone does not explain the extreme N loading in 2013. Rather, the interannual contrast among cumulative nitrate flux (Fig. 1b) suggests that antecedent drought conditions (2012) stored reactive N in the soil and then this excess N was mobilized during spring runoff. Departures between cumulative nitrate flux and cumulative discharge in 2013 support our hypothesis (Fig. 1b). The intense precipitation that occurred in the early spring of 2013 (~ doy 110–150; April and May) corresponds to the fastest increase in nitrate flux in the available record (2010–2015; Fig. 1b). The combined effects of elevated discharge and high nitrate concentrations resulted in a cumulative nitrate flux that was 118% greater than the average of the other five years resulting in a 34% increase (10.5 vs. 7.8 mg N L^{-1}) in the flow-weighted mean annual nitrate concentration in 2013 compared to the average over that same period.

The transition from drought conditions in 2012 to spring 2013 was abrupt; many UMRB areas flipped from precipitation deficits >250 mm to surpluses in excess of 250 mm in less than three months (i.e. over 500 mm gain). The popular media dubbed this "weather whiplash" (O'Hanlon). We quantify a weather whiplash index (WWI) as the total precipitation from January to June (2013) minus the total precipitation from July to December (2012), divided by the total precipitation over that entire period. Positive WWI indicates switching from dry to wet conditions during the twelve-month period; the magnitude of WWI indicates the intensity of that change during the same period. The 2012–2013 whiplash cycle was historically extreme (Fig. 2a) and spatially extensive (Fig. 2b). The 2012 U.S. drought was among the most severe, extensive and costly for the UMRB (Peterson et al. 2013), which includes four of the top states for maize and soy production (Illinois, Iowa, Indiana and Missouri), the U.S.'s two most valuable agricultural commodities (Hatfield et al. 2013). These four UMRB states contribute 48% of N loading to the Mississippi River (Alexander et al. 2008).

Examining the WWI of climate models indicates that weather whiplash in the UMRB will increase in frequency and intensity as climate changes (Fig. 3). Moreover, average trends in weather whiplash predicted by 30 future climate models (Fig. 3 black line) are conservative compared to the observed changes (Fig. 3 green dashed line) in weather whiplash in the Iowa River basin (1978–2015). We compared 30 downscaled precipitation projections (each denoted by a line) from the 30 models used in the CMIP5 (see details in Methods) to project future whiplash

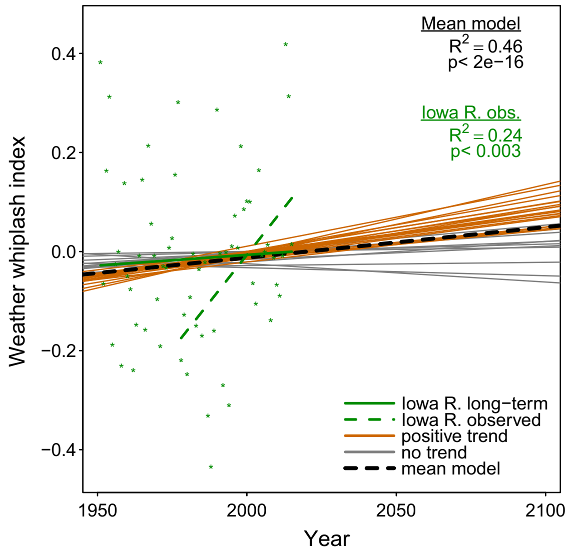

Fig. 3 Weather whiplash changes over time from 30 model realizations (*solid lines*). The *orange lines* indicate significant positive trends in weather whiplash models (n = 19) and *grey lines* indicate models without significant trends (n = 11). Actual data from the Iowa River and their best-fit linear trend (*dashed green line*) are shown for the period of nitrate data availability (1978–2015) and precipitation data availability (1950–2015, *solid green line*)

scenarios. Of these 30 models, 19 predict an increase in weather whiplash over time (orange lines, Fig. 3) and 11 predict no trend in weather whiplash over time (grey lines, Fig. 3a). Variance in modeled whiplash (Fig. S2) approximates the variance in observed weather whiplash from the Iowa River basin (Fig. S2, green box). Matching the modeled and observed variance in weather whiplash is a critical component to understanding the probability of extreme events, including high riverine nitrate concentrations that may cause exceedance of the EPA's drinking water standards. Cyclic patterns in the observed or climate model predicted WWI were not evident; therefore, the deviation between modeled and observed weather whiplash (Fig. 3) is due to either short-term variability (37 years of data are available) or an under estimation of the precipitation changes by the climate models. If the observed pattern of rapid changes in weather whiplash persist, this would further exacerbate related issues including flood prediction, crop productivity and environmental quality.

Weather whiplash strongly influences spring nitrate concentrations in long-term monitoring data from agricultural watersheds in the UMRB (US EPA) (Fig. 4a, S3). Across the UMRB, dry springs following wet autumns result in the lowest spring nitrate concentrations; wet springs following dry autumns result in the highest spring nitrate concentrations (Fig. 4a). Our hierarchical regression model used to describe this relationship explains 81% (conditional R^2) of the variation in spring nitrate concentrations with approximately half of this variation explained by weather whiplash (i.e., random slopes effects) and the other half by site effects (i.e. random intercepts caused by e.g. land use intensity, topography, etc.). By combining the projected weather whiplash from all 30 climate models (Fig. 3) and the relationship between spring nitrate and weather whiplash (Fig. 4a), we project spring riverine nitrate concentrations will continue to climb through 2100 (Fig. 4b). Extreme events (indicated by the 97.5% credible interval, upper dashed green line for the Iowa River basin) rise even faster than the mean nitrate concentration (solid green line; Fig. 4b). The faster increase in extreme events results in an increasing frequency of spring nitrate concentrations exceeding the E.P.A. drinking water standard (Fig. 4c). Again, our projected exceedance estimates are low relative to the observed exceedance (Fig. 4c), which we attribute to the conservative nature and uncertainty of our weather whiplash model projections being derived from the entire hindcast model period (1951–2015) as opposed to the period of spring nitrate data for the Iowa River (1978–2015) (Fig. 3).

Scientists are beginning to investigate how climate change will interact with land management to affect surface water quality (Howarth et al. 2012; Baron et al. 2012; Kaushal et al. 2014). Connections between weather variation and water quality have been noted for single drought-flood events (Kaushal et al. 2008), long-term data in a limited number (≤3, all within the same state) of watersheds (David et al. 1997; Royer et al. 2006) or hypothesized from modeling exercises (Donner et al. 2002). However, to our knowledge, this study is the first to empirically demonstrate the connection between increased long-term weather variation due to changing climate and the subsequent effects on water quality across multiple decades in an extensive agricultural region. Our data expands on previous work (David et al. 1997; Royer et al. 2006; Kaushal et al. 2008; David et al. 2010) to suggest that the spring 2013 pulse of riverine nitrate export is not a unique episode, but rather a normal, widespread, and recurring event sensitive to changes in seasonal

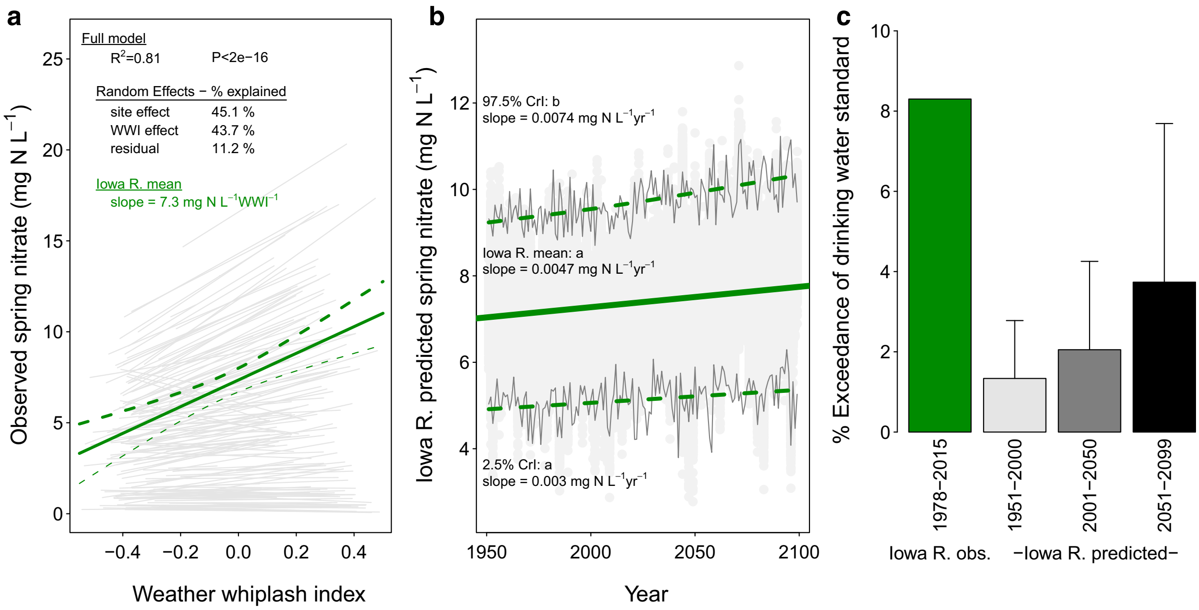

Fig. 4 **a** Increasing weather whiplash drives higher spring (May and June) riverine nitrate concentrations in observational data from 2645 site-years across the UMRB. The trend line (*solid green line*) and credible intervals (*dashed green lines*) shown are from the Iowa River Basin and trend lines for the other 164 sites monitored in the UMRB (*light grey lines*). Incorporating this relationship into models projecting spring riverine nitrate concentrations predicts that: **b** mean (*solid green trend line*) and extreme events (*upper dashed green trend line*) in spring nitrate will continue to increase due to climate change (different *lower case letters* indicate significantly different slopes) and **c** the probability of exceeding the E.P.A. drinking water limit of 10 mg NO_3^--N L^{-1} will also increase in the future

precipitation. We show that antecedent climate can poise soil conditions for greater in riverine nitrate fluxes (Figs. 1, 2). Furthermore, climate change will likely result in a stronger weather whiplash with frequent summer droughts coupled to increasingly wet springs (Fig. 3) (Hatfield et al. 2013). Increased weather whiplash will bring about increased spring stream nitrate concentrations and associated challenges in managing surface waters for drinking water quality (Fig. 4). While our analysis clearly indicates weather whiplash is connected to the magnitude of N loss, we do not evaluate how shifting patterns in weather whiplash will affect the timing of loading, which is an important consideration for understanding coastal hypoxia development. Demonstrating the connection between climate variability and water quality leads us to posit that climate change will amplify water quality problems in the agricultural Midwest unless substantial changes are made in management.

The UMRB is beginning to show improvements in water quality (Murphy et al. 2013) after decades of decline (Sprague et al. 2011). Unfortunately, increasingly variable weather may counteract these improvements by enhancing N loading to streams and rivers. Currently, farmers are advised to add supplemental N fertilizer during wet springs to account for early season losses (Fernandez 2009). As weather whiplash increases in this region (Fig. 3), it is likely that land managers will respond to wetter springs by applying more N fertilizer (Hatfield et al. 2013). Without future changes in land management, the nascent water quality improvements in the region (Murphy et al. 2013) may quickly dissipate due to unforeseen interactions between climate and agriculture. This may further increase the economic damage associated with a changing climate as more municipalities construct and operate nitrate removal systems to meet drinking water standards. Currently, the Des Moines Water Works (Iowa, USA) operates a large nitrate removal facility in order to comply with the E.P.A. drinking water standard. The facility cost \$4.1 million to build and \$7000 USD/day to operate. In 2015, the city operated the facility for a record 177 days at a cost of ~\$1.5 M USD and requires

$80 M in upgrades in the near future (Des Moines Water Works 2016b). As weather whiplash (Fig. 3) and the associated increase in spring nitrate concentrations (Fig. 4a, b) combine to increase the likelihood of exceeding the EPA safe drinking water standard (Fig. 4c), more local municipalities in agricultural regions will be forced to invest in nitrate removal systems to meet their drinking water needs.

Current economics are driving agricultural intensification in the U.S. and across the globe (Donner and Kucharik 2008; Secchi et al. 2008). In the Midwestern US, this intensification is interacting with climate change to affect water quality. Unchecked, it is possible that weather whiplash and agricultural activities will combine to form a positive feedback loop that motivates farmers to apply more fertilizer to offset excess losses resulting from wetter springs, a practice that is currently being suggested by local managers (Fernandez 2009). Unfortunately, this potential for amplification of water quality problems occurs at a time when the need to reign in the environmental impacts of excessive fertilizer use is becoming widely recognized (Force 2013). Combined, our observations illustrate a harbinger of a future in which increased climatic variation amplifies negative trends in water quality in a region already grappling with impairments (Paulsen et al. 2006).

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Author's contribution T.D.L and A.J.B. conceived the study, assembled the data and produced preliminary results. D.A.R-I developed the WWI. The remaining authors collected and analyzed data, contributed to the interpretation and all authors contributed to writing the paper. Statistical analyses were performed by T.D.L.

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