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# Effects of climate and winter cover crops on nutrient loss in agricultural watersheds in the midwestern U.S.

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**Abstract**

Nutrient runoff from agricultural regions of the midwestern U.S. corn belt has degraded water quality in many inland and coastal water bodies such as the Great Lakes and Gulf of Mexico. Under current climate, observational studies have shown that winter cover crops can reduce dissolved nitrogen and phosphorus losses from row-cropped agricultural watersheds, but performance of cover crops in response to climate variability and climate change has not been systematically evaluated. Using the Soil & Water Assessment Tool (SWAT) model, calibrated using multiple years of field-based data, we simulated historical and projected future nutrient loss from two representative agricultural watersheds in northern Indiana, USA. For 100% cover crop coverage, historical simulations showed a 31–33% reduction in nitrate ($NO_3^-$) loss and a 15–23% reduction in Soluble Reactive Phosphorus (SRP) loss in comparison with a no-cover-crop baseline. Under climate change scenarios, without cover crops, projected warmer and wetter conditions strongly increased nutrient loss, especially in the fallow period from Oct to Apr when changes in infiltration and runoff are largest. In the absence of cover crops, annual nutrient losses for the RCP8.5 2080s scenario were 26–38% higher for $NO_3^-$, and 9–46% higher for SRP. However, the effectiveness of cover crops also increased under climate change. For an ensemble of 60 climate change scenarios based on CMIP5 RCP4.5 and RCP8.5 scenarios, 19 out of 24 ensemble-mean simulations of future nutrient loss with 100% cover crops were less than or equal to historical simulations with 100% cover crops, despite systematic increases in nutrient loss due to climate alone. These results demonstrate that planting winter cover crops over row-cropped land areas constitutes a robust climate change adaptation strategy for reducing nutrient losses from agricultural lands, enhancing resilience to a projected warmer and wetter winter climate in the midwestern U.S.

**Keywords** Nutrient pollution, Agricultural watersheds · Nitrate losses · Soluble reactive phosphorus losses · Climate variability · Cover crops · Climate change · Adaptation · SWAT

Extended author information available on the last page of the article

## 1 Introduction and background

Nutrient pollution is an important and intensifying global problem (Dodds et al. 2009), and nutrient loss from agricultural areas in the midwestern United States (U.S.) has resulted in the eutrophication of many important inland and coastal water bodies, such as Lake Erie and the Gulf of Mexico (Osterman et al. 2005; Pearl et al. 2016; Essig 2017; Robertson and Saad 2011;). In response to this global environmental challenge, researchers, farmers, and agricultural managers have developed new conservation strategies for reducing nutrient losses from agricultural areas. One promising strategy is the use of winter cover crops, such as annual ryegrass (*Lolium multiflorum*) or cereal rye (*Secale cereal*), which function, among other things, as a biological storage and release system for nutrients. Winter cover crops are planted when the fields would normally be fallow, starting after the traditional "cash crop" harvest in the fall (typically mid-October), and terminating the cover crop before the cash crop is planted in the spring (typically mid-May) (Hanrahan et al. 2018; Kaspar and Singer 2011). In the midwestern U.S. the cover crop is typically not harvested, but practices vary in other regions and parts of the world. The cover crop retains soil nutrients during the fallow season (October–April), which encompasses a particularly vulnerable period for nutrient runoff to adjacent ditches and streams (Christopher et al. 2021; Speir et al. 2022). Furthermore, cover crop roots can enhance water retention in the soil (Basche and DeLonge 2017; Yang et al. 2020), and the above-ground canopy intercepts precipitation that would normally fall on bare soil. Thus, cover crops reduce surface runoff, soil erosion and leaching and, in turn, nutrient losses from fields to waterways (Hanrahan et al. 2018; Trentman et al. 2020; Speir et al. 2021, 2022; Gupta et al. 2023). In midwestern farms, when the cover crop is terminated in spring, the biomass stays on the fields and gradually releases nutrients as the cover crop decomposes, providing a source of nutrients during the cash crop growing season (Brunetto et al. 2011; Christopher et al. 2021; Cober et al. 2018). Over time, cover crops can also enrich the soil by increasing the accumulation of organic matter, especially when combined with no-till soil management practices (Kaspar and Singer 2011).

While it is well established that cover crops are effective at reducing nutrient runoff from farmland under current climate conditions (Kaspar et al. 2007; Kaspar and Singer 2011; Hanrahan et al. 2018; Trentman et al. 2020; Christopher et al. 2021; Speir et al. 2021, 2022), relatively little research has quantified how the performance of cover crops varies from year-to-year in response to climate variability, such as interannual precipitation variability. Using observed data from a multi-year field sampling campaign, Trentman et al. (2020) and Speir et al. (2021) examined the interaction between cover crop planting and runoff from fields to waterways, and confirmed that precipitation variability and storm intensity were important controls on nutrient losses; however, the analysis was constrained by relatively short records. The use of models can help extend these results to cover a wider range of climatic conditions and management actions. Moreover, only a few studies have explored how cover crop performance and overall nutrient reductions may be altered by systematic changes in hydrologic response due to climate change, such as increased precipitation intensity, conversion of snowfall to rain, loss of snow cover, and increased surface runoff in cool season (Wang et al. 2018; Malone et al. 2020; Lychuk et al. 2021; Gupta et al. 2023). Recent review articles have argued that cover crops may significantly mitigate increased nutrient loading in response to climate change (Kaye and Quemada 2017; Altieri and Nicholls 2017), but these conclusions have only very recently been well supported by quantitative modeling studies (Malone et al. 2020; Gupta et al. 2023, concurrent with our study). Here, we use an integrated hydrology and water quality simulation model driven by (a) long-term historical meteorological data and (b) long-range climate change projections to test the hypothesis that water quality benefits from cover crops will be robust to projected future changes in temperature and precipitation. The results provide new evidence that winter cover crops can effectively reduce nutrient runoff from cropland under future climate conditions.

Specifically, in this paper we (1) quantify how interannual precipitation variability affects nutrient loss, with and without winter cover crops, (2) simulate how climate change and altered hydrologic responses will affect nutrient loss in agricultural watersheds without adaptive actions, and (3) simulate the performance of cover crops in reducing nutrient loss under a wide range of climate change scenarios. We hypothesized that projected increases in winter and spring precipitation and loss of snow cover would systematically increase runoff in mid-winter and early spring (Byun et al. 2019; Hamlet et al. 2020), a time when fields are typically fallow and unprotected by vegetative cover, resulting in increased nutrient loss through surface runoff and subsurface leaching. We also hypothesized that, if the greatest climate change effects are observed in winter and spring, winter cover crops would be especially effective at reducing climate impacts, because cover crops store nutrients and reduce nutrient loss most effectively during the fallow season.

# 2 Methods

## 2.1 Study area

Our study area is comprised of two representative agricultural watersheds in northern Indiana (IN) in the midwestern U.S.: Shatto Ditch (SDW) (1339 ha), and Kirkpatrick Ditch (KDW)(2577 ha) (Fig. 1). We chose these specific watersheds for this modeling study primarily because cover crops have been planted over a substantial percentage of the croppable areas of these watersheds for a number of years, ranging from 23 to 68% of croppable area from 2008 to 2019 at Shatto, and 12–32% of croppable acres from 2016 to 2019 for Kirkpatrick (Supp. Mat. Table SM8). Flow and nutrient concentrations have been measured at the outlet of each watershed since 2007 and 2015 in SDW and KDW, respectively. These relatively long-term observations provide detailed data for model calibration and validation. The two watersheds also have contrasting agricultural management characteristics. SDW is extensively tile drained, and no-till farm management practices are used over most of the basin. KDW, by comparison, has less tile drainage, and many farmers in the basin still use conventional till approaches. Soil characteristics are also different in the two watersheds. In the SDW, soils are Alfisols with loam and loamy sand texture, whereas KDW soils are finer textured Mollisols, mostly silty clay loams (Christopher et al. 2021; Supp. Mat. pg 8–27). Corn and soybeans are the dominant crop rotations in both basins (Fig. 1), as is true for much of the surrounding region.

## 2.2 Integrated hydrology and water quality simulation model

The hydrology and water quality simulation model used in our study is the well-known Soil and Water Assessment Tool (SWAT) (Gassman et al. 2007), which has been widely used in assessing climate change impacts on agricultural watersheds (Gassman et al. 2007; Ficklin et al. 2009; Van Liew et al. 2012). For this study, the model is implemented at very high

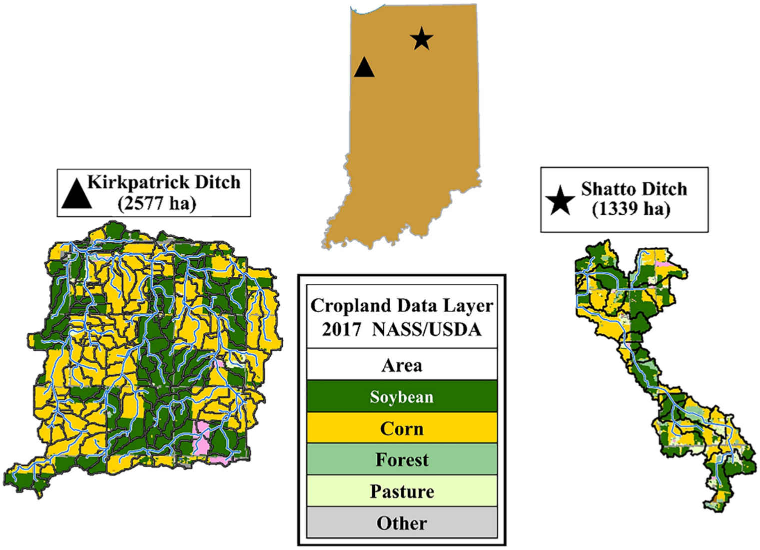


**Fig. 1** Maps of Shatto Ditch and Kirkpatrick Ditch watersheds in northern IN. Cropping patterns are shown for water year 2017. Fine-scale watershed boundaries used in SWAT modeling are shown in black, and natural flow paths deriving from GIS analysis are shown in blue. (Crop data obtained from the U.S. Department of Agriculture (USDA), National Agricultural Statistics Service.)

resolution (35 subwatersheds, 123 hydrologic response units (HRUs) for SDW, and 193 subwatersheds, 265 HRUs for KDW) (Fig. 1) in order to capture the location of cover crops in the basin and analyze the spatial variability of runoff generation and nutrient leaching processes over the two basins. The SWAT models for SDW and KDW were calibrated using 16 selected model parameters, which were identified at the outset of the project using detailed sensitivity studies (See Supp. Mat. Table SM9).

Initial sensitivity studies demonstrated that the SWAT simulations of percent reduction in nutrient loss scale linearly with % cover crop area in the model for both watersheds (Supp. Mat., Figure SM9). Using Monte Carlo experiments that varied the location of cover crop plantings, the SWAT models were also found to be relatively insensitive to cover crop placement (Supp. Mat. pg 36–40). These preliminary findings made organizing the remainder of the SWAT runs relatively easy, because we needed only to simulate the nutrient losses for no cover crops (NOCC) and a fixed 100% coverage of croppable area (100CC) in each case. The results for other cover crop percentages are then linear between these two extremes, and the effects of any other percent cover crop coverage of interest can be estimated using simple linear interpolation. For calibration runs we used a single randomly assigned, but fixed, cover crop scenario for each percent coverage in the model calibration runs (ranging from 11 to 67% for different years—see Supp. Mat. Table SM8). We note that these characteristics of small and relatively homogeneous watersheds are expected, but may not be present in larger and more heterogeneous watersheds.

### 2.3 Representation of cover crops in the SWAT model

Cover crops are simulated as cereal ryegrass in the SWAT model, planted each year on Oct 17, and terminated (but not harvested) on May 1. The SWAT model treats the cover crop in the same way as any other crop, increasing biomass with increasing heat units each day, provided the temperature is above a minimum threshold for growth, and cumulative heat units are below the specified heat units at maturity (Supp. Mat. pg 7). These model parameters control when the plants can start growing, how fast they grow (accumulate biomass) in response to heat units, and how soon they will mature. Comparison with observations (Christopher et al. 2021) shows good overall agreement for fall/spring peak cover crop biomass in the SWAT simulations (Supp. Mat. pg 35–37). Under climate change, due to a warmer, wetter growing season, cool-season cover crops may grow more quickly, achieve higher peak biomass, and/or mature earlier in the spring. Higher cover crop biomass generally implies greater retention of nutrients (Christopher et al. 2021), although the effects are ultimately limited by rooting depth and available nutrients in the soil.

### 2.4 Streamflow and water quality measurements for model calibration and validation

For KDW, we obtained continuous daily streamflow estimates from the USGS gage located at the watershed outlet (USGS 03363350; WY 2016–2019). For SDW, 1-day-lagged, basin-area-adjusted streamflow measurements from the nearby Eel River (USGS 03328500) were used to estimate daily streamflow at the basin outlet (WY 2008–2019). Short-term streamflow measurements from an automated USGS streamflow gauge installed in the SDW (WY 2016–2019) were also used as a cross check for the basin-area-adjusted Eel data sets; although, for consistency through time, only adjusted measurements from the Eel were used in our analysis.

Observed nitrate ($NO_3^-$) and soluble reactive phosphorus (SRP) concentration data were collected using grab samples taken at 2-week intervals at the watershed outlets (Hanrahan et al. 2018; Speir et al. 2022). Daily values between grab-sample data points were interpolated using the R package "*Loadflex*" (Appling et al. 2015). For $NO_3^-$, *Loadflex* was trained on the grab sample data, and used streamflow regression combined with interpolated residuals to estimate intermediary values between grab samples. For SRP, simple rectangular interpolation was used, because regression with streamflow was not statistically significant for SRP. By construction, *Loadflex* values at daily time step exactly match the grab samples used to train the *Loadflex* model, but *Loadflex* estimates of values between grab sample data points are relatively uncertain and may contain substantial errors in some cases. As discussed in more detail later, this is an important consideration when evaluating the performance of the water quality simulations.

Finally, concentration and flow data were combined to calculate daily and monthly loads, which were then normalized by the total watershed area to estimate yield (nutrient losses per unit area) for $NO_3^-$ (kg N/ha) and SRP (kg P/ha).

### 2.5 Historical meteorological driving data sets

Special meteorological data sets through WY 2019 based on interpolated station data were used for initial calibration and validation of the SWAT model (Supp. Mat., pg 27). For the main simulations, a daily historical meteorological data set from water years 1916–2016 at 1/16th degree resolution (about 5 km × 7 km) was used as forcing data for the SWAT models. These long-term data sets are based on interpolated weather station data, but also account for precipitation gauge undercatch (underestimation due to measurement errors), which is a significant source of bias in precipitation measurements in the Midwest region (see Huidobro Marin et al. 2023; Byun and Hamlet 2018 for additional details). Cutting off the first nine months of the driving data set to create a time series of complete water years (WY 1916–2016), and allowing one complete WY for model spin up, we simulated daily streamflow and nutrient losses from the Shatto and Kirkpatrick basins from WY 1917–2016 (100 years).

### 2.6 Climate change scenarios

Statistically downscaled climate change scenarios, which are described in more detail by Byun and Hamlet (2018) and Hamlet et al. (2020), were prepared for the Midwest region as a whole and the Indiana Climate Change Impacts Assessment (INCCIA), respectively. The projections encompass two greenhouse gas concentration scenarios (high-RCP8.5, and medium-RCP4.5) and three future 30-year periods centered on the 2020s, 2050s, and 2080s. The scenarios are based on the *Hybrid Delta* (HD) statistical downscaling technique (Hamlet et al. 2013; Tohver et al. 2014; Byun and Hamlet 2018), which perturbs a long historical record based on 10 selected global climate model (GCM) projections that span the range of temperature and precipitation change from a larger ensemble of 31 GCMs included in the Coupled Model Intercomparison Project Phase 5 (CMIP5) (Taylor et al. 2012; Byun and Hamlet 2018). CMIP5 provided climate change projections for the Intergovernmental Panel on Climate Change (IPCC) Fifth Assessment Report (IPCC 2013). The HD approach perturbs an existing historical meteorological driving data set from 1915 to 2016. This technique retains the same sample size as the historical baseline data set for each future greenhouse gas concentration scenario, and individual WYs can be directly compared between historical and future data sets. (See Supp. Mat. pg 28–29 for additional discussion regarding the selection of climate change scenarios, and a summary of projected changes in temperature and precipitation.)

To simplify the analysis for discussion, we only show results for the 2080s RCP8.5 scenarios in the main body of the manuscript. We chose this scenario because it represents the largest climate change effects on nutrient losses, and also because the aggressive RCP8.5 concentration scenario closely follows the observed trajectory of historical and current greenhouse gas concentrations (Schwalm et al. 2020). For completeness, however, results for three time periods (2020s, 2050s, 2080s) and the RCP4.5 and RCP8.5 concentration scenarios are shown for both watersheds (Supp. Mat., pg. 42–53, Figure SR1–SR12). Key results for all scenarios are also tabulated in the main document. The results from earlier periods are similar in character and seasonal timing to the 2080s scenarios in each case, but warming and precipitation change are smaller in magnitude for the earlier periods (Hamlet et al. 2020; Supp. Mat., Figure SM1). For a given time period, RCP4.5 warming and precipitation changes are smaller than RCP8.5 values. The results for RCP4.5 for the 2080s, for example, are comparable to RCP8.5 for the 2050s.

### 2.7 Model validation

Figure SM2 and Table SM10, provide an overview of model performance for the calibration period (2010–2016 for SDW; 2016–2019 for KDW). For SDW only, longer runs added some additional data from 2008–2009 and 2017–2019 to the validation period (Figure SM2 and Table SM11).

For SDW over the calibration period alone (2010–2016), performance statistics based on the correlation coefficient and Nash Sutcliff Efficiencies (NSE) are excellent for discharge (streamflow), and good for $NO_3^-$ and SRP losses. Performance over the short validation period 2017–2019 is relatively poor in both watersheds (Figure SM2, Tables SM10 and SM11), and likely reflects errors in fine-scale meteorological driving data for the model. The fact that the KDW calibration runs only extend over this relatively problematic period also explains the relatively poor NSE scores for KDW compared to SDW. Fundamental uncertainties in the interpolated daily water quality observations also have substantial effects on these error statistics, particularly for 2016–2019 for KDW.

Model limitations notwithstanding, based on the good to excellent results for the majority of the years for Shatto (2010–2016), we have confidence in the results for the limited purpose of examining the sensitivity to climate change and cover crop coverage, especially when percent changes are averaged over a large number of years and ensemble members, as in the analyses carried out here.

### 2.8 Overview of SWAT simulations

Using the calibrated SWAT models, we first simulated historical conditions over 100 years at daily time step (WY 1917–2016), and quantified the relationship between annual precipitation and nutrient loss. We then evaluated the long-term average response to the use of cover crops on 100% of the row-crop agriculture in the two watersheds. Although this level of coverage is difficult to achieve in practice, we chose to apply cover crops to 100% of the row-crop land area, because the effects of cover crops scale linearly with cover crop coverage in the model simulations (Supp. Mat., Figure SM9), and therefore, simulating 0% coverage and 100% coverage captures the full range of effects. We then simulated the effects of climate change alone on nutrient losses without cover crops (i.e., the effects of climate change alone, without any adaptation). Finally, we simulated the combined effects of cover crops (100% coverage) and climate change to assess the performance of cover crops under a warmer and wetter future climate projected for the study region (Byun and Hamlet 2018; Hamlet et al. 2020).

### 2.9 Overview of data processing steps to summarize results

To quantify the effects of climate variability on nutrient losses and show the modeled sensitivity to 100% cover crop implementation for the twentieth century climate, we prepared scatter plots of annual precipitation vs. nutrient losses for the historical climate, and composite mean plots with and without cover crops for the period from WY 1917–2016. The linear relationship between precipitation and nutrient loss was quantified using least-squares regression.

For the future climate scenarios, we prepared scatter plots of annual precipitation vs. nutrient losses and composite mean plots for monthly data, comparing historical and future values without cover crops in each case. These plots show the simulated effects of climate change alone. Climate change simulations show a range of values based on 10 climate change scenarios, whereas the historical baseline simulations are a single time series. We note, however, that the historical baseline and projected future simulations are also uncertain due to model parameter uncertainty, errors in driving data, and other factors. These kind of uncertainties in the historical and future runs, however, do not strongly affect our results, since we base our conclusions primarily on percent changes in the ensemble mean climate change results relative to the historical baseline conditions, which effectively removes any model bias from the analysis.

Finally, to show the combined effects of climate change and cover crops on nutrient losses, we prepared composite mean plots of monthly nutrient losses for historical climate and future climate with and without cover crops. We then summarized the long-term average seasonal and annual values of nutrient losses for different combinations of climate (historical and future) and cover crop implementation (NOCC and 100CC) using bar plots. Percent changes were calculated relative to the historical runs without cover crops. The future values in these analyses were reported as the ensemble mean (i.e., average results for 10 GCM scenarios).

# 3 Results and discussion

## 3.1 Effects of the twentieth century climate variability on nutrient losses and cover crop performance

The SWAT simulations from WY 1917–2016 for both SDW and KDW show approximately linear relationships between annual precipitation in each water year and simulated annual nutrient losses (Figs. 2, 3). When cover crops were simulated over 100% of the croppable area in the watershed, there were systematic reductions in $NO_3^-$ losses regardless of the annual precipitation, although we note that these reductions varied from year to year (as do

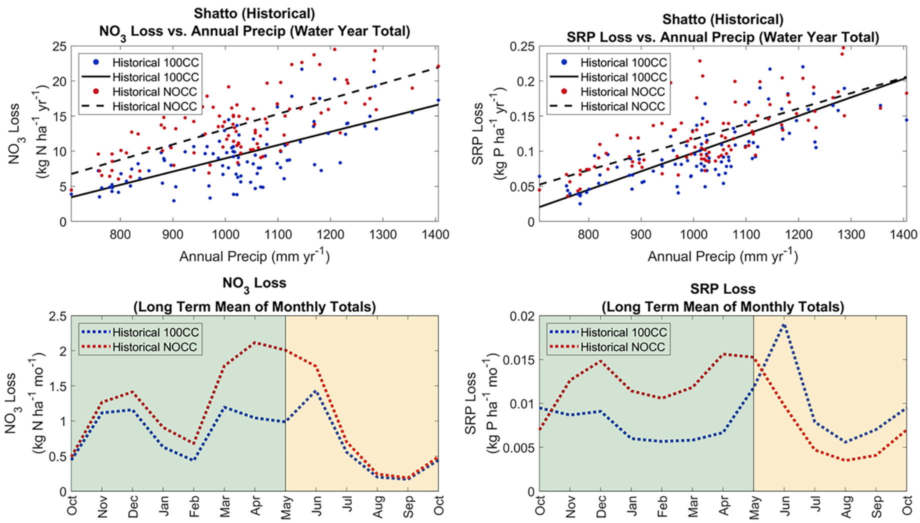


**Fig. 2** Upper panels: scatter plots of annual precipitation vs. annual nutrient losses for Shatto from historical simulations (1917–2016). Straight lines in the upper panels are least-square regression fits to the no cover crop (NOCC) data and 100% cover crop (100CC) data respectively. Lower panels: composite mean plots for monthly nutrient losses with (100CC) and without (NOCC) cover crops. Fallow period (Oct–Apr) when cover crops are present is shown in green in the lower panels

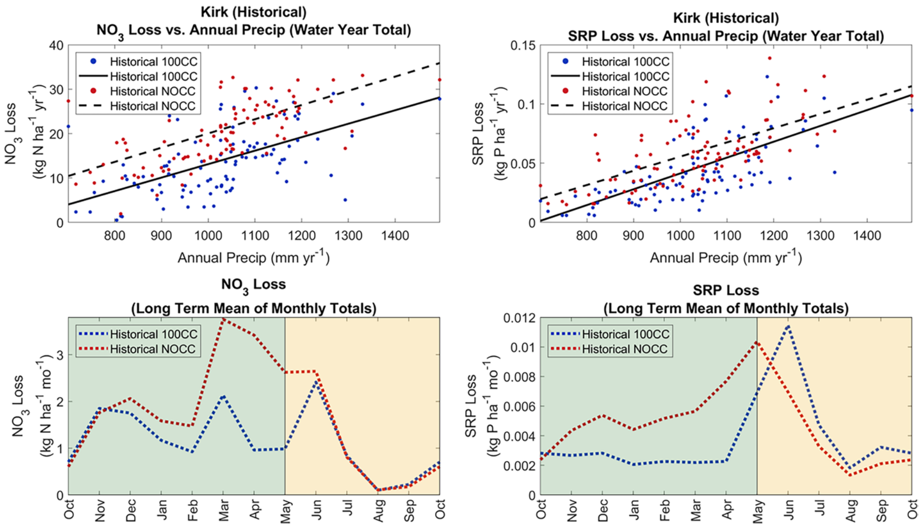


**Fig. 3** Upper panels: scatter plots of annual precipitation vs. annual nutrient losses for Kirkpatrick from historical simulations (1917–2016). Straight lines in the upper panels are least-square regression fits to the no cover crop (NOCC) data and 100% cover crop (100CC) data respectively. Lower panels: composite mean plots for monthly nutrient losses with (100CC) and without (NOCC) cover crops. Fallow period (Oct–Apr) when cover crops are present is shown in green in the lower panels

annual losses without cover crops). By comparison, for SRP, reductions in nutrient loss due to cover crops were largest in years with relatively low precipitation, while there was little or no reduction due to cover crops in years with the highest annual precipitation.

As expected based on results from previous observational studies (Hanrahan et al. 2018; Christianson et al. 2018, 2021; Speir et al. 2022), the effectiveness of cover crops in reducing watershed $NO_3^-$ losses is greater than that simulated for SRP losses, and reductions in both nutrients were most pronounced in the fallow period when cover crops were present. For the SWAT simulations reported here, there is a 31–33% reduction in $NO_3^-$ loss for 100% cover crop coverage, substantially greater than the 15–23% reduction in SRP loss for 100% coverage (Figs. 2, 3 and Table 1).

Interestingly, the addition of cover crops is shown to increase simulated SRP losses in the main growing season (May–Sept) in both watersheds (Figs. 2, 3 and Table 1). Cover crops extract N and P from the soil bring them to the surface in the form of cover crop

**Table 1** Percent changes in nutrient losses (1917–2016) for 100% cover crop coverage (100CC), relative to no cover crop coverage (NOCC)

| Historical | | | |
|---|---|---|---|
| Watershed (nutrient) | Fallow period (%) | Main crop period (%) | Water year total (%) |
| SDW ($NO_3^-$) | −30 | −32 | −31 |
| KDW ($NO_3^-$) | −35 | −28 | −33 |
| SDW (SRP) | −39 | 38 | −15 |
| KDW (SRP) | −51 | 17 | −23 |

biomass, and then release N and P when the cover crop decomposes on the fields (Brunetto et al. 2011; Cober et al. 2018). In the simulations that include cover crops, this release of nutrients in spring results in a distinct peak in losses in June for both nutrients in both watersheds, whereas without cover crops the nutrient losses peak earlier (Fig. 2 and 3). However, for SRP, the cover crop also systematically increases total losses in the main growing season, whereas for $NO_3^-$, there is no increase. One the one hand, it stands to reason that storing nutrients in the winter (Christopher et al. 2021) and releasing them in the main growing season could potentially increase nutrient loss in the main growing season, especially for $NO_3^-$ for which contributions from the decomposing cover crop add to the spring fertilizer application for corn. On the other hand, additions of relatively limited $NO_3^-$ in spring could simply result in more rapid early growth of the main crop, greater uptake of $NO_3^-$, and therefore little or no change in $NO_3^-$ loss in the normal growing season. By comparison, additional sources of SRP from the decomposing cover crop would be expected to increase SRP losses, because SRP is already relatively abundant in the environment, and uptake by the main crop would likely not change appreciably with increased supply.

Currently, confirming these simulated effects using observations is problematic due to relatively coarse sampling intervals, limited sample size, and a lack of consistent meteorological conditions in control and treatment data sets. Future studies to confirm if cover crops do in fact enhance main crop biomass and $NO_3^-$ uptake rates in the primary growing season would be instructive.

### 3.2 Effects of climate change on nutrient losses without cover crops

We hypothesized that climate change would increase surface runoff and nutrient loss in the fallow period, due to projected increases in late fall, winter, and spring precipitation, loss of snow cover, and conversion from snow to rain due to warming (Byun and Hamlet 2018; Byun et al. 2019), which was confirmed by the SWAT simulations (Figs. 4 and 5). In the absence of cover crops, annual nutrient losses were 26–38% higher for $NO_3^-$, and 9–46% higher for SRP (Table 2 under the RCP8.5 2080s scenario). For the 2050s (Supp. Mat. Figure SR2, SR5, SR8, SR11), percent increases in $NO_3^-$ loss due to climate change alone are comparable to results for concurrent modeling studies over Illinois reported by Gupta et al. (2023). For the fallow period, percent increases in nutrient loss were even larger (53–65% for $NO_3^-$ and 26–81% for SRP) (Table 2). We note, however, that annual changes in SRP for SDW are relatively small (9%), despite higher SRP losses in the fallow period (26%) (Table 2). When we plotted precipitation vs nutrient loss (Figs. 4 and 5), we found that nutrient loss is still linearly related to precipitation under climate change, but, except for SRP for Shatto, the slope of the regression line tends to be steeper than for the historical simulations. That is, a larger increase in nutrient loss occurs under climate change for the same amount of increase in annual precipitation, presumably due to loss of snow and more surface runoff and soil leaching occurring in the fallow period in the warmer, wetter climate change simulations. This is important, because the twentieth century precipitation trends to date have been strongly positive over the Midwest region (Cherkauer et al. 2021), and precipitation is projected to increase substantially in the future (Supp. Mat. Figure SM1). This implies steadily increasing nutrient losses over time historically, and reductions in the overall effectiveness of some alternative management practices designed to reduce future nutrient impacts in downstream water bodies, such as reduced fertilizer application.

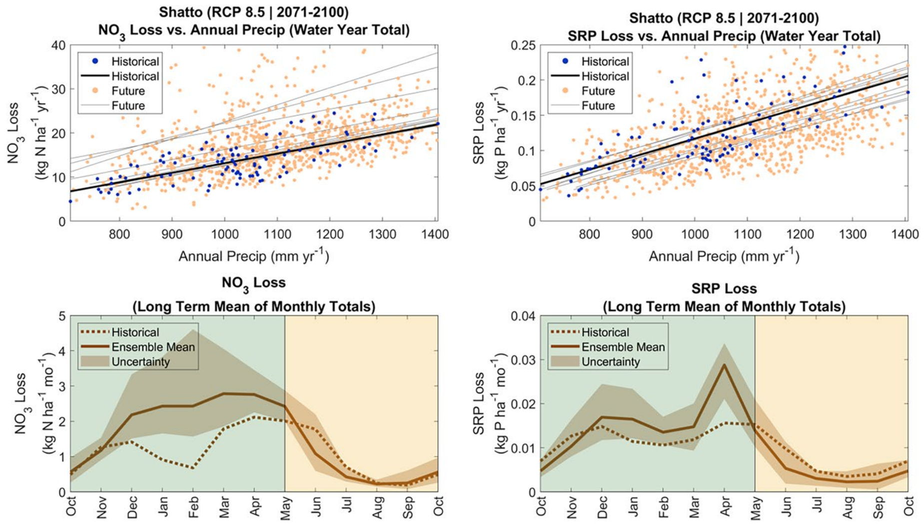


**Fig. 4** Effects of climate change (RCP8.5 2080s) on nutrient loss from Shatto without cover crops. Upper panels: scatter plots of annual precipitation vs. annual nutrient losses for historical and future conditions. Light gray lines show the linear fit for the data from each of 10 global climate projections. Lower panels: monthly composite mean plots of nutrient losses under projected future climate. Tan shaded area shows the range of 10 climate change projections. Dark brown line shows the ensemble mean of the future projections. For consistency with other figures, the cool-season fallow period (Oct–Apr) is shown in green and the traditional warm-season growing period as light tan in the lower panels

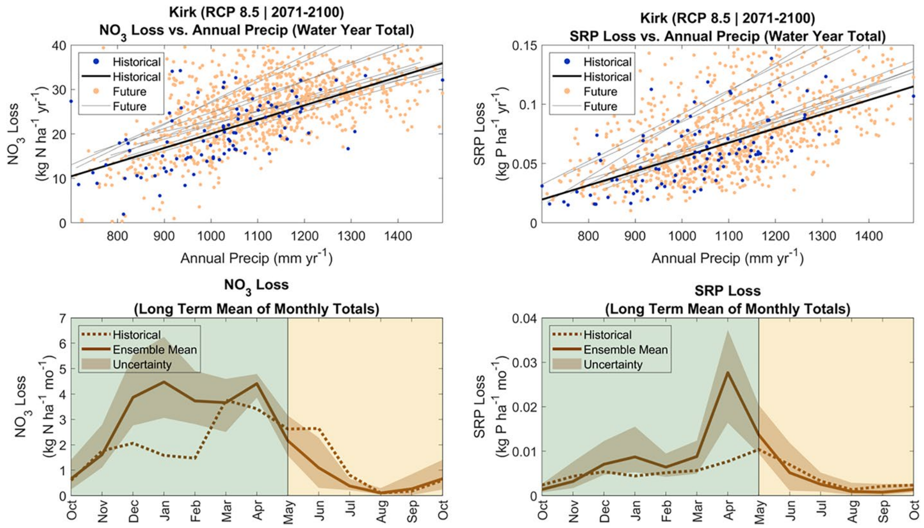


**Fig. 5** Effects of climate change (RCP8.5 2080s) on watershed nutrient loss from Kirkpatrick without cover crops. Upper panels: scatter plots of annual precipitation vs. annual nutrient loss for historical and future conditions. Light gray lines show the linear fit for the data from each of 10 climate change projections. Lower panels: monthly composite mean plots of nutrient losses under projected future climate. Tan shaded area shows the range of 10 climate change projections. Dark brown line shows the ensemble mean of the future projections. For consistency with other figures, the cool-season fallow period (Oct–Apr) is shown in green and the traditional warm-season growing period (May–Oct) as light tan in the lower panels

**Table 2** Percent change in ensemble mean projected future nutrient losses without cover crops relative to historical baseline without cover crops

| RCP 8.5 2080s | | | |
|---|---|---|---|
| Watershed (nutrient) | Fallow period (%) | Main crop period (%) | Water year total (%) |
| Shatto ($NO_3^-$) | 65 | −11 | 38 |
| Kirkpatrick ($NO_3^-$) | 53 | −37 | 26 |
| Shatto (SRP) | 26 | −28 | 9 |
| Kirkpatrick (SRP) | 81 | −4 | 46 |

### 3.3 Combined sensitivity to climate change and cover crops

We also summarized the simulated nutrient losses under different combinations of land use and climate for the worst-case RCP8.5 2080s future projections (Figs. 6 and 7). Without cover crops, we have already shown that nutrient losses increase substantially under climate change, particularly during the fallow season (Figs. 4, 5 and Table 1). Because this seasonal timing aligns with the time of year that cover crops most strongly limit nutrient losses, we hypothesized that cover crops would effectively reduce nutrient losses under climate change scenarios, which was confirmed in the simulations. With 100% cover crop

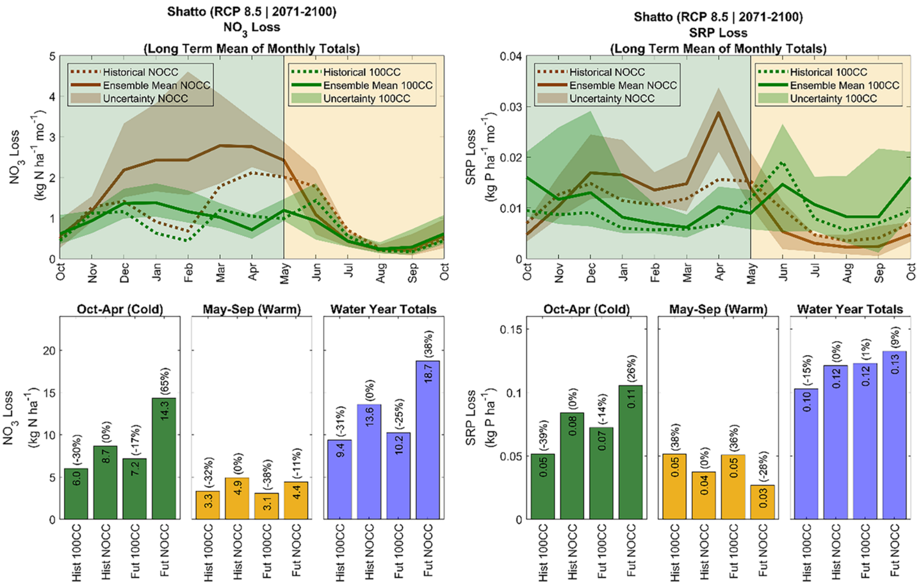


**Fig. 6** Top panels: composite mean plots and range (shaded area) for different combinations of climate (historical and 2080s RCP8.5 future projections) and cover crop coverage (NOCC and 100CC) for Shatto. Lower panels: long-term average total nutrient losses as a function of season (Oct–Apr, May–Sept, Water Year), climate, and cover crop coverage. Ensemble mean values are used for the projected future values shown in the lower panels. The value and percent changes relative to the Historical No Cover Crop (Hist NOCC) values are shown as an inset number and number in parentheses respectively for each bar in the lower panels

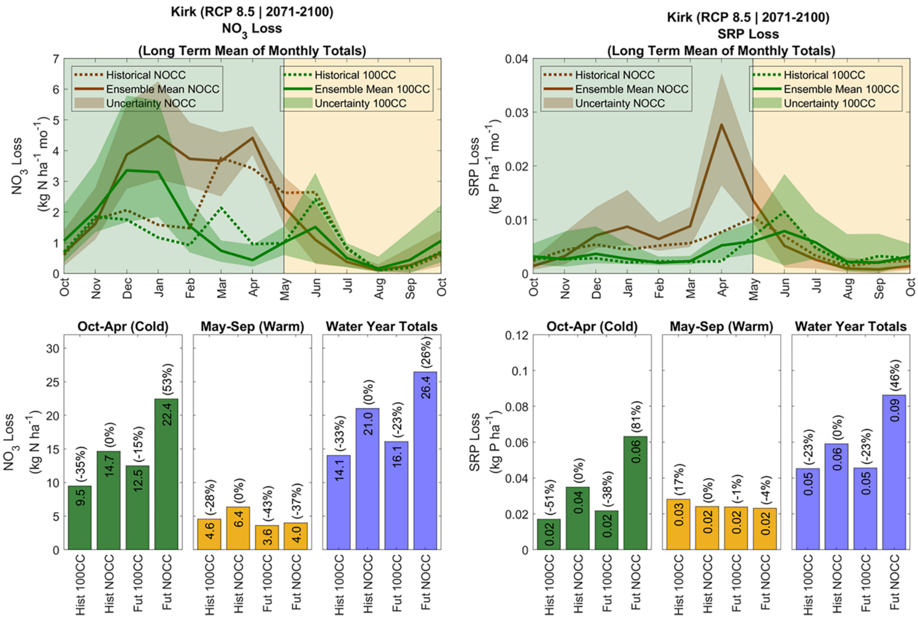


**Fig. 7** Top panels: composite mean plots and range (shaded area) for different combinations of climate (historical and 2080s RCP8.5 future projections) and cover crop coverage (NOCC and 100CC) for Kirkpatrick. Lower panels: long-term average total nutrient losses as a function of season (Oct–Apr, May–Sept, Water Year), climate, and cover crop coverage. Ensemble mean values are used for the projected future values shown in the lower panels. The value and percent changes relative to the Historical No Cover Crop (Hist NOCC) values are shown as an inset number and number in parentheses respectively for each bar in the lower panels

coverage under future climate scenarios, we simulated annual yields (nutrient losses per unit area) that were less than or equal to the historical baseline with 100% cover crop coverage in 19 out of 24 scenarios (lower panels, Figs. 6 and 7; Table 3 and 4). We have already shown that cover crops are effective in reducing nutrient losses for the historical climate (Figs. 2 and 3; Table 1), but the future simulations show that these reductions can be effectively maintained in most cases, even for the most extreme scenarios of future climate. For the more moderate RCP4.5 scenarios, Fut100CC values are less than or equal to Hist100CC values in all cases (Table 3 and 4, Fig. SR1–SR3, Fig. SR7–SR9).

For the RCP8.5 2080s scenario, cover crops applied over 100% of the simulated croppable area reduce water year $NO_3^-$ losses by 39–45% and SRP losses by 7–47 percent. Reductions in the fallow period are even larger: 44–50% reduction in $NO_3^-$ losses and 36–67% reduction in SRP losses respectively. Comparing these results to those in Table 1 for the historical climate, we show that cover crops will be more effective in the future as winter and spring surface runoff increase, retaining a systematically greater fraction of the available nutrients that contribute to watershed nutrient losses. This is likely due to systematic increases in biomass of the simulated cover crop in a warmer, wetter climate.

The simulations shown in Figs. 6 and 7 for RCP8.5 represent a worst-case scenario for future climate and nutrient loss, but the full range of climate change projections for RCP 4.5 and RCP8.5 for the 2020s, 2050s, and 2080s confirm that these findings are robust for a wide range of climate projections (Supp. Mat., pg. 42–53, Figure SR1–SR12, Table 3, 4).

**Table 3** Summary of effects of cover crops on annual $NO_3$- losses for historical climate and ten climate change scenarios for two midwestern agricultural basins. Primary numbers shown are the simulated long-term average yield for the water year (kg N/ha). Numbers in parentheses are the percent change relative to the Historical No Cover Crop (Hist NOCC) simulations. Future climate change results are ensemble mean values

$NO_3^-$

| Scenario | Basin | Hist NOCC | Hist 100CC | Fut NOCC | Fut 100CC | Fut 100CC < = Hist 100CC? |
|---|---|---|---|---|---|---|
| RCP4.5 2020s | Shatto | 13.6 (0%) | 9.4 (−31%) | 13.8 (+1%) | 8.6 (−37%) | **Yes** |
| | Kirkpatrick | 21.0 (0%) | 14.1 (−33%) | 21.9 (+4%) | 13.0 (−38%) | **Yes** |
| RCP4.5 2050s | Shatto | 13.6 (0%) | 9.4 (−31%) | 15.3 (+13%) | 9.2 (−32%) | **Yes** |
| | Kirkpatrick | 21.0 (0%) | 14.1 (−33%) | 23.5 (+12%) | 13.5 (−36%) | **Yes** |
| RCP4.5 2080s | Shatto | 13.6 (0%) | 9.4 (−31%) | 15.4 (+14%) | 9.1 (−33%) | **Yes** |
| | Kirkpatrick | 21.0 (0%) | 14.1 (−33%) | 23.8 (+13%) | 13.8 (−34%) | **Yes** |
| RCP8.5 2020s | Shatto | 13.6 (0%) | 9.4 (−31%) | 14.1 (+4%) | 8.9 (−34%) | **Yes** |
| | Kirkpatrick | 21.0 (0%) | 14.1 (−33%) | 22.7 (+8%) | 13.5 (−36%) | **Yes** |
| RCP8.5 2050s | Shatto | 13.6 (0%) | 9.4 (−31%) | 16.1 (+18%) | 9.5 (−30%) | **No** |
| | Kirkpatrick | 21.0 (0%) | 14.1 (−33%) | 24.8 (+18%) | 14.3 (−32%) | **No** |
| RCP8.5 2080s | Shatto | 13.6 (0%) | 9.4 (−31%) | 18.7 (+38%) | 10.2 (−25%) | **No** |
| | Kirkpatrick | 21.0 (0%) | 14.1 (−33%) | 26.4 (+26%) | 16.1 (−23%) | **No** |

**Table 4** Summary of effects of cover crops on annual SRP losses for historical climate and ten climate change scenarios for two midwestern agricultural basins. Primary numbers shown are the simulated long-term average yield for the water year (kg P/ha). Numbers in parentheses are the percent change relative to the Historical No Cover Crop (Hist NOCC) simulations. Future climate change results are ensemble mean values

SRP

| Scenario | Basin | Hist NOCC | Hist 100CC | Fut NOCC | Fut 100CC | Fut 100CC < = Hist 100CC? |
|---|---|---|---|---|---|---|
| RCP4.5 2020s | Shatto | 0.12 (0%) | 0.10 (−15%) | 0.12 (−1%) | 0.09 (−23%) | **Yes** |
| | Kirkpatrick | 0.06 (0%) | 0.05 (−23%) | 0.06 (0%) | 0.04 (−38%) | **Yes** |
| RCP4.5 2050s | Shatto | 0.12 (0%) | 0.10 (−15%) | 0.13 (+4%) | 0.10 (−19%) | **Yes** |
| | Kirkpatrick | 0.06 (0%) | 0.05 (−23%) | 0.07 (+15%) | 0.04 (−35%) | **Yes** |
| RCP4.5 2080s | Shatto | 0.12 (0%) | 0.10 (−15%) | 0.12 (+3%) | 0.10 (−19%) | **Yes** |
| | Kirkpatrick | 0.06 (0%) | 0.05 (−23%) | 0.07 (+15%) | 0.04 (−38%) | **Yes** |
| RCP8.5 2020s | Shatto | 0.12 (0%) | 0.10 (−15%) | 0.12 (+1%) | 0.10 (−21%) | **Yes** |
| | Kirkpatrick | 0.06 (0%) | 0.05 (−23%) | 0.06 (+5%) | 0.04 (−38%) | **Yes** |
| RCP8.5 2050s | Shatto | 0.12 (0%) | 0.10 (−15%) | 0.13 (+6%) | 0.10 (−16%) | **Yes** |
| | Kirkpatrick | 0.06 (0%) | 0.05 (−23%) | 0.07 (+25%) | 0.04 (−33%) | **Yes** |
| RCP8.5 2080s | Shatto | 0.12 (0%) | 0.10 (−15%) | 0.13 (+9%) | 0.12 (+1%) | **No** |
| | Kirkpatrick | 0.06 (0%) | 0.05 (−23%) | 0.09 (+46%) | 0.05 (−23%) | **Yes** |

Specifically, the nutrient losses with 100% cover crop coverage for the future projections are predominantly less than or equal to the historical climate baseline with 100% cover crops for annual totals (i.e., Fut100CC < =Hist100CC). For $NO_3^-$, only the RCP8.5 scenarios for the 2050s and 2080s show small increases in the future projections with cover crops when compared to historical simulations with 100% cover crops (Table 3). For SRP, only SDW for RCP8.5 2080s shows an increase in yield (Table 4) in comparison with historical simulations. For the fallow period, future projections with 100% cover crop coverage also show comparable levels of nutrient losses to historical climate with 100% cover crop coverage, typically differing by at most a few percent. Our results support the conclusion that there would be substantial reductions in nutrient loss under historical conditions for 100% cover crop coverage, and that these reductions in annual nutrient losses would be sustained, or even improved, in the majority of cases for the projected future climate. Thus, the use of cover crops is shown to be an effective and robust adaptation strategy for reducing nutrient impacts under climate change.

We note that in the modeling scenarios presented here, agronomic practices and land management did not vary and a corn-soy bean rotation was maintained throughout the duration of the modeling period (i.e., through 2100). It seems likely that agricultural producers will also respond to a changing climate by changing crops, adjusting cropping systems, increasing subsurface drainage systems (i.e., tile drains) to cope with increased spring precipitation, or adopting other conservation practices. To the extent such changes in farming practices occur in the future, the water quality benefits of cover crops could be greater or lesser than presented here.

### 3.4 Potential impacts to viability of cover crops in a future climate

Previous research has suggested that despite the potential benefits of a warmer winter climate on crop growth (including cover crops), the potential for systematically drier future conditions in the early fall, like those observed in recent decades in historical records, could pose an obstacle to cover crop germination under climate change (Gampe et al. 2021). The SWAT vegetation growth model does not explicitly simulate the germination process; however, it simulates the growth of the cover crop in the same manner as any other crop, and reacts to changing conditions (such as increased growing degree days and water availability) in a fairly realistic way. In assessing these potential impacts, we first note that there is no projected systematic change in precipitation in October for Indiana in the future climate projections used for this study, and precipitation in the remainder of the cool season is strongly increased for essentially all GCM projections (Hamlet et al. 2020; Supp. Mat. Figure SM1). Secondly, in the SWAT simulations, the cover crop was planted on October 17 each year, which is typically well after the transition from late-summer/early fall drought conditions in late September to cooler, wetter weather by mid-October. Taken together, this implies that there are no systematic increases in drought stress in the future projections informing this study that would impact success in germinating the cover crop in the simulations. Lastly, even if drought conditions in mid-October systematically increased in the future, planting the cover crop a few weeks later would likely avoid these impacts given the warmer conditions and increased precipitation projected for the cool-season as a whole. Thus, evidence of historical increases in drought stress in the late summer and early fall notwithstanding, our simulations based on GCM projections and a mid-October planting date do not confirm this potential impact pathway for cover crops.

### 3.5 Implications of alternative management strategies

Alternative management strategies for winter cover crops may have some important effects on reductions in nutrient losses. In the midwestern U.S., farmers are now commonly planting the cover crop before the main crop is harvested in the fall. This has the potential to increase biomass and nutrient retention earlier in the water year, and/or increase peak biomass of the cover crop. This practice, however, may also expose the cover crop to late summer drought, which is projected to increase in intensity under climate change in the Midwest (Supp. Mat., Figure SM1). Our results also suggest that increased cover crop biomass could potentially increase SRP losses during the regular growing season. Harvesting the winter cover crop in spring for animal fodder or other purposes (rather than leaving it on the fields) could provide additional farm income, and may also reduce added nutrient losses during the main growing season when cover crops are present.

### 3.6 Potential effects of basin scale on model design and sensitivity

Our study has focused on two small representative agricultural watersheds. The relatively fine-scale and high-resolution analysis presented here is meaningful in a management context and has been helpful in identifying important mechanisms and processes using observations and models. Large-scale studies, however, are also needed to evaluate how the performance of cover crops would scale up in larger watersheds, such as the Wabash River, which drains approximately 60% of the state of Indiana and a portion of Illinois. Because simulations of percent reduction in nutrient loss scale linearly with treated cover crop area (see earlier discussion, Supp. Mat. Figure SM9), large-scale results might also be expected to scale linearly with treated area percentage (i.e., superposition of linear effects in each subwatershed), especially if cover crops are implemented evenly over the entire watershed. Routing and storage effects, and specifically the storage of nutrients in soil, ditches, or river channels, however, could introduce non-linearities related to upstream and downstream locations. Downstream agricultural areas near the basin outlet would presumably contribute to nutrient loading very much like the small-scale watersheds in this study (because travel time, internal storage, and lag effects are relatively small), whereas upstream areas far from the basin outlet might be more affected by substantial time lags, and/or nutrient storage effects in soils or river channel sediments. At very large scales (e.g., for the Mississippi River basin and associated impacts to the Gulf of Mexico), there is evidence to suggest that lag times for nutrient accumulation are on the order of decades, due to natural storage effects in the environment (Van Meter and Basu 2017). If these assertions also apply to more moderately sized river basins, incorporating these fundamental time lags in models will be a crucial (and currently unaddressed) component of large-scale studies addressing eutrophic conditions in downstream waterways (Basu et al. 2022).

## 4 Summary of key findings

Two high-resolution SWAT models were forced by (a) long-term daily historical meteorological data from 1916 to 2016, and (b) an ensemble of 60 future climate projections from the Indiana Climate Change Impacts Assessment, based on two greenhouse gas concentration scenarios (RCP4.5 and RCP8.5), three future time periods (2020s, 2050s, 2080s), and ten representative global climate model projections from the CMIP5.

Natural variability of annual precipitation is a strong control on annual nutrient losses from agricultural watersheds for both historical conditions and climate change scenarios. SWAT simulations show an approximately linear relationship between annual precipitation and yield (annual nutrient losses per unit area). Increasing precipitation trends imply steadily increasing nutrient losses over time under historical conditions, and reductions in the overall effectiveness of some management strategies designed to reduce nutrient loss in future (e.g., reduced fertilizer application).

Cover crops applied over 100% of the simulated croppable area in the two representative watersheds reduced water-year losses of $NO_3^-$ by 31–33% and SRP by 15–23% for the historical climate from 1917 to 2016. In the fallow period, percent reductions in nutrient losses were 30–35% for $NO_3^-$ and 39–51% for SRP.

Under the worst-case 2080s RCP8.5 climate change scenario, water year precipitation remains a strong interannual control on nutrient losses, but the slope of the linear relationship is increased in most cases, which implies a systematic increase in nutrient losses for a given amount of precipitation. For the RCP8.5 2080s climate change scenario, without cover crops, simulated annual nutrient losses increased by 26–38% for $NO_3^-$, and 9–46% for SRP. Percent increases in nutrient losses in the fallow period were 53–65% for $NO_3^-$ and 26–81% for SRP.

For the 2080s RCP8.5 climate change scenarios, cover crops applied over 100% of the simulated croppable area reduce water year $NO_3^-$losses by 39–45% and SRP losses by 7–47%, greater percent reductions than for the historical climate (except for Shatto SRP). Reductions in the fallow period are even larger: 44–50% reduction in $NO_3^-$ losses and 36–67% reduction in SRP losses, respectively. Comparing simulations of cover crops combined with climate change projections for 60 climate scenarios shows robust performance of cover crops in achieving comparable levels of nutrient loss to those simulated for cover crops combined with historical climate. These results demonstrate that cover crops will be substantially more effective (i.e., achieving greater percent reductions in nutrient losses) in the future climate. Thus, cover crops are expected to serve as a sustainable and resilient climate adaptation strategy: (a) effectively reducing nutrient losses in the current climate, and (b) sustaining these reductions in nutrient losses even in a warmer and wetter climate that would otherwise substantially increase nutrient losses.

Simulated increased losses in SRP during the main crop growing season when cover crops are present, but none for $NO_3^-$ losses, suggests a need for different management strategies in different geographic settings. When downstream water bodies are sensitive to SRP inputs (many freshwater systems), harvesting the cover crop in spring might prove to be an effective way to further enhance reductions in annual P load. This approach is not commonly used in the Midwest at the present time, but could be in the future. For $NO_3^-$ sensitive systems (many marine systems), our simulations suggest there would be less benefit to harvesting the cover crop in the Midwest, since additional $NO_3^-$ inputs from the decomposing cover crop seem to be effectively taken up by the main crop in the simulations. Observed studies are needed to confirm these effects in the model simulations.

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**Data availability** Data and code for the project are currently archived on *Mendelay Data* (Reserved https://doi.org/10.17632/sgdbjd3vst.1). These resources are not yet publicly available at the time of this writing, but will be made so upon publication of this and several other journal articles. A more detailed description of modeling parameters and configuration files is also given in the Supplemental Material for the paper.

## Declarations

**Ethics approval** N/A.

**Consent to participate** N/A.

**Consent for publication** N/A.

**Competing interests** The authors declare no competing interests.

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