Flood Risk Reduction from Agricultural Best Management Practices

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Research Impact Statement: Agricultural best management practices (BMPs) can reduce flood risk, providing a co-benefit to nutrient reduction.

ABSTRACT: Best management practices (BMPs) play an important role in improving impaired water quality from conventional row crop agriculture. In addition to reducing nutrient and sediment loads, BMPs such as fertilizer management, reduced tillage, and cover crops could alter the hydrology of agricultural systems and reduce surface water runoff. While attention is devoted to the water quality benefits of BMPs, the potential co-benefits of flood loss reduction are often overlooked. This study quantifies the effects of selected commonly applied BMPs on expected flood loss to agricultural and urban areas in four Iowa watersheds. The analysis combines a watershed hydrologic model, hydraulic model outputs, and a loss estimation model to determine relationships between hydrologic changes from BMP implementations and annual economic flood loss. The results indicate a modest reduction in peak discharge and economic loss, although loss reduction is substantial when urban centers or other high-value assets are located downstream in the watershed. Among the BMPs, wetlands, and cover crops reduce losses the most. The research demonstrates that watershed-scale implementation of agricultural BMPs could provide benefits of flood loss reduction in addition to water quality improvements.

(KEYWORDS: agricultural BMPs; flood loss estimation; flood damage; wetlands; rural.)

INTRODUCTION

Cultivation and land conversion practices associated with intensive row crop agriculture continue to impair water quality in the United States (U.S.) Midwest (Alexander et al. 2008; Blann et al. 2009; David et al. 2010; Robertson et al. 2014; Lamba et al. 2015; Kalkhoff et al. 2016; Jones et al. 2018). In 2008, the Gulf Hypoxia Task Force convened by the U.S. Environmental Protection Agency issued an Action Plan calling for states along the Mississippi River to develop nutrient reduction plans (Mississippi River/ Gulf of Mexico Watershed Nutrient Task Force 2008). In response, each state adopted the Gulf Hypoxia Task force targets and set nutrient reduction targets based on the prevalent point and nonpoint source activities. The State of Iowa in 2013 instituted the Iowa Nutrient Reduction Strategy, which established goals of a 41% reduction in nitrogen and a 29% reduction in phosphorus from nonpoint sources (Iowa Department of Agriculture and Land Stewardship et al. 2017). To achieve the nutrient reduction goals, Iowa has promoted the adoption of agricultural best management practices (BMPs), including reduced tillage, improved fertilizer management, cover crops,
bioreactors, edge-of-field installation of wetlands, and vegetated buffer zones.

Although the principal goal of agricultural BMPs is to improve water quality, they also have potential to mitigate river flooding by reducing surface runoff, increasing groundwater infiltration, and decreasing surface travel time. Flooding is the costliest natural hazards in the U.S., with annual damages averaging nearly $8 billion (National Weather Service 2017). In the agricultural-dominated state of Iowa, floods caused more than $11 billion in property and crop loss during the decade 2007-2016 (HVRI 2016). Efforts in Iowa to reduce flood risk have largely focused on traditional approaches, such as dams, levees, floodwalls, and property buyouts. But do agricultural BMPs also reduce flood risk? If so, which BMPs are most effective at loss reduction?

The objective of this study is to assess the influence of agricultural BMPs on flood risk reduction. Using a case study of rural watersheds in Iowa, we quantify and compare economic flood losses across scenarios of agricultural practices. The methodology links hydrological modeling, flood frequency analysis, and flood loss assessment to estimate annual losses to agriculture and the built environment.

AGRICULTURAL PRACTICES AND FLOOD IMPACTS

A range of practices are available to producers to mitigate water quality impacts from row crop agriculture. In-field practices, such as improved nutrient management and reduced tillage, reduce nutrient and sediment loss, retain acreage in production, and minimize costs to farmers. Other practices such as cover crops, controlled drainage, and saturated buffers also provide significant benefits but require additional implementation cost (Iowa Department of Agriculture and Land Stewardship et al. 2017). Agricultural BMPs like wetland restoration, grass waterways, and riparian buffers require targeted retirement of some agricultural land, reducing overall agricultural returns, yet potentially providing greater nutrient export reduction and other benefits per unit area.

Assessing benefits of agricultural BMPs is challenging due to the multiple impacts on hydrology, nutrient cycling, soil fertility, and other processes. Previous studies have largely focused on assessment of BMP performance in reducing nutrient and sediment loss and the subsequent impacts on water quality (Parajuli et al. 2013; Weissteiner et al. 2013; Kladivko et al. 2014; Yeo et al. 2014; McLellan et al. 2015; King et al. 2016; Merriman et al. 2018) (see also study reviews in Hashemi et al. 2016; Liu et al. 2017). BMPs that slow runoff are effective in reducing sediment detachment and transport (Bosch et al. 2013; Mitchell et al. 2018), although effectiveness can vary depending on watersheds characteristics, BMPs location, and storm magnitude. Gitau et al. (2010) argued that water quality improvements may be difficult to observe if they are offset by negative effects of land use changes unrelated to BMPs. Bosch et al. (2013) and Giri et al. (2014) showed that BMPs successfully reduce nutrient loads, especially when implemented in places generating a large amount of pollutants. Lam et al. (2011) found that load reduction may be unequal across targeted pollutants depending on soil characteristics and land topography. Rittenburg et al. (2015) and Brooks et al. (2015) emphasized the role of flowpaths in sediment and nutrient transport and recommended to apply BMPs based on site soil and climate characteristics. Accurate evaluation of BMPs effectiveness is further challenged by uncertainties on land conditions and farming practices (Kurkalova 2015) and lag times between BMPs implementation and water quality improvement (Meals et al. 2010). But overall, there is general agreement that widespread, site-specific adoption of different BMPs can steadily and significantly improve water quality.

Changes in flow regime and discharge from BMPs may also affect the frequency of downstream flood events. In watersheds where row crops dominate the landscape, small changes in the field-scale water budget may yield large changes in watershed-scale hydrologic response. Incremental changes in field management, cropping patterns, transition from perennial to annual crops, and increases in landscape-scale drainage contribute to watershed-scale increases in the rainfall-runoff response and result in more erosive rivers in agricultural landscapes (Randall and Iragavarapu 1995; Schilling et al. 2008; Schottler et al. 2014; Foufoula-Georgiou et al. 2015; Kelly et al. 2017; Dalzell and Mulla 2018). Previous studies on the effect of agricultural practices on stream discharge have reported mixed results. Gassman et al. (2010) found an increase in discharge following a 10-year implementation of conservation practices targeting sediment and nutrient reduction, although the authors attributed this increase to the installation of tiled terraces. Schilling et al. (2014) analyzed the effects on flood events of introducing switchgrass and different crop rotation into a corn and soybean-dominated landscape and reported a reduction in both number of flood events and frequency of severe events at the 8-digit watershed level. Meanwhile, Dakhlalla and Parajuli (2016) projected the effect of paralleled terraces, grassed
waterways and detention ponds on peak flows, and found that spatially widespread adoption of multiple BMPs reduce peak flow at the 8-digit watershed scale.

The economic benefits of BMP flow reduction remain unclear and largely unexplored. In general, the economic costs and benefits vary by type (direct/indirect), measurability (material/intangible), spatial scale (local/regional), and temporal scale (short, medium, long term) (De Groot et al. 2002; Merz et al. 2010). The most common paradigm for assessing the economic benefits of flood risk reduction is quantifying preventing losses. Brander et al. (2013) reviewed studies on flood control, water supply, and water quality functions provided by wetlands and found that a frequent approach for quantifying wetland benefits is comparison with the cost of equivalent man-made infrastructure. Analyses on the effects of floods commonly estimate and compare losses ex-ante and ex-post, or for current and alternative scenarios (Shreve and Kelman 2014; Poussin et al. 2015). For example, Kousky et al. (2013) examined the cost–benefit relationship of preventing conversion of natural and agricultural areas in the floodplain to residential use at the parcel level, and showed that avoided losses mostly offset missed development opportunities. Watson et al. (2016) used scenario analysis to assess the influence of wetlands on flood hydrographs and downstream economic losses and found reductions of 54% to 78% in expected annual losses to buildings.

Collectively, studies quantifying avoided flood loss from BMPs have focused on urban BMPs and found that they offer significant benefits in loss reduction. However, it remains unclear if agricultural BMPs can also produce meaningful damage-reduction benefits. Examples of scenario analyses in rural contexts are few ( Förster et al. 2008), and to the best of our knowledge none examine the monetary benefits of BMPs. We address these knowledge gaps in this exploratory study, by implementing a methodology that varies watershed contexts, flood return periods, and BMP scenarios to quantify the flood risk reduction benefits of agricultural BMPs.

STUDY AREA

We selected four 12-digit watersheds within the Middle Cedar River basin, in Eastern Iowa, as our study area (Figure 1). Encompassing approximately 6,250 km², the Middle Cedar is an 8-digit watershed extending across 10 counties and including the cities of Cedar Falls, Waterloo, and Cedar Rapids. Within the Middle Cedar River basin, we focused on four subwatersheds: Wolf Creek (12-digit hydrologic unit code [HUC] 070802050809), Miller Creek (070802050905), Rock Creek (070802051001), and Pratt Creek (070802051101). Rock Creek and Pratt Creek are headwater streams, whereas the Wolf Creek and Miller Creek watersheds receive flow from upstream basins (Table 1). About 85% of the land in these four watersheds is classified as cultivated (Homer et al. 2015). Corn and soybean are the prevalent crops, accounting for about 97% of the total cultivated area on average in the period 2000–2018 (Table 1). The only significant inhabited center is La Porte City, a town of about 2,000 inhabitants located near the outlet of Wolf Creek watershed (Figure 1). La Porte City experienced major flooding in 1993 and 2008.

The Middle Cedar watershed is among nine priority watersheds identified under the Iowa Nutrient Reduction Strategy (Iowa Department of Agriculture and Land Stewardship 2017). Miller Creek, Rock Creek, and Pratt Creek were identified as demonstration projects, and along with Wolf Creek are targeted for implementation through a $4M Regional Conservation Partnership Program grant under the U.S. Department of Agriculture. The Middle Cedar is also among the focal watersheds of a $96M Disaster Resilience grant under the U.S. Department of Housing and Urban Development (Iowa Watershed Approach 2016). The disaster resilience project is developing a watershed management plan whose implementation will require coordination across stakeholders. The interest of multiple partners and the significant level of federal funding makes the Middle Cedar watershed well suited for analysis of the potential co-benefits of agricultural BMPs.

METHODOLOGY

Conceptually, modeling the translation of agricultural scenarios to expected annual flood loss would progress sequentially from scenario formulation to basin hydrologic analysis, to stream and floodplain hydraulic analysis, to flood loss assessment. For this project, however, we sought to bypass the hydraulic analysis using an existing set of hydraulic modeling outputs: 1-m flood depth grids recently produced by the Iowa Flood Center (IFC) in the statewide floodplain mapping initiative (Gilles et al. 2012). Flood depth grids are becoming more widely available nationwide, as flood studies are updated using geographic information system (GIS)-based tools and communities seek to better quantify and communicate flood risk. Our methods
leverage the depth grid data to gain efficiencies in assessment of alternative land management practices and have potential to benefit similar efforts where depth grids have been developed. Because depth grids depict flood boundaries based upon annual probabilities of occurrence, we assume that floods of the same annual probability occur simultaneously throughout a given watershed. This assumption of spatially uniform flood frequency across a watershed is most valid at small spatial scales. As the smallest hydrologic unit defined by the U.S. Geological Survey (USGS) is the HUC12 (subwatershed) scale, we selected the four study watersheds at this scale.

We split the modeling process into two independent modules (Figure 2). In Module 1, stream discharges were estimated for a set of baseline and alternative scenarios using a Soil and Water Assessment (SWAT) model (Neitsch et al. 2011). The SWAT hydrograph for each scenario was then transformed into a discharge–frequency relationship. In Module 2, we used the IFC depth grids in a HAZUS-MH flood model (Scawthorn et al. 2006) to estimate building and agricultural losses and determine the loss–discharge relationship. Combining the discharge–frequency relationship from Module 1 and the loss–discharge relationship from Module 2, we quantified the relationship between economic loss and flood frequency. This enabled the computation of the average annual loss (AAL), the metric we used to compare the risk reduction benefits of the BMP scenarios.

Discharge–Frequency Analysis (Module 1)

SWAT Scenario Analysis. We estimated landscape-scale hydrologic responses to changes in land cover and land management with SWAT. SWAT is a

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**TABLE 1. Study watersheds description.**

| Study watershed | Wolf Creek | Miller Creek | Rock Creek | Pratt Creek |
|-----------------|------------|--------------|------------|------------|
| Headwater       | No         | No           | Yes        | Yes        |
| Gauged          | Yes        | No           | No         | No         |
| HUC12 watershed area (km²) | 146.58 | 78.21 | 98.62 | 128.27 |
| HUC10 watershed area (km²) | 845.92 | 171.71 | 98.62 | 128.27 |
| Urbanized area in 500-year floodplain (km²) | 1.96 | 0.56 | 0.42 | 0.51 |
| Urbanized area in 1,000-year floodplain (km²) | 8.9% | 4.1% | 4.6% | 4.2% |
| Estimated population | <3,000 | <1,500 | <200 | <300 |
| HUC12 | <7,500 | <1,800 | <200 | <300 |
| HUC10 | <7,500 | <1,800 | <200 | <300 |
| Land use/land cover area (km²) | | | | |
| Cultivated crops | 115.58 | 64.71 | 88.38 | 111.25 |
| Of which Corn | 59.66 | 34.93 | 46.54 | 56.87 |
| Soybean | 54.33 | 28.62 | 41.51 | 52.94 |
| Developed (open space) | 7.79 | 4.45 | 4.78 | 6.27 |
| Pasture and hay | 4.94 | 2.00 | 1.93 | 4.57 |
| Forest | 5.48 | 0.32 | 0.50 | 0.91 |
| Grassland | 2.37 | 2.51 | 1.21 | 2.36 |
| Wetlands and open water | 7.22 | 2.60 | 0.66 | 0.57 |
| Other | 3.19 | 1.63 | 1.17 | 2.34 |

500-year floodplain boundary based on Iowa Statewide Floodplain Mapping Initiative data (Gilles et al. 2012).
The model is primarily intended for application to agricultural watersheds and can simulate a wide variety of agricultural management practices and crop rotations under varying climate scenarios (Arnold et al. 1998; Arnold and Fohrer 2005; Gassman et al. 2010). The key inputs are soils, land cover, and topography (slope), which were intersected to generate Hydrologic Response Units (HRUs): the basic computational unit of the model. Land cover data are based on the 2008 Cropland Data Layer (National Agricultural Statistics Service, U.S. Department of Agriculture 2012; Han et al. 2014), which includes data for major and minor crop types as well as nonagricultural land classes. Pixel resolution for the 2008 Cropland Data Layer is 30 m. We reclassified some data classes (0.25% of the original Cropland Data Layer) into available similar classes to simplify the spatial data and reduce the number of model HRUs. For example, sweet corn (0.17%) was reclassified as corn. Topography data are based on a digital elevation model (pixel size = 30 m) from the National Elevation Dataset (U.S. Geological Survey 2016), whereas soils data are from the county-level Soil Survey Geographic (SSURGO) database downloaded from the Web Soil Survey (Soil Survey Staff et al. 2019). SSURGO data for the study watershed had a minimum map unit size of 684 m² (excluding edge polygons). The model extent was the 12-digit watershed for headwater streams Rock and Pratt Creek, and the entire drainage area for Wolf Creek (10-digit HUC 0708020508) and Miller Creek (0708020509) (Figure 1). The final number of model HRUs ranged from 1,684 (Rock Creek) to 7,528 (Wolf Creek).

SWAT requires daily weather inputs of precipitation, temperature, relative humidity, wind speed, and solar radiation. Weather input data were derived from next generation weather radar (NEXRAD) data for precipitation and Climate Forecast System Reanalysis (CFSR) (Fuka et al. 2014) for remaining weather data. The spatial weather data (NEXRAD and CFSR) are represented in the model as a synthetic network arranged on a grid (NEXRAD: 4 km spacing; CFSR: roughly 30 km spacing). SWAT automatically selects gauge points that are close to the centroid of model subbasins. For NEXRAD data, the number of synthetic gauges located within the watershed boundary ranged from 6 (Rock Creek) to 49 (Wolf Creek). For CFSR data, the number of gauges ranged from 2 to 3. SWAT operates at a daily time-step and key model outputs are streamflow as well as sediment and nutrient export. For this study, we used only the daily streamflow outputs to focus on the hydrologic effects of BMPs on flood damage.

We began with a Baseline scenario to simulate current conventional agricultural practices, in which corn and soybean crops are grown in a two-year rotation typical for the Upper Midwest. Tillage, fertilizer application, and planting/harvest dates are based on farmer surveys (Minnesota Department of Agriculture 2007) and feedback from local stakeholders and commodity groups. We calibrated and validated SWAT against measured flow data from the Wolf Creek watershed. To do so, we ran the model for 12 years from 2002, January 1 through 2013, December 31. The first two years of model results were treated as a warm-up period and we discarded the results, leaving 10 years of model results to compare against observed flow data. We calibrated SWAT for the five-year period from 2009, January 1 through 2013, December 31 and validated for the five-year period from 2004 January 1 through 2008 December 31. We assessed agreement between observed and
modeled flow using mean daily flow and Nash–Sutcliffe efficiency (NSE) and percent bias (PBIAS) (cf. Moriasi et al. 2015; Ahmadisharaf et al. 2019). For NSE, a value of 1 indicates perfect agreement between observed and predicted values, whereas values >0.5 are generally considered satisfactory for monthly flow. For PBIAS, values <15% are generally considered satisfactory (Moriasi et al. 2015; Ahmadisharaf et al. 2019), with 0 being the ideal PBIAS.

We performed model calibration and validation for the Wolf Creek watershed for hydrology. In the absence of water quality monitoring data for sediment or nutrients in the study watersheds, we relied on calibration parameters from similar modeling efforts in the Minnesota River Basin (Dalzell et al. 2012; Pennington et al. 2017; Dalzell and Mulla 2018) to manually calibrate these models in the Middle Cedar River basin (see Table S1 provided in Supporting Information for parameters specification). Evaluation of alternative management scenarios to achieve water quality goals are based on relative differences in nutrient export compared to the baseline management scenario. Because SWAT is designed to simulate agricultural management impacts on water quantity and quality for ungauged watersheds (Gassman et al. 2007), we applied the calibration parameters established for the Wolf Creek watershed to the remaining watersheds (Miller, Pratt, and Rock Creek) without further modification. As such, differences in SWAT outputs across basins result from physical differences in watershed inputs, namely: soils, land cover, topography, and watershed size. Differences in soils, land cover, and topography are relatively minor across the study watersheds; the soils are derived from glacial tills and the landscape has flat to gently rolling topography. While land use in all watersheds is dominated by corn and soybean row crop agriculture (Table 1), small differences in infrastructure and built-up areas play an important role in the economic impacts of flood events and provide the backdrop for our analysis.

Following model calibration and validation, we applied alternative land use/land cover (LULC) scenarios (Table 2) designed to progress toward goals identified by the Iowa Nutrient Reduction Strategy (Iowa Department of Agriculture and Land Stewardship et al. 2017). These scenarios were developed by applying an optimization framework that identified cost-minimizing landscapes for a variety of nitrogen and phosphorus reduction targets (Hawthorne, P.L., Institute on the Environment, 2016, unpublished data). We used integer programming optimization to identify the management practices for each HRU that would meet the specified nutrient load reduction objective while also minimizing the total cost of BMP implementation across all farms. We calculated BMP cost as the difference in estimated farm returns between the BMP scenario and the conventional baseline, representing a simple estimate of farmer willingness to accept payments to switch management practices.

We applied the optimization to develop scenarios that met nonpoint source load reduction objectives of 41% for nitrogen and 29% for phosphorus. We also developed optimized scenarios designed to meet the intermediate nutrient reduction goals of 20% N reduction and 15% P reduction (Iowa Department of Agriculture and Land Stewardship et al. 2017). Each of these nitrogen and phosphorus reduction scenarios simulated adoption of optimal suites of practices in the watershed, including cover crops, fertilizer management, no-tillage, combinations of the above, as well as grassed waterways and afforestation. Figure 3 shows as example the spatial distribution of the Baseline and optimized scenarios for the Wolf Creek watershed. Corresponding scenarios in the other study watersheds show some quantitative differences in the composition of practices but overall follow the trend described in Table 2.

Next, we developed a scenario focused on the widespread adoption of cover crops (winter rye). In
meetings with farmers, watershed coordinators, the Iowa Soybean Association and the city of Cedar Rapids, local stakeholders reported strong interest in cover cropping and significant recent increases in its implementation. This scenario is the same as the Baseline, with cover cropping occurring at the end of the harvesting season.

Finally, we built a Wetlands scenario based on the simulation of constructed wetlands in headwater reaches, to reflect the interest of local stakeholders in this practice. Wetlands are a featured practice in local watershed management plans. Information about siting restored wetlands was incorporated into the wetland scenario simulated in SWAT. We set wetland size to 2% of the upland contributing area to conform to State of Iowa guidelines for wetland development under the Conservation Reserve Enhancement Program (CREP) (Iowa Department of Agriculture 2009). The average water depth for simulated wetlands was 1 m under typical conditions. At water depths >1.25 m, the model released excess water to the downstream network over a 10-day period until the target storage condition was reached (Neitsch et al. 2011).

**Flood Frequency Analysis.** We ran a 33-year SWAT simulation from 1981 January 1 through 2013 December 31, using CFSR precipitation data as input, to generate a longer set of model output for extraction of low probability events. The SWAT simulations output daily average streamflow. Because annual exceedance discharges are estimated by fitting a probability distribution to a series of annual peak flows, we first had to estimate instantaneous peak flows from the daily mean flows output from SWAT. Fill and Steiner (2003) summarized empirical relationships between daily mean and instantaneous peak discharges developed for watersheds throughout the world. We investigated the applicability of available relationships developed for basins in North America described in Fuller (1914) and Gray (1973) by comparing predicted and observed instantaneous peaks at three USGS stream gauging stations in our study area (Figure 4).

The relationship described by Fuller (1914) fit the USGS gauge data with the lowest mean absolute error and had a mean 16% error across the three locations. It is based on observed flows in 24 river basins in the eastern U.S., with drainage areas ranging from 3 to 150,000 km²:
\[ Q_p = Q(1 + 2.66A - 0.3), \]  

(1)

where \( Q_p \) is the instantaneous peak flow, \( Q \) is the daily mean flow, and \( A \) is the drainage area in km².

We applied Equation (1) to the maximum daily mean flow from each water year in the 33-year simulated record to estimate the annual instantaneous peak flow at each watershed outlet. Following Bulletin 17B guidelines for flood frequency analysis (Interagency Committee on Water Data 1982), we calculated annual exceedance probability discharges at each watershed outlet for the simulated 33-year period by fitting a log-Pearson Type III probability distribution to the annual instantaneous peak series. We then calculated quantiles from the fitted distribution representative of the 2-, 5-, 10-, 25-, 50-, 100-, 200-, and 500-year return period (or 50%, 20%, 10%, 4%, 2%, 1%, 0.5%, and 0.2% annual exceedance) discharges at each watershed outlet.

Loss–Discharge Analysis (Module 2). We used the HAZUS-MH (v.3.1, Federal Emergency Management Agency, Washington, D.C.) flood loss estimation model to quantify the relationship between peak discharge and economic loss. HAZUS-MH is a GIS-based software for probabilistic and deterministic estimation of risk from riverine and coastal floods (FEMA 2012). HAZUS-MH risk assessment combines flood hazard, exposure (buildings, crops), and fragility, to compute the spatial distribution of direct damage and economic loss. The damage estimation applies depth-damage functions to estimate damage to buildings, and duration-damage functions to estimate damage to crops. HAZUS-MH multiplies the resulting damage states by building values and crop prices to determine economic loss.

For building damage, there is general consensus that among flood characteristics, depth is the most influential (Kreibich et al. 2009; Merz et al. 2010) (see also Dang et al. 2011; Qi and Altinakar 2011; Ahmadisharaf et al. 2015 on the importance of flood velocity and duration for damage estimation). HAZUS-MH uses empirical functions relating flood depth and building damage, defined for specific building types (e.g., residential with 1, 2 or more floors, commercial, industrial, public occupancies; see FEMA 2012). For agricultural damage, flood duration and time in the growing season are among the most influential parameters ( Förster et al. 2008). Prolonged plant submersion can cause plant death, forcing replanting following spring floods or lost crops for summer floods. Inundation damage can not only affect crops in the ground, but also harvested and stocked crops, livestock, rural buildings, machinery, soil, and perennial plants.
Brémond et al. (2013) reviewed 26 studies on quantification of agricultural loss from natural hazards. They identified season (time), water depth, flood duration, water velocity, sediment deposit, contamination, and water salinity as important elements for estimating crop damage. The Agricultural Flood Damage Analysis (AGDAM) methodology, developed by the U.S. Army Corps of Engineers, includes five of these elements. AGDAM is expressed by the formula (USACE 1985):

$$L = p \cdot A \cdot Y \cdot D(t) \cdot R(t),$$  (2)

where, for a given crop, \(L\) = loss in US$, \(p\) = per unit crop price, \(A\) = flooded cultivated area, \(Y\) = annual crop yield, \(t\) = Julian date of flood, \(D\) = % harvest loss, and \(R\) = flood duration multiplier. HAZUS-MH uses the AGDAM methodology to compute agricultural damage (FEMA 2012). The cultivated area coincides with the floodplain extent, whereas the remaining parameters are default values that can be edited to customize agricultural and flood damage conditions.

Loss estimates from flood models are uncertain due to variations in input hazard, exposure, and damage parameters (Tate et al. 2015). Agricultural losses vary depending on flood depth and duration, crop type, crop maturity at the time of the flood, and market price (Merz et al. 2010). Given the agriculturally dominated setting of the study watersheds, we sought to assess the robustness of the BMPs benefit estimates to assumptions in the agricultural modeling. In a previous flood loss assessment in the Middle Cedar River Basin, Maroof (2016) varied crop type, flood date, flood duration, yield, and per unit price to model a total of 18 loss scenarios. Among them, we identified the lowest, median, and highest loss estimates, and used the corresponding date and price parameters to generate a low, median, and high agricultural loss scenario (Table 3). HAZUS-MH defines \(R\) multipliers for flood durations of three and seven days. In absence of a reliable damage-duration function for shorter flood duration, we interpolated \(R\) between 0 (flood duration = 0, i.e., no damage) and the three-day duration value, and assigned a value of \(R\) to each flood event analyzed (Table 3). We made this assumption based on previous simulations at the HUC12 level demonstrating that even for the most severe flood, the duration is unlikely to exceed three days. We used HAZUS-MH default values for all other parameters in the AGDAM formula. We then applied each agricultural loss scenario to each BMP scenario.

**Flood Loss Analysis**

We combined Module 1 and Module 2 results to develop loss–frequency relationships for each BMP scenario. To do so, a discharge value for a given BMP scenario and return period (from Module 1) is entered as an independent variable in the loss-discharge curve (from Module 2) for a given agricultural loss scenario. The corresponding loss value is linearly interpolated and linked with the corresponding frequency of the discharge (from Module 1). Pairs of values determined in this way are used to construct the loss–frequency relationship for each BMP scenario in each loss scenario. We then measured the loss reduction benefits of each scenario using the AAL, which is the expected flood loss in a given year:

$$\text{AAL} = \sum_{i=2}^{8} 0.5 \cdot (f_{i-1} - f_i) \cdot [L(f_{i-1}) + L(f_i)],$$  (3)

where \(L\) is economic loss as a function of flood frequency \(f\) and \(i\) is the index of the 8 frequencies considered, from 0.002 (500-year return period) to 0.5 (two-year return period). In practical terms, the AAL is the average of losses corresponding to eight return periods weighted by the corresponding frequency, and approximates the area beneath the loss-frequency curve. We used 0.5 and 0.002 as upper and lower limits for flood frequency, based on the assumptions that no loss occurs for an event with return period less than two years, and that the contribution to AAL for events with a return period higher than 500 years is negligible due to the very low frequency (see Ward et al. 2011 for guidance on the choice of return periods).

**RESULTS**

The following section presents results for the discharge-frequency, loss-discharge, and loss-frequency analyses. We use Wolf Creek (gauged, nonheadwater, urban, and rural) and Pratt Creek (ungauged, headwater, and rural only) to illustrate and compare the findings. The Supporting Information contains graphical results for all watersheds, BMP scenarios, and agricultural loss scenarios.

**Discharge–Frequency Analysis (Module 1)**

Comparison of simulated and observed flow data (Figure 5) shows good overall performance of the SWAT model. Following performance criteria from Moriasi et al. (2015), the monthly NSE values are very good for both the calibration and validation periods (0.75 and 0.91, respectively). Daily NSE values were 0.64 (satisfactory) and 0.72 (good) for the model calibration and validation periods, respectively. In general, the model tended to under predict daily average peak flow values more often than it over
predicted them. The overall PBIAS is 18.0 and 23.7 for the calibration and validation periods respectively. These PBIAS values are slightly outside the satisfactory range (<15%) of guidance provided by Moriasi et al. (2015). A seasonal analysis of model performance is provided in Supporting Information (Figures S1–S3). Given the tendency for SWAT to underpredict peak event flows indicated by the PBIAS values, results presented here should be considered as conservative estimates of the magnitude of flood events.

The resulting discharge values for the baseline and alternative scenarios are provided in Figure 6 for Wolf and Pratt Creek watersheds. Overall, the Wetlands, Cover Crop, and N41 scenarios (Table 2) provided the largest reduction in peak flow, especially for high flood frequencies (≥0.1). The Cover Crop scenario performed consistently better than the Baseline scenario across all return periods and all watersheds. For high flood frequencies, the alternative scenarios generally had a positive or negligible effect on peak discharge. In the Miller, Pratt, and Rock Creek watersheds, this effect declined for lower frequencies, whereas in Wolf Creek the peak reduction increased or remained constant with decreasing frequency.

In a few cases for low frequencies (≤0.01), the alternative BMP scenarios produced a slightly higher discharge than the baseline. The BMPs show the tendency of becoming less effective at retaining water and slowing down runoff as return period and rainfall magnitude increase. We hypothesize that such ineffectiveness produces higher runoff for some BMPs in particular locations. However the runoff increase is quite small and makes it difficult to identify a clear pattern of BMPs or locations that might generate it.

**Loss–Discharge Analysis (Module 2)**

HAZUS-MH computed both structural (buildings) and agricultural loss. The relationship between discharge and economic loss is monotonically increasing and nonlinear. Figure 7 shows the loss-discharge curves for the median agricultural loss scenario (curves for the low and high agricultural loss scenarios follow a similar pattern and can be found in the Supporting Information). Although the four study watersheds are rural, the Wolf Creek watershed includes the urban area of La Porte City (Figure 1). There is approximately four times more urbanized area in the Wolf Creek floodplain than the other watersheds (Table 1), and additional exposed built assets produce a loss-discharge relationship in Wolf Creek that is distinct compared to the other watersheds. Because the discharge–frequency analysis in Module 1 is independent of the loss–discharge analysis in Module 2, the range of the discharge values differs between Figures 6 and 7.

**Loss–Frequency Analysis**

Do agricultural BMPs reduce flood risk? In both absolute dollars and performance relative to baseline, the answer is yes. We estimated losses for each BMP scenario by combining discharge-frequency and loss-discharge curves, and comparing each BMP loss to the Baseline scenario across return periods. Figure 8 shows the results of this analysis for Wolf Creek and Pratt Creek watersheds. The BMPs are most effective for high frequency flood events, with the largest percentage difference found for the two-year flood.

One exception to this finding is a large percentage difference observed for the 500-year flood event in Wolf Creek watershed. Large differences from one return period to the next occur when the discharge for the Baseline scenario falls in the steeper part of the loss-discharge curve, but the discharge for the alternative scenario remains in the flatter part of the curve. Slope changes in the loss-discharge curve occur because flood depth and related losses do not grow linearly with discharge, especially in urban environments. For example, the improved performance of the alternative BMPs between the 200- and

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**TABLE 3. Agricultural analysis parameters applied in HAZUS-MH.**

| Loss scenario | Flood date | D multiplier (harvest loss) | Crop price (US$ per bushel) | Reference year(s) of price |
|---------------|------------|-----------------------------|-----------------------------|-----------------------------|
|               |            | Corn | Soybean | Corn | Soybean |                        |                              |
| Low           | May 15     | 0.52 | 0.25    | 2.60 | 7.36    | 1979–1997               |                              |
| Median        | June 15    | 0.88 | 0.725   | 3.50 | 8.65    | 2015                    |                              |
| High          | July 15    | 1.00 | 0.96    | 6.92 | 14.40   | 2012                    |                              |

| Flood event | R multiplier (flood duration) |
|------------|-----------------------------|
| 2-, 5-year flood | 0.25 (one day) |
| 10-, 25-year flood | 0.50 (two days) |
| 50-, 100-, 200-, 500-year flood | 0.75 (three days) |

aHAZUS-MH default value.
FIGURE 5. SWAT modeled and observed flow in Wolf Creek watershed in the period 2004–2013. NSE, Nash–Sutcliffe efficiency; PBIAS, percent bias.

FIGURE 6. Frequency–discharge relationship for Wolf and Pratt Creek watersheds in Baseline and alternative scenarios.

FIGURE 7. Loss-discharge curves for Wolf and Pratt Creek watersheds.
500-year events on Wolf Creek (Figure 8) is caused by a corresponding sharp change in slope on the loss-discharge curve (Figure 7). Although the baseline and alternative scenarios produce similar losses for the 200-year return period ($Q < 682 \text{ m}^3/\text{s}$), the losses are quite different for the 500-year return period ($Q_{\text{baseline}} = 703 \text{ m}^3/\text{s}$, $Q_{\text{alternative}} < 682 \text{ m}^3/\text{s}$). The increase in inundated urban assets moving from 200- to 500-year floodplain greatly exceeds the increase in inundated urban assets from 100- to 200-year floodplain.

The nonlinearity of loss-discharge curves has a two-fold explanation. First, HAZUS-MH depth-damage functions are not linear, and when flood depth reaches certain thresholds it triggers higher levels of damage. Second, properties and values in urban environment are discretely distributed within the 500-year floodplain. This means that as the return period increases and the floodplain boundaries expand, the progression of losses is highly irregular and greatly increases when a high-value structure (e.g., commercial building with basement floors) is inundated. Crops are instead approximately uniform in fields and agricultural damage modeled by AGDAM (Equation 2) simply occurs when crops become flooded, regardless of flood depth.

Which agricultural BMPs are the most effective at flood loss reduction? The Wetlands scenario provides the biggest benefit for flood loss reduction, outperforming all other scenarios for all return periods in all watersheds. This finding was not unexpected, given that wetlands store and slowly release large volumes of water, reducing peak flows and flood depth. The Cover Crop and N41 scenarios also reduced flood loss, although their benefits vary with return period and across watersheds. At high return periods ($\geq 100$-year), the performance of the BMP scenarios is similar, in some cases resulting in slightly higher losses than the Baseline scenario. Only the Wetlands and the Cover Crop scenarios consistently perform better than the Baseline scenario.

### Average Annual Loss

The main study objective was to quantify the absolute and comparative benefits in flood loss reduction from agricultural BMPs. Because streamflows are stochastic, results from any particular return period provides an incomplete understanding of future flood losses.
risk. As such, we used the loss–frequency relationship to calculate the AAL (Equation 3) for each BMP scenario. Table 4 aggregates the AAL results across the four study watersheds, and presents them in absolute terms as total AAL and in relative terms as the percent loss reduction from the Baseline scenario. All of the alternative BMP scenarios reduced flood risk from the Baseline scenario. The Wetlands scenario provided the largest loss reduction, whereas the P15, P29, and N20 scenarios provided the least (Table 4).

The loss estimates were robust across varying input assumptions for agricultural damage analysis in the HAZUS-MH. To assess robustness of the agricultural loss estimates to variations in crop price, yield, and flood timing, we computed AALs for the high, medium, and low agricultural loss scenarios. As expected, the AALs increase moving from the low to high agricultural loss scenarios, primarily due to the increased value of agricultural assets. For each BMP, the AALs for the median agricultural loss scenario were 40% higher than the low loss scenario, whereas the high loss scenario was 74% higher. The variability in losses across agricultural loss scenarios is heavily influenced by flood event timing and crop price, indicating the complexity of determining precise and reliable estimations. The results expressed in percentage reduction from baseline demonstrate the robustness of the loss reduction findings to changes in agricultural loss modeling parameters.

In watersheds with urban land use, building losses greatly exceeded agricultural losses. This is borne out in the findings for Wolf and Miller Creeks. Figure 9 profiles the relative contribution of buildings and crops to the AAL estimates, with the percentage reduction from baseline listed at the end of each bar. Given that Pratt and Rock Creek watersheds are mostly rural with limited built environment in the floodplains, the losses primarily reflect crop losses. By contrast, the larger size of Wolf Creek and the presence of La Porte City near the basin outlet explain the higher absolute losses there. The urban area also affects the loss composition for Wolf Creek, with building losses far exceeding agricultural. Similar to Table 4, the Wetlands, Cover Crop, and N41 scenarios are the most effective at flood loss reduction.

DISCUSSION

In-Field BMP Scenarios

We selected a diverse but limited subset of possible landscape scenarios to explore the potential of improved agricultural BMPs to mitigate flooding. The scenarios are aligned with stated goals of the Iowa Nutrient Reduction Strategy. In-field BMPs simulated in the Cover Crop, N20, N41, P15, and P29 scenarios (Table 1) are currently being implemented by local stakeholders and are relevant in the study watersheds because of the feasibility of potentially increased adoption.

We found that all in-field BMP scenarios modestly reduce peak discharge and economic loss (Table 4 and Figure 9). The Cover Crop and N41 scenarios had twice the percentage reduction as other in-field scenarios in the Wolf and Rock Creek watersheds, whereas the rate reduction was similar across all in-field BMPs in the Miller and Pratt watersheds. These differences may be explained by watershed-specific spatial configuration of optimized landscape, as well as watershed size, shape, and time of concentration. Cover cropping reduces soil moisture, facilitating infiltration, and water storage in the soil in the growing season. The Cover Crop, N20, and N41 scenarios implement cover cropping more diffusely than the P15 and P29 scenarios. This explains the generally better performance of cover cropping as a BMP, which generated less runoff and a lower discharge for simulated flood events.

Although the practices embedded in the N20, P29, and P15 scenarios may be effective for reducing nutrient loss, we find that they only weakly reduce flood risk. Additionally, these scenarios incorporated only a selected subset of potential agricultural BMPs. Our analysis did not consider other practices that could also reduce streamflow and flood damage, such as drain water management, riparian or saturated buffers, or increased planting of perennials.

Wetlands Scenario

The Wetlands scenario was the most effective at reducing flood loss, for all return periods and in all watersheds. Due in large part to their positioning in

| Scenarios | AAL (million US$) | % Reduction from baseline |
|-----------|-------------------|---------------------------|
| Baseline  | High 2.80 |  Low 1.60 | High 5.1 |  Low 4.2 |
| Cover crop| High 2.66 |  Low 1.54 | High 2.4 |  Low 2.2 |
| N20       | High 2.74 |  Low 1.57 | High 2.4 |  Low 2.2 |
| N41       | High 2.64 |  Low 1.51 | High 5.8 |  Low 5.5 |
| P15       | High 2.75 |  Low 1.58 | High 2.0 |  Low 1.8 |
| P29       | High 2.72 |  Low 1.56 | High 2.9 |  Low 2.8 |
| Wetlands  | High 1.71 |  Low 0.99 | High 39.1|  Low 38.5|
headwater reaches in the scenarios, wetlands mitigate peak flows by intercepting water upland, reduce synchronized volumes of water flowing into the main watercourse, and increase travel time to the watershed outlet. By contrast, the in-field BMPs were applied more broadly across the watershed, have a lower rate of water interception, and provide a lower mitigation of peak flows, which also decreased with chance of exceedance. Overall, the reduction in discharge and loss from wetlands specifically designed for water filtering and quality improvement warrants more detailed study.

Some differences in scenario modeling, however, limit the comparability of the in-field BMPs and wetland performances. While the in-field scenarios were developed based on an optimization process of both nutrient reduction and implementation costs, the Wetlands scenario was built using the CREP guidelines for construction of new wetlands. CREP’s primary objectives are denitrification and phosphorous reduction, and its guidelines define criteria for identifying a site and wetland size. Despite not setting a specific water quality goal, CREP wetlands are expected to effectively remove nutrients (Helmers et al. 2009; Drake et al. 2018).

Our analysis also did not estimate the construction and maintenance costs of new wetlands. Such costs depend on land value, productivity, and crop price, which vary during the lifetime of a wetland (Hyberg et al. 2015). The generic upstream collocation of wetlands does not allow a thorough analysis of their effects on water quality and costs, which is beyond the scope of this work (see Keeler et al. 2019 on economic efficiency of BMPs allocation). Nonetheless, wetlands construction is commonly considered as a BMP for water quality improvement and the results highlight the potential for significant peak flood reduction.

### Urban vs. Agricultural Losses

While the loss reduction provided by in-field BMPs is modest relative to baseline conditions, total losses are much higher when built environment (residential, commercial, and service buildings) is in the floodplain, and particularly near the watershed outlet. Predictably, the magnitude of losses increases with the valuation of flood-exposed elements, as buildings have a much higher monetary value than field crops. This is evident in the AAL estimates from the four

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**FIGURE 9.** Average annual loss (AAL) by best management practices (BMP) scenario in all study watersheds. Percentage indicates deviation from the Baseline scenario.

| Scenario | Wolf Creek | Miller Creek | Rock Creek | Pratt Creek |
|----------|------------|--------------|------------|------------|
| Baseline | 75.2%      | 60.3%        | 34.4%      | 33.0%      |
| Cover Crop | 75.6%      | 60.5%        | 34.5%      | 33.0%      |
| N20      | 79.2%      | 60.2%        | 34.5%      | 33.0%      |
| N41      | 75.1%      | 60.4%        | 34.5%      | 33.0%      |
| P15      | 75.2%      | 60.3%        | 34.5%      | 33.0%      |
| P29      | 75.2%      | 60.3%        | 34.5%      | 33.0%      |
| Wetlands | 78.0%      | 62.2%        | -30.6%     | -23.7%     |

| Buildings | 24.8% | -4.2% | -1.5% | -5.2% |
| Agricultural | 24.8% | -1.1% | -2.2% | -41.1% |

| Losses (million US$) | 0.0 | 0.2 | 0.4 | 0.6 | 0.8 | 1.0 | 1.2 | 1.4 | 1.6 |
|----------------------|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| Buildings            | 24.8% | -4.2% | -1.5% | -5.2% |
| Agricultural         | 24.8% | -1.1% | -2.2% | -41.1% |
study watersheds. While each watershed is decidedly rural and agricultural with low population density, the magnitude and composition of losses show a strong positive relationship with the presence of built environment. This finding held even in Miller Creek, in which the buildings were few (<20) and spatially fragmented (Figure 9).

The urban footprint for La Porte City lies almost entirely within the 500-year floodplain of Wolf Creek, and estimated damage to the built environment is high. Although the percent loss reduction from the BMPs is in line with other watersheds, the absolute value of actual and avoided losses is much higher. Since the BMPs are installed upstream of La Porte City, flood mitigation from BMPs propagates downstream directly benefitting the city. In such a configuration where BMPs benefit both agricultural and urban assets, the amount of avoided losses can become substantial.

**Modeling Uncertainty**

Our sequential linkage of SWAT, flood frequency analysis, and HAZUS-MH increases the potential propagation of uncertainty. In SWAT, the simulated management practices were applied homogeneously to the landscape and are based on what is typical for the watersheds. However, actual management and drainage practices have considerable spatial and temporal heterogeneity in their application. While the SWAT calibration and validation results indicate the simulated practices adequately represent watershed hydrology, it is possible that different management decisions could influence watershed behavior in ways that change flood peaks. Similarly, epistemic uncertainty in our approach may also be linked to our selection of SWAT. While this application of SWAT is appropriate (to simulate management impacts on water quantity in an agricultural watershed), selection of a different watershed scale hydrologic model may result in different simulated streamflow responses to different storm events. A cross-model comparison of responses to different storm events was beyond the scope of this analysis.

For the flood frequency analysis, we used relationships identified by Fuller (1914) to transform SWAT daily mean discharge into instantaneous peak flows, and then Bulletin 17B methods to estimate annual exceedance flow probabilities. While the log-Pearson Type III probability distribution and the methods in Bulletin 17B are widely applied, limitations exist (England et al. 2019), in particular the assumption of stationarity (see Judi et al. 2018 on this issue), and high uncertainties in estimated quantiles. But due to short periods of record and nonstationarity in observed data, high uncertainty in estimated flow quantiles is common to all hydraulic design and floodplain mapping analyses. Future changes in the frequency of intense storm events (Kunkel et al. 1999; Janssen et al. 2014; Malikpour and Villarini 2017) could produce watershed runoff responses not adequately represented at the daily time step. However, this would unlikely impact the relative response among scenarios, because the assumptions regarding land management practices and daily weather inputs are uniform across scenarios.

Peak flows were used as the basis for both IFC’s depth grid processing and the flood frequency analysis. However, the definition of an extreme flood can hinge on more than peak flow. Alternative approaches might consider exceedance probabilities of a different hydrograph parameter or of multiple parameters (Brunner et al. 2016; Brunner et al. 2017). For example, one could analyze events corresponding to joint probability of exceedance of peak flow and flood duration, given the importance of flood duration for agricultural damage. If the analysis were extended to larger watersheds with longer response, flood duration should also be considered in the flood frequency analysis.

Uncertainties in the flood depth grids include potential vertical and horizontal error in the underlying terrain data, parameterization of physical processes in stream hydraulic models, and estimated probabilities of exceedance for assigned streamflows (Merwade et al. 2008; Bales and Wagner 2009; Cook and Merwade 2009). Because each depth grid is the result of a single chance of exceedance at the watershed scale, the use of depth grids in evaluating changes in the landscape requires assuming that discharge values associated to a certain probability of exceedance occur simultaneously in all of the streams throughout the watershed. As the validity of this assumption is greatest at small spatial scales, our analyses at the HUC12 watershed scale minimize its impact. In utilizing a static set of depth grids, we also assumed the hydraulic conditions in the stream network did not change over the duration of the SWAT simulations. Call et al. (2017) showed that as the geometry of channels change, flood frequencies also can change in the time span of a few decades. For example, if channels contracted (expanded) in the 30-year period of the SWAT simulation, flood frequency would increase (decrease) in the same period and our results would be underestimated (overestimated), since curves in Figure 6 would shift up and right (down and left). While channel geometry adjustment is impossible to account for in watersheds that are not specifically monitored, it adds uncertainty to the results.

In HAZUS-MH, we performed a simple assessment of the robustness of the agricultural loss estimation component by comparing AAL estimates across low, median, and high agricultural loss scenarios (varying crop price, yield, flood timing). Table 4 indicates that
CONCLUSIONS

Due to persistent and growing challenges of nutrient pollution in the Mississippi River basin, there has been an increasing implementation of agricultural BMPs to minimize soil loss and impaired water quality. Our study investigates the potential of such practices to also reduce surface runoff and economic flood loss in agriculturally dominated watersheds. We integrated a hydrologic model widely used in agricultural watersheds (SWAT) with existing flood depth grids and a standard flood loss estimation model (HAZUS-MH) to quantify the reduction in flood risk from selected agricultural BMPs. The high number of modeled contexts (i.e., watersheds, flood events, BMP scenarios, and loss scenarios) enables multiple comparisons to understand the effect of BMPs on watershed hydrology.

We found that all of the BMP scenarios decreased stream discharge and AAL. The Wetlands, Cover Crop, and 41% nitrogen reduction scenarios performed the best in terms of loss reduction. The risk reduction benefit of agricultural BMPs was modest in entirely rural watersheds, but much higher in watersheds where urban centers and/or buildings lie in the floodplain. Overall, the study findings support the notion that the benefits of agricultural BMPs extend beyond their primary scope of improving water quality, and that multiple benefits should be considered when planning for these BMPs.

SUPPORTING INFORMATION

Additional supporting information may be found online under the Supporting Information tab for this article: SWAT model parameters, box and whisker plots of monthly NSE values, frequency-discharge curves (Module 1) for all watersheds; loss-discharge curves (Module 2) and frequency-loss charts for all watersheds and all agricultural loss scenarios.

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