Agricultural Flood Vulnerability Assessment and Risk Quantification in Iowa

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Abstract
Agricultural lands are often impacted by flooding, which results in economic losses and causes food insecurity across the world. Due to the world's growing population, land-use alteration is frequently practiced to meet global demand. However, land-use changes combined with climate change have resulted in extreme hydrological changes (i.e., flooding and drought) in many areas. The state of Iowa has experienced several flooding events over the last couple of decades (e.g., 1993, 2008, 2014, 2016, 2019). Also, agribusiness is conducted across 85 percent of the state. In this research, we present a comprehensive assessment for agricultural flood risk in the state of Iowa utilizing most up-to-date flood inundation maps and crop layer raster datasets. The study analyzes the seasonal variation of the statewide agricultural flood risk by focusing on corn, soybean, and alfalfa crops. It also investigates the crop frequency layers and corn suitability rating datasets to reveal regions with lower or higher productivity ratings. Additionally, a terrain-based flood model is used to analyze performance against the FEMA maps. The research discusses the potential mitigation activities for the most vulnerable watersheds in the state. The analysis shows that nearly a half-million acres of cornfields and soybean fields are located in the 2-year flood zone. We also found that terrain-based flood maps are a reliable alternative for agricultural flood risk assessment based on their dynamic structure, rapid update capability, and performance compared to FEMA maps.

Keywords: flood risk quantification, agricultural vulnerability, flood vulnerability, flood risk assessment, floods

1. Introduction

Flooding leads to excessive economic losses and severe environmental impacts (i.e., soil loss, contamination) on agricultural lands every year. Recent studies suggest that food security is under critical risk in numerous countries due to flooding (Del Ninno et al., 2003; Oskorouchi and Sousa-Poza, 2021; Balana et al., 2016; Vahedifard et al., 2016). On a global scale, flooding is ranked as the second driving factor resulting in livestock and crop production losses between 2008 to 2018 (FAO, 2021). The United States has experienced several devastating flooding events in urban and agricultural areas, leading the federal government creating the Federal Crop Insurance Program (FCIP) in 1938 to provide insurance for farmlands and reimburse for crop losses against natural disasters (i.e., flooding, drought) (Crane-Droesch et al., 2019). The Federal Crop Insurance Corporation (FCIC) insured almost four hundred thousand acres of farmland in 2020 (RMA, 2021). Over $8 billion in crop loss is estimated, and nearly $2 billion in federal relief funds have been distributed for the Midwest Flood of 1993 (Sarmiento and Miller, 2006). Climate change triggers extreme flooding events more frequently (Tripathi et al., 2014). Recent studies reveal that the magnitude and probability of extreme floods are forecasted to soar in agricultural regions (Slater et al., 2019; Mallakpour and Villarini, 2015; Slater and Villarini, 2016). Therefore, sustainable agriculture is challenged by constant flood risk (Beddington et al., 2012). Thus, investigating the underlying causes is essential for taking the required measures to overcome the risk.

Intensive land-use modification and climate change are contributing factors to hydrological alterations and extreme events (e.g., floods, droughts) in agricultural lands (Lee and Brody, 2018; Hazarika et al., 2015; Aich et al., 2016; Benito et al., 2010). However, land-use alteration has been widely practiced in many regions (Meyfroidt et al., 2013; Houghton et al., 2012; Borelli et al., 2017). The implication of land-use changes is highlighted in several studies to understand flooding impacts in the downstream regions (Wheater and Evans, 2009; Bruzzone, 2013). Although land-use changes contribute significantly to peak flows to downstream regions (Apollonio et al., 2016), less mature vegetation (Anderson et al., 2006) and tile drainage (Thomas, 2015) are found to be the primary reasons that cause downstream flooding due to agricultural practices. Even though flooding impacts on farmlands that are only prone to a greater magnitude of flooding events (e.g., 100-year, 200-year) can be reduced by practicing certain mitigations, the damage is inevitable for areas within the more frequent flood zones, such as 2-year and 5-year return period zones. Exploring potential flooding impacts and productivity levels of those farmlands can be helpful in decision making (Xu et al., 2020; Teague et al., 2021) and justifying further actions. These actions can be land preservation with a structural or non-structural measure or land acquisition to create wetlands or ponds.

1.1. Agricultural Flood Risk Assessment

Flood risk studies on agricultural lands produce valuable input for securing and maintaining food production for the world's growing population and understanding mitigation solutions for downstream regions. The benefits of the mitigation efforts can be effectively implemented by

prioritizing regions with up-to-date risk assessments (Yildirim, 2017; Alabbad et al., 2021). Agricultural flood risk assessments also aid in the application of mitigation decisions (Sermet et al., 2020), such as identifying agriculture fields to be removed from production (Tapia-Silva et al., 2011), land-use changes (Schilling et al., 2014), drainage networks (Gambolati et al., 2006), levees (Olson and Morton, 2012), dikes (Tran et al., 2018), and dam construction (Navarathinam et al, 2015). Because these mitigation practices are costly, a detailed flood risk assessment allows maximizing benefits to achieve feasible solutions (Yildirim and Demir, 2021). An ideal benefit-cost analysis should include risk products as input to determine whether mitigation decisions may succeed or fail for the area of interest. Thus, datasets and models should be rigorously selected to provide accurate results. Then, the risk assessment can be conducted on a large scale to gain insight into the vulnerability of the area.

1.2. Agricultural Loss Quantification

Agricultural loss quantification often requires the latest datasets to provide the most recent crop risk for an area of interest. Accurately quantified losses can be helpful to support informed decisions for flood management (Haltas et al., 2021; Ewing and Demir, 2021). Recent developments in web systems and geospatial technologies (Agliamzanov et al., 2020; Sit et al., 2019) allow accessing and analyzing large-scale datasets (Ebert-Uphoff et al., 2017) like high-resolution flood inundation maps, statewide agricultural land-use rasters, and property repositories. High-quality crop information and flood inundation data are essential for the accurate estimation of agricultural loss quantification. Although remote-sensing-based flood maps are utilized for loss quantification (Rahman et al., 2016), those datasets (e.g., soil moisture, flood map imagery) are prone to errors (Hornbuckle et al., 2017), leading to inaccurate estimations (Rahman and Di, 2019). On the other hand, a reliable estimate should include the proper dollar amount of inputs and outputs of crop production, such as the price of the year, the average harvest cost of the year, the average yield of the season, and government incentives (Downton and Pielke, 2005). The data requirements that we defined above must be satisfied for the agricultural loss quantification to minimize and eliminate errors. Thus, the quality and timeliness of the datasets determine the accuracy of the risk products, therefore, the mitigation decisions.

1.3. Scope of the Research

Understanding agricultural flood risk provides invaluable information to decision-makers as they plan mitigation efforts to reduce potential losses. However, the task requires substantial technical and domain knowledge, such as flood mapping, spatial data analysis, database management, and loss quantification methodologies (Yildirim and Demir, 2019). Conducting a large-scale agricultural flood loss assessment can reveal significant insights into prioritizing regions and supporting mitigation decisions. For Iowa, agricultural practices are an essential component of the state's economy; therefore, a statewide agricultural loss investigation is crucial to perceive potential risks. Because the major communities experienced several flood events in the past, potential mitigation efforts can be deduced from a large-scale risk assessment. Several studies have

been carried out at different scales (e.g., watershed, county, city) for the state of Iowa, such as Middle Cedar (Maroof, 2016; Antolini et al., 2020), North Racoon (Schilling et al., 2014), Freemont County (Crow, 2014), and Cedar Falls-Waterloo (West, 2010). However, these studies are rather limited to reflect the overall agricultural flood risk of the state. Because agriculture is intensively practiced across Iowa, a statewide risk assessment is critical to identify regions for potential mitigation applications.

This research proposes a comprehensive agricultural flood risk assessment for the state of Iowa. Nearly 25 million acres of agricultural land are analyzed with high-resolution statewide flood inundation maps. So, the results reveal the total acres of land that are located in different flood zones, for instance, 2-, 5-, 10-, 25-, 50-, 100-, 200-, and 500-year flood zones. The study investigates the seasonal variation (i.e., from 2016 to 2020) of the widely grown crop types (e.g., corn, soybeans, alfalfa) and highlights the vulnerable watersheds in the region. Additionally, crop frequency layers and corn suitability rating datasets are employed to understand future crop losses and analyze the productivity of regions prone to flooding. Thus, those regions can be prioritized for preserving farmlands or selected as potential mitigation sites to reduce urban flooding downstream. The results are generated on different watershed scales (hydrological unit code (HUC)-8 and HUC-12) to discuss the overview of the state and the most vulnerable regions. The study also investigates the performance of terrain-based flood model outputs for agricultural flood loss assessments. Therefore, a new data source can be explored for conducting agricultural flood risk assessments.

In the following sections, the methodology provides information about the study region, data sources, data processing, and agricultural loss quantification. In the results section, statewide agricultural losses, crop frequency layer analysis, and corn suitability rating analysis are presented. The section presents watershed-scale assessments for the most impacted regions. Additionally, a recently developed flood mapping model (a terrain-based model) is evaluated and compared to FEMA maps for agricultural flood loss analysis. In conclusion, key findings, challenges, and future work are presented.

2. Methodology
2.1. Study Region
The state of Iowa is located in the midwestern region of the United States between the Missouri and Mississippi rivers, as illustrated in Figure 1. The state also has three major streams namely the Cedar River, the Des Moines River, and the Iowa River. Several large communities are located on those rivers, such as Cedar Falls, Cedar Rapids, Des Moines, Iowa City, and Waterloo. The landscape is heavily altered by agriculture practices, primarily for corn and soybean farmlands. The state has nearly 13-million-acres of cornfields and 9 million-acres of soybean fields (NASS, 2020). Landscape alterations such as tile drainage and intensive agricultural land use lead to sedimentation (Xu et al., 2019) and hydrologic regime changes (i.e., higher peak flow frequency) in many watersheds throughout the region (Thomas, 2015; Wehmeyer et al., 2011). Iowa has experienced heavy flood losses in both urbanized and agricultural lands. Since 1953, 29 flood-

related disaster declarations have been made for the state (FEMA, 2021). Over the last couple of decades, Iowa has been impacted by significant flood events (i.e., 1993, 2008, 2014, 2016, and 2019). The region is prone to extreme flood events for both urban and agricultural lands.

2.2. Data Sources

Statewide inundation maps developed by the Iowa Flood Center (Gilles et al., 2016) are utilized to carry out agricultural flood risk analysis. The Federal Emergency Management Agency (FEMA) and the United States Army Corps of Engineers (USACE) generated the inundation maps using high-resolution (1-meter) light detection and ranging (LiDAR) data. The USACE creates the inundation maps for the northwestern part of the state, and FEMA completes the remaining regions of the state. The maps are produced based on probability-based scenarios using the United States Geological Survey (USGS) historic gauge records to identify discharges for 2-year, 5-year, 10-year, 25-year, 50-year, 100-year, 200-year, and 500-year events to feed the hydraulic model. In Figure 2, a 100-year flood scenario map is demonstrated for Iowa. The flood maps are reprojected, transformed, and stored on the PostgreSQL server for the analysis.
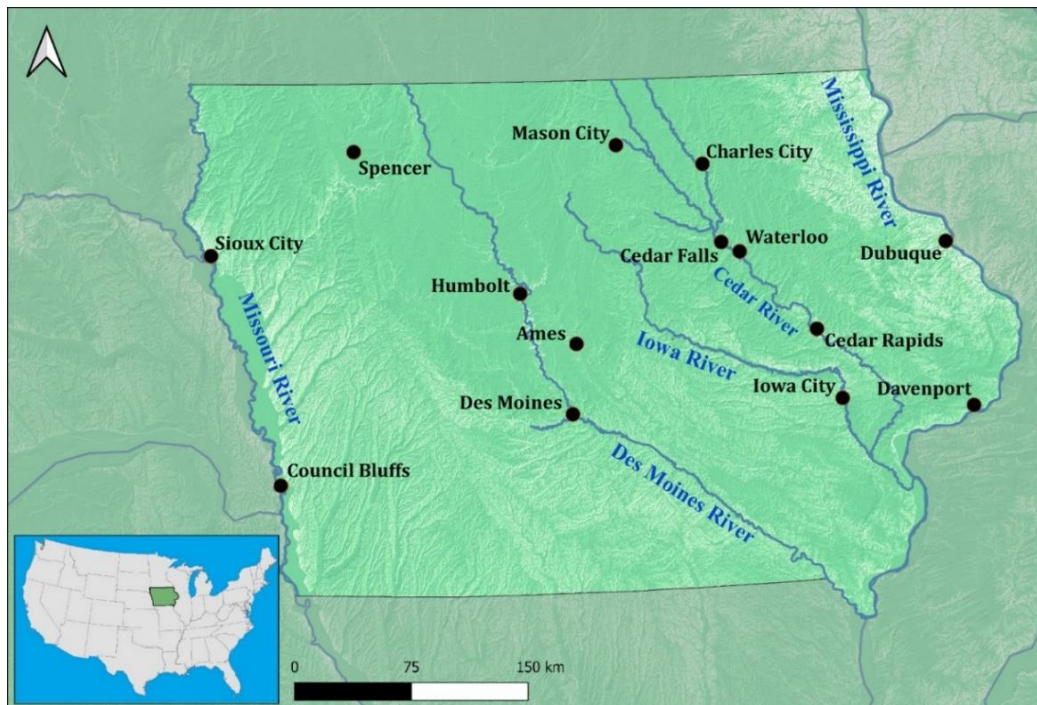

Figure 1. Major communities and streams in the study region

The National Agricultural Statistics Service (NASS) releases land cover datasets and other land classifications acquired using remote sensing technologies for the conterminous United States (Han et al., 2012). NASS made the dataset publicly available through a web-based system called "Cropland Data Layer" (CDL) (Johnston, 2013). We collected crop cover datasets for Iowa between 2016 to 2020 and crop frequency layers for corn and soybean crops through the CDL.

The crop cover datasets include all crop types that are planted in the state within a specific year. For our analysis, we only consider alfalfa, corn, soybeans, sweet corn, and grassland. The crop frequency layers contain crop-specific (i.e., cotton, corn, soybean, and wheat) planting frequencies based on historical remotely sensed data (Boryan et al., 2014). Corn and soybean frequency layers are collected due to the dominant crop regime in the state. Frequency layers are stored in raster format in the PostgreSQL server.
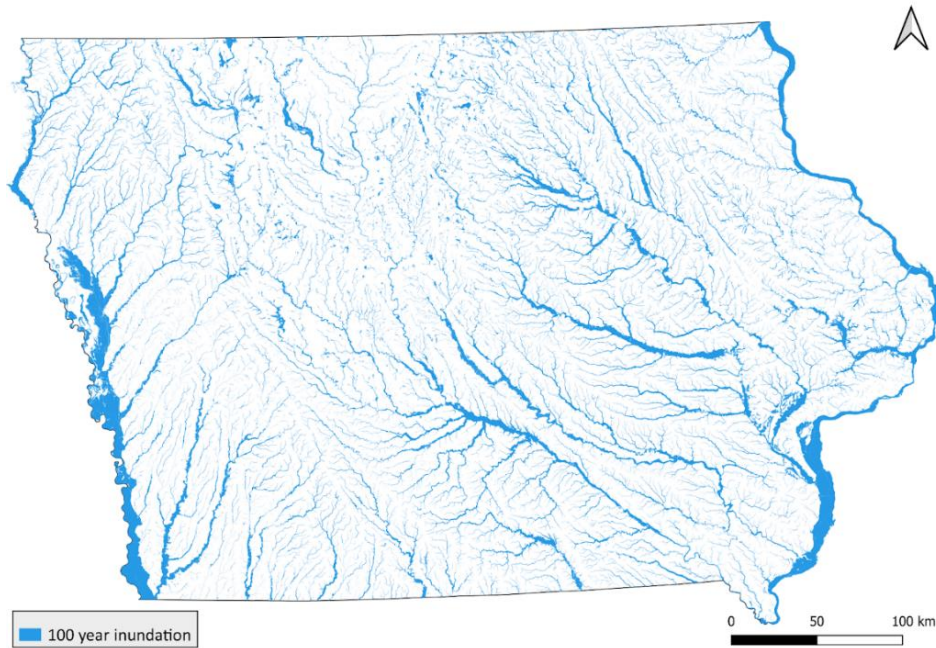

Figure 2. 100-year flood inundation map in Iowa

We also acquired the Corn Suitability Rating (CSR) from the SSURGO (Soil Survey Geographic database) dataset, which was created by the United States Department of Agriculture (USDA) Natural Resources Conservation Service (NRCS). SSURGO provides CSR, which indexes a land's productivity between 0 to 100 (Secchi et al., 2009). 100 means the land is very productive, and 0 means the land has poor productivity. The collected data layers are generated at a 30-meter resolution in a raster format, and they are stored on the PostgreSQL server for our analysis.

Crop yields, prices, harvest costs, and government incentive datasets are critical to quantifying agricultural losses. The USDA collects yields (USDA, 2021a; USDA, 2021b; USDA, 2021c; Johanns, 2021a), prices (Johanns, 2021b), costs (Plastina, 2021), and incentives (Plastina and Leibold, 2019; Plastina and Liebold, 2021) for alfalfa, the parameters like cost, price, and yield are used as static numbers for our estimations. However, these parameters are available on a yearly basis for corn and soybean crops in Iowa, so custom values are considered due to the variance in parameters such as farming seasons from 2016 to 2020 and geolocations (i.e., county).

2.3. Data Processing

In the study, we collected an extensive dataset for flood maps, land use rasters, CSR rasters, crop frequency layers, and crop yield/price/cost data to carry out a comprehensive agricultural flood impact assessment for the state. The datasets are handled in open-source databases, libraries, and geographic information systems (GIS) software such as QGIS, PostgreSQL, and PostGIS. Geographic datasets (i.e., flood maps, agricultural rasters) are reprojected to the Albers Equal Area projection because it preserves the area. So, underestimation or overestimation of the inundated agricultural area can be avoided. Using QGIS and its server connection to PostgreSQL, we reviewed data tables to ensure data distortion and missing regions were avoided in the study area. Due to the complexity of handling hundreds of data tables, we created a web service using PHP to migrate all data tables to the PostgreSQL server. Afterward, the database is designed to create a relational data model between our data tables and determine the data formats (i.e., integer, decimal, rast, geom). The following queries are optimized for estimating inundation areas and average annual losses. Figure 3 lays out the steps for the data processing workflow.
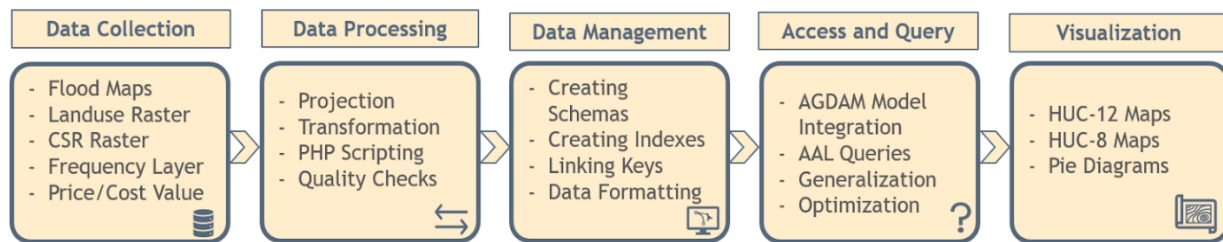

Figure 3. Data life cycle for agricultural flood loss assessment framework

Although existing software and tools are available to conduct agricultural flood impact (i.e., Hazard United States (HAZUS)), PostgreSQL, PostGIS, and PHP scripting allowed us to automate handling and processing large-scale datasets more efficiently. The Agricultural Flood Damage Analysis Model (AGDAM), which will be explained in the following section, is replicated using PostgreSQL queries. Additionally, the optimized queries are scalable to conduct flood impact analysis for other agricultural regions or analyze new datasets with few adjustments.

In the CSR and crop frequency data layers, raster histograms are utilized to reveal inundated areas in the study area. We classified the CSR raster into four groups based on the suitability rate percentile, such as greater than 80 percent, 80 to 60 percent, 60 to 40 percent, and 40 to 15 percent. The rate under 15 percent is subtracted from our analysis to avoid overestimating inundated agricultural areas because these regions are not farmlands. Similar to the CSR dataset, crop frequency layers are classified into three groups based on the consecutive times of planting the same crop. Finally, the results are visualized using Hydrologic Unit Code (HUC) at HUC-12 and HUC-8 level utilizing QGIS software.

2.4. Agricultural Loss Quantification

In the literature, several studies suggest that the duration and time of the year (Julian day) are the main factors in estimating agricultural losses (Morris and Hess, 1988; Dutta et al., 2003; Posthumus et al., 2009; Brémond et al., 2013). The AGDAM model is one of the most preferred models that considers flood duration and the time of year for agricultural flood loss quantification (Maroof, 2016). Therefore, we employed the AGDAM methodology to quantify agricultural losses due to floods. The USACE developed the methodology with the given function below (USACE, 1985):

$$L_S = A(p \cdot Y - H) \cdot D(t) \cdot R(t) \qquad\qquad (Eq.\, 1)$$

where "L_s" stands for loss (is USD) for a specific flood scenario, "A" is the inundated ag-land; "p" is the unit price of the crop (price per bushel); "Y" is for the crop yield (bushels per acre); "H" is the harvest cost ($ per acre); "D" is crop loss at the "t" day, and "R" is a crop loss modifier based on the flood duration. Each crop type's unique loss function indicates crop loss for a given time of the year and flood duration modifier. In this study, three different time of the year are selected to estimate losses based on crop growth. For instance, May 15, June 15, and July 15 are selected for corn and soybean crops to estimate low, medium, and high losses, respectively. Additionally, the loss analysis is conducted considering three-day and seven-day flood durations. We stored the functions in the PostgreSQL database for the agricultural loss estimation calculations.

Using the AGDAM model, agricultural flood losses are estimated in eight flood scenarios: 2-, 5-, 10-, 25-, 50-, 100-, 200-, and 500-year return period floods. Then, we estimated the average annual loss (AAL) in the HUC-12 watershed level using the following equation:

$$
\begin{aligned}
AAL = \; & L_{500}P_{500} + (P_{500} - P_{200})\left(\frac{L_{500} + L_{200}}{2}\right) + (P_{200} - P_{100})\left(\frac{L_{200} + L_{100}}{2}\right) \\
& + (P_{100} - P_{50})\left(\frac{L_{100} + L_{50}}{2}\right) + (P_{50} - P_{25})\left(\frac{L_{50} + L_{25}}{2}\right) + (P_{25} - P_{10})\left(\frac{L_{25} + L_{10}}{2}\right) \\
& + (P_{10} - P_5)\left(\frac{L_{10} + L_5}{2}\right) + (P_5 - P_2)\left(\frac{L_5 + L_2}{2}\right) \qquad\qquad (Eq.\, 2)
\end{aligned}
$$

AAL is significant to reveal the risk for the studied region. So, we estimated AAL based on land use from 2016 to 2020 for corn, soybean, alfalfa, and sweet corn. After estimating the losses for every HUC-12 watershed, the results are aggregated to HUC-8 level watersheds for visualization and communication.

3. Results & Discussion

In this study, agricultural flood risk assessments were conducted for nearly 25 million acres of agricultural land in the state of Iowa. Because corn and soybean crops are dominant in the region, we used land use data from the previous five years for those crops to investigate seasonal variation

in flooding impacts. Alfalfa and sweet corn layers are also extracted from the Cropland Data Layer to analyze flood risk for these crops. AALs are estimated for the HUC-12 watershed level using probability-based scenarios for each crop type. The HUC-12 scale AALs are aggregated to the HUC-8 watershed level to deliver the flood risk overview for the whole state.

Table 1. Impacted agricultural area based on probabilistic flood scenarios (acre)

	Year	2-yr	5-yr	10-yr	25-yr	50-yr	100-yr	200-yr	500-yr	Total
Alfalfa	*2016*	8k	13k	17k	21k	23k	26k	28k	31k	779k
	2017	3k	7k	10k	13k	14k	16k	18k	20k	665k
	2018	4k	9k	11k	14k	16k	19k	19k	22k	693k
	2019	4k	8k	10k	13k	14k	18k	18k	21k	682k
	2020	6k	11k	15k	19k	20k	25k	25k	29k	734k
Corn	*2016*	281k	531k	686k	879k	958k	1,175k	1,307k	1,504k	17.0 M
	2017	271k	515k	664k	851k	927k	1,139k	1,269k	1,459k	16.5 M
	2018	268k	506k	655k	838k	914k	1,120k	1,244k	1,432k	16.3 M
	2019	253k	488k	630k	815k	885k	1,095k	1,122k	1,318k	17.0 M
	2020	280k	529k	686k	878k	955k	1,172k	1,291k	1,489k	17.2 M
Grassland	*2016*	266k	437k	526k	631k	657k	743k	748k	815k	7.43 M
	2017	259k	426k	512k	614k	639k	723k	727k	791k	6.98 M
	2018	240k	398k	481k	579k	605k	686k	687k	751k	6.83 M
	2019	198k	331k	402k	488k	511k	582k	587k	643k	6.59 M
	2020	199k	333k	404k	490k	514k	586k	588k	646k	6.50 M
Soybean	*2016*	152k	298k	390k	500k	556k	696k	822k	953k	11.8 M
	2017	169k	326k	428k	545k	606k	754k	882k	1,023k	16.5 M
	2018	168k	329k	431k	552k	612k	766k	901k	1,045k	12.8 M
	2019	149k	293k	384k	498k	550k	692k	725k	859k	11.8 M
	2020	153k	304k	398k	513k	571k	717k	841k	976k	12.3 M
Sweet Corn	*2016*	91	192	247	349	362	437	548	456	11k
	2017	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
	2018	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
	2019	17	33	45	62	72	83	104	118	6k
	2020	11	20	27	37	40	51	62	64	7k

In Table 1, inundation area estimates are provided for alfalfa, corn, grassland, soybeans, and sweet corn with eight probability-based flood scenarios. Table 2 shows the inundated area ratio to the total area for a specific crop type. Corn has the highest inundation area compared to other crop types in all years and in all flood scenarios. Corn is also found to have the largest area within the flood zones for each scenario. The second most inundated land use is grassland. However, a flood loss estimate was not performed for grassland. Because grasslands are one of the most dominant land-use types in the state, we estimated the inundation area for each year and scenario to reflect the potential flooding impact on a major land use type.

Table 2. Inundated area rates for crop types using probability-based scenarios (percentage)

|	Year	2-yr	5-yr	10-yr	25-yr	50-yr	100-yr	200-yr	500-yr
Alfalfa	*2016*	1.03	1.67	2.18	2.70	2.95	3.34	3.59	3.98
	2017	0.45	1.05	1.50	1.95	2.11	2.41	2.71	3.01
	2018	0.58	1.30	1.59	2.02	2.31	2.74	2.74	3.17
	2019	0.59	1.17	1.47	1.91	2.05	2.64	2.64	3.08
	2020	0.82	1.50	2.04	2.59	2.72	3.41	3.41	3.95
Corn	*2016*	1.65	3.12	4.03	5.16	5.62	6.90	7.67	8.83
	2017	1.64	3.13	4.03	5.16	5.63	6.91	7.70	8.85
	2018	1.65	3.11	4.03	5.16	5.62	6.89	7.65	8.81
	2019	1.49	2.87	3.71	4.80	5.21	6.44	6.60	7.76
	2020	1.62	3.07	3.98	5.09	5.54	6.80	7.49	8.64
Grassland	*2016*	3.58	5.88	7.08	8.49	8.84	9.99	10.06	10.96
	2017	3.71	6.10	7.33	8.80	9.15	10.36	10.41	11.33
	2018	3.51	5.82	7.04	8.47	8.85	10.04	10.05	10.99
	2019	3.01	5.02	6.10	7.41	7.76	8.83	8.91	9.76
	2020	3.06	5.12	6.21	7.54	7.91	9.01	9.04	9.94
Soybean	*2016*	1.29	2.53	3.31	4.24	4.71	5.90	6.97	8.08
	2017	1.03	1.98	2.60	3.31	3.68	4.58	5.35	6.21
	2018	1.31	2.57	3.37	4.32	4.79	5.99	7.05	8.17
	2019	1.26	2.48	3.25	4.21	4.65	5.85	6.13	7.26
	2020	1.24	2.47	3.24	4.17	4.64	5.83	6.84	7.94
Sweet Corn	*2016*	0.83	1.75	2.25	3.17	3.29	3.97	4.98	4.15
	2017	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
	2018	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
	2019	0.28	0.55	0.75	1.03	1.20	1.38	1.73	1.97
	2020	0.16	0.29	0.39	0.53	0.57	0.73	0.89	0.91
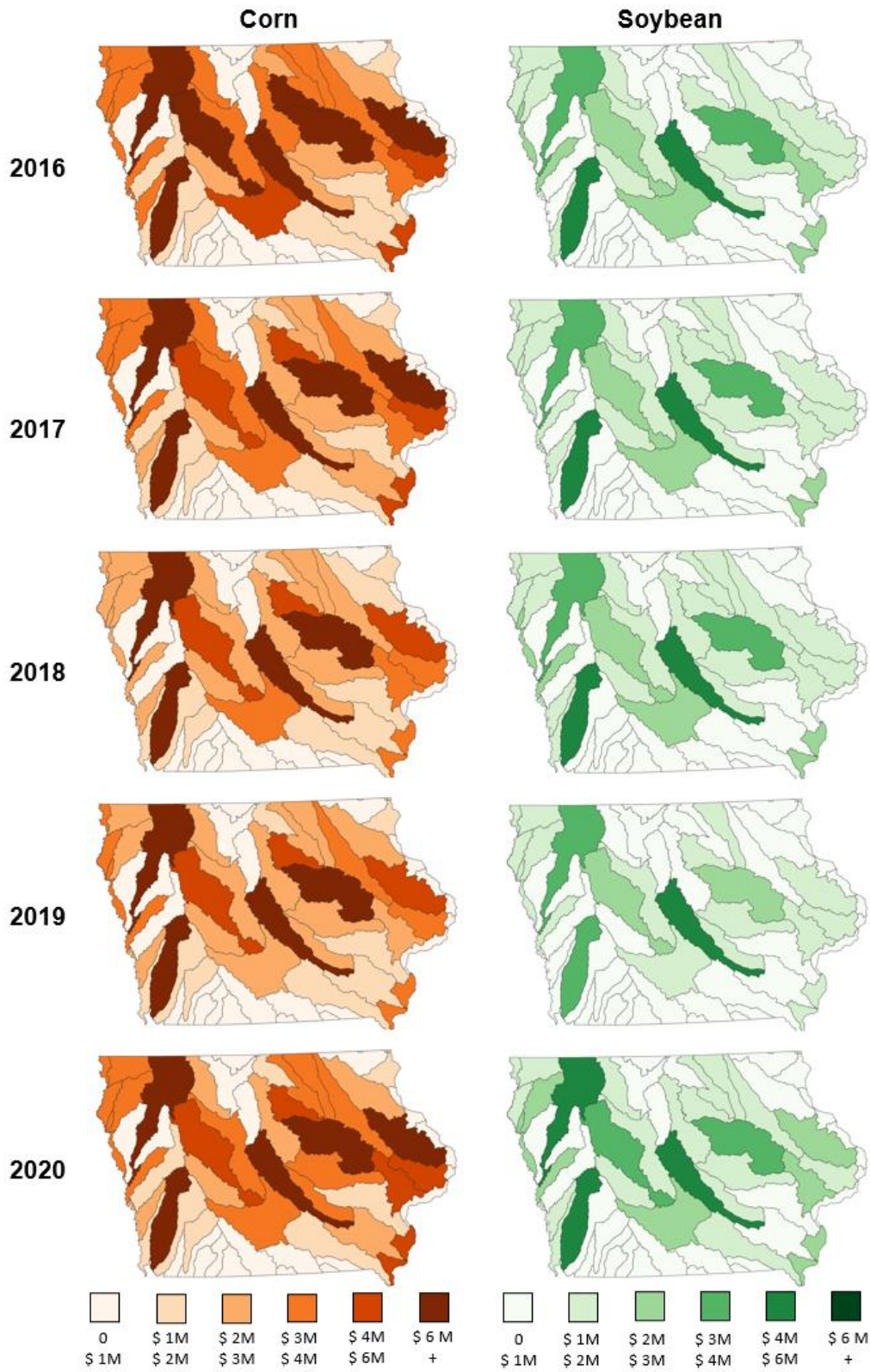
Figure 4. Estimated AAL in 3 days duration flood for corn and soybean 2016 to 2020

Sweet corn is estimated as the least inundated crop type. Due to the lower inundation area, we combined AAL estimates for sweet corn with the corn crop for the statewide loss assessment. Inundation areas slightly change for each crop type in all years at the statewide evaluation. The inundated area ratio also remains almost the same for each crop type in all years (see Table 2). An overview of flood risk assessment for corn, soybean, and alfalfa crops is given at the HUC-8 scale in the following section. Then, we discussed CSR and crop frequency layer analysis at the statewide scale, and reflected on the most vulnerable watersheds. In the final analysis, a detailed risk assessment of the most impacted watersheds is evaluated by considering corn suitability ratings.

3.1. Statewide Agricultural Flood Risk

We conducted a statewide agricultural flood risk assessment for corn, soybean, and alfalfa crops using land-use data from 2016 to 2020. The outlining reason for selecting multiple years is to understand whether the losses vary from season to season or not. Our analysis indicates only slight changes in estimated losses for corn and soybean crops in the state (see Figure 4). There is a homogenous estimated loss distribution within the HUC-8 watershed level. In particular, some of the watersheds are prone to more flood losses, such as the Skunk River watershed (central Iowa), North Racoon watershed (central Iowa), Middle Cedar watershed (Eastern Iowa), and West Nishnabotna watershed (Southwestern Iowa). Except for West Nishnabotna, the majority of these watersheds have a large scale stream running through them. However, the AAL is also estimated to be high for the watershed.
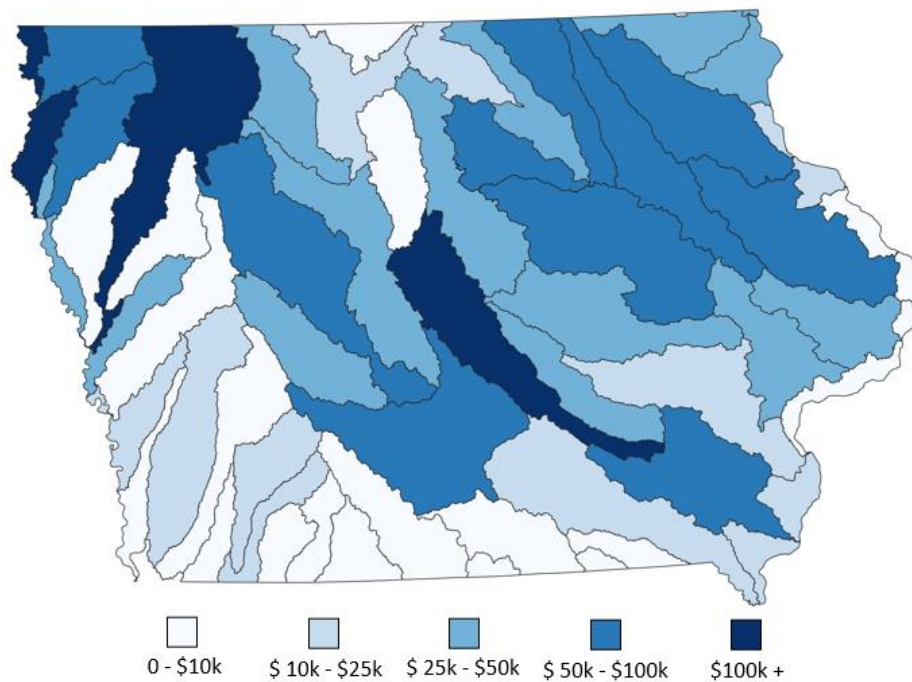

Figure 5. Estimated AAL in 3 days duration flood for alfalfa in 2020

Regarding corn losses, average annual loss (AAL) estimates reach more than $6 million with the highest AAL estimate for soybeans is over $4.5 million. Although corn and soybean crops are impacted at different levels, the most vulnerable regions are the same for both of these analyses. In addition, some large communities are located within those regions (i.e., Cedar Rapids, Cedar Falls, Des Moines, Waterloo). In the following section, we will discuss analysis for these regions in details.

Alfalfa is at the top five preferred crop types in Iowa, but it has a significantly lower land area compared to corn and soybean. Therefore, the AAL for alfalfa is estimated to be very low compared to other crop types. The highest loss is estimated at just over a hundred thousand US dollars for a watershed in central Iowa. The spatial distribution of the losses is very similar to corn and soybeans, with a slight variation. In Figure 5, AALs for alfalfa are demonstrated for the year 2020 land use data.

3.2. Crop Frequency and CSR Analysis

Crop frequency and corn suitability rating (CSR) datasets are analyzed with the statewide flood inundation maps in the study. One of the objectives for the analysis is to investigate potential mitigation options and identify the regions that may require protection from the potential flooding impact. Quantifying the regions where productivity is considerably lower than other regions can be an input for decisions like putting farm fields out of production or wetland restoration for mitigation efforts. In contrast, in higher productivity areas with higher flooding risks, quantification can aid in the protection of fertile farmlands. On the other hand, crop frequency data provides insights into future crop choices in farmlands (Boryan, 2014).

Table 3. Distribution of the corn and soybean fields that are constantly under risk based on crop frequency data (mile square)

	Frequency Range	2-yr	5-yr	10-yr	25-yr	50-yr	100-yr	200-yr	500-yr
Corn	> 9	110	210	270	360	380	450	460	520
	6 – 9	500	950	1,230	1,590	1,750	2,530	2,180	2,940
	< 6	340	550	660	790	850	1,160	980	1,270
	Total	940	1,710	2,160	2,740	2,980	4,150	3,620	4,740
Soybean	> 9	0	0	0	0	10	10	10	10
	6 - 9	290	580	760	980	1,100	1,680	1,400	1,980
	< 6	480	870	1,090	1,380	1,490	2,000	1,780	2,250
	Total	780	1,450	1,850	2,370	2,600	3,690	3,190	4,250

We found that the 2-year flood zone is frequently utilized for agricultural purposes, particularly for corn farming (See Table 3). Therefore, mitigation efforts may be needed to reduce potential flooding impacts for the region. At this point, CSR can be a vital resource to analyze with flood maps to support mitigation decisions. Our analysis shows that nearly two thousand square miles

of farmland with a CSR of between 15% and 40% is within the 2-year flood zone (See Table 4). In addition, more than three thousand square miles of land in the 2-year flood zone has a CSR greater than 80%. In the next section, the CSR analysis is discussed for the most vulnerable watersheds on a HUC-12 scale.

Table 4. Economic impact variability of the cornfields based on corn suitability rating (CSR) and FEMA flood maps (mile square)

CSR Ratio	2-yr	5-yr	10-yr	25-yr	50-yr	100-yr	200-yr	500-yr
> 80%	3,300	6,000	7,600	9,500	10,600	13,400	13,400	16,000
60 - 80%	7,100	12,400	15,400	18,500	19,900	24,000	23,000	26,800
40 - 60%	1,800	3,400	4,400	5,800	6,000	10,300	7,300	11,100
15 - 40%	1,700	2,500	3,000	3,500	3,600	4,100	4,100	4,300
Total	13,900	24,300	30,300	37,300	40,100	51,800	47,800	58,300

3.3. Watershed-level CSR Analysis

This section provides a detailed corn suitability rating analysis for the most vulnerable four watersheds: Middle Cedar, West Nishnabotna, North Racoon, and Skunk River watersheds. Average annual losses for 2-year and 5-year floods are provided along with the CSR information for each HUC-12 watershed. As described previously, CSR is grouped into four parts. The first group is the ratio greater than 80 percent (represented as red in Figure 6), between 60 to 80 percent (represented as orange), 40 to 60 percent (represented as yellow), and 15 to 40 percent (represented as green). For each group, an inundated area is estimated for a specific scenario (i.e., 2-year, 5-year). The area is divided into the total estimated inundated area to reflect the percentage of each group.
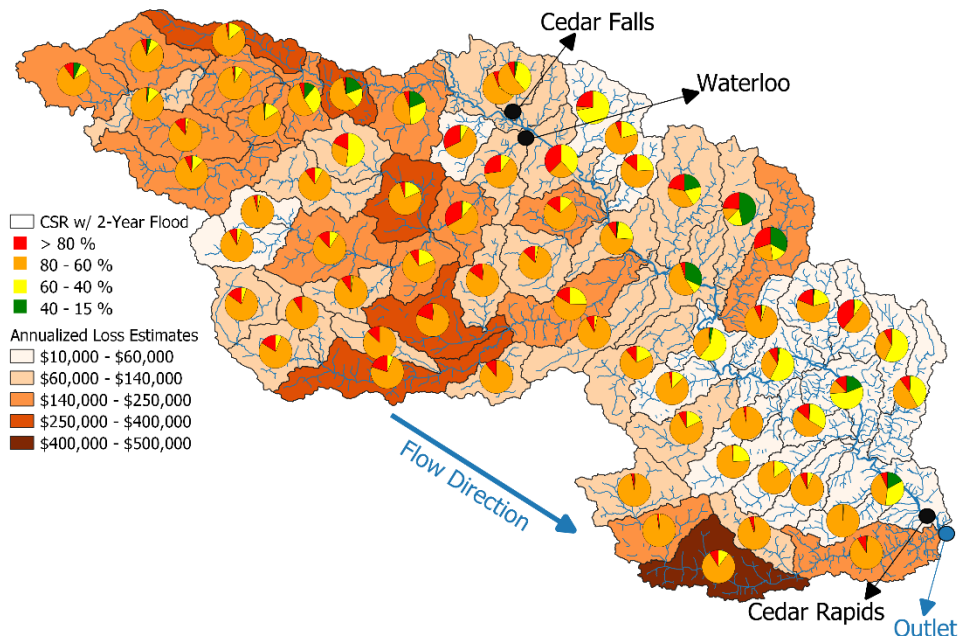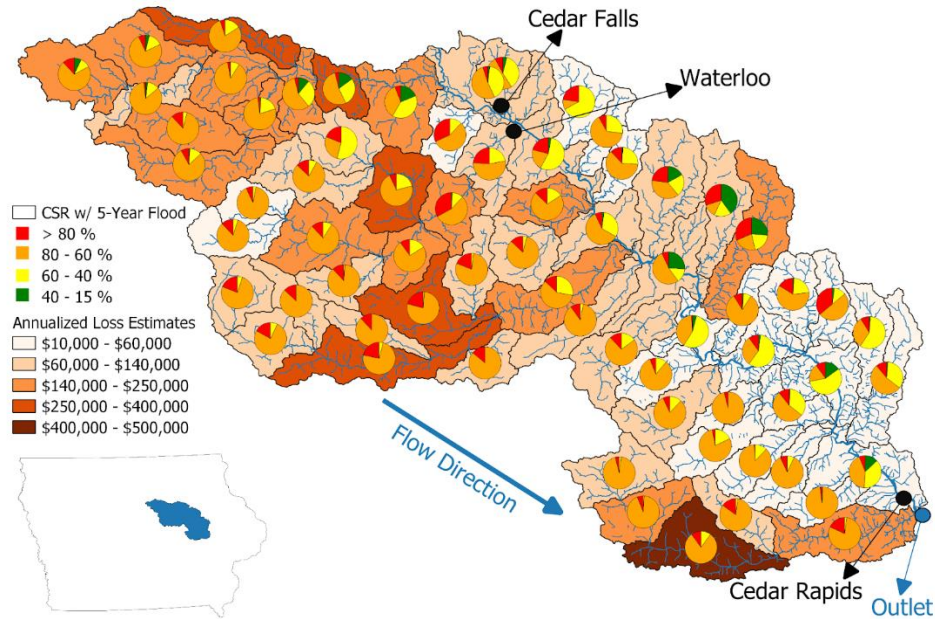
Figure 6. Distribution of CSR for 2- and 5- year flood scenario in Middle Cedar watershed

In Figure 6, AAL and CSR distribution are provided with 2-year and 5-year flood scenarios in the Middle Cedar watershed (Eastern Iowa). Three major cities that have experienced flooding several times are located within the watershed. Larger AALs are mostly estimated for the upstream part of the watershed. In both scenarios, the majority of HUC-12s have a CSR of 60 to 80%. However, some of the HUC-12s have lower CSR in the northern part, where they also have higher AAL estimates. Further study is needed to reveal the potential mitigation opportunities beneficial to major cities in the region for mitigating urban flooding.

The North Racoon watershed is similar to the Middle Cedar watershed in that it includes a large community, Des Moines which is the capital of the state. The city was impacted by significant flooding events many times in the past decades (i.e., in 1993, 2008, and 2014). Estimated AAL reaches nearly a quarter-million US dollars in some of the HUC-12s in the North Racood watershed, most of which have higher CSR than neighboring watersheds for both scenarios. Particularly in the lower AAL watersheds, they also have lower CSR. It is challenging to justify mitigation decisions because the potential loss is estimated at up to twenty-six thousand US dollars, which is very low compared to other regions. A thorough benefit-cost assessment for the central part of the watershed is critical for mitigation decisions to lower the potential risk to Des Moines. Figure 7 delivers an overview of estimated annual flood loss and the distribution of the CSR for 2-year and 5-year flood scenarios.

The study reveals that the Skunk River and West Nishnabotna watersheds have high AAL estimates (Figure 8). The AAL estimate reached over eight million US dollars for the Skunk River and nearly seven million US dollars for the West Nishnabotna watersheds. Based on CSR analysis, the Skunk River watershed has lower CSR values in the upstream region. However, AAL estimates are also lower for those HUC-12 watersheds. So, a detailed flood mitigation study may be required

for flood reduction in the downstream regions. Unlike the Skunk River, West Nishnabotna's HUC-12 watersheds within the 2-year and 5-year flood zones show higher CSR values than any other region. Therefore, HUC-12s with the higher AAL estimates may require flood protection measures (i.e., levees) to reduce agricultural losses. To avoid more significant losses, the potential impacts of West Nishnabotna must be thoroughly investigated.
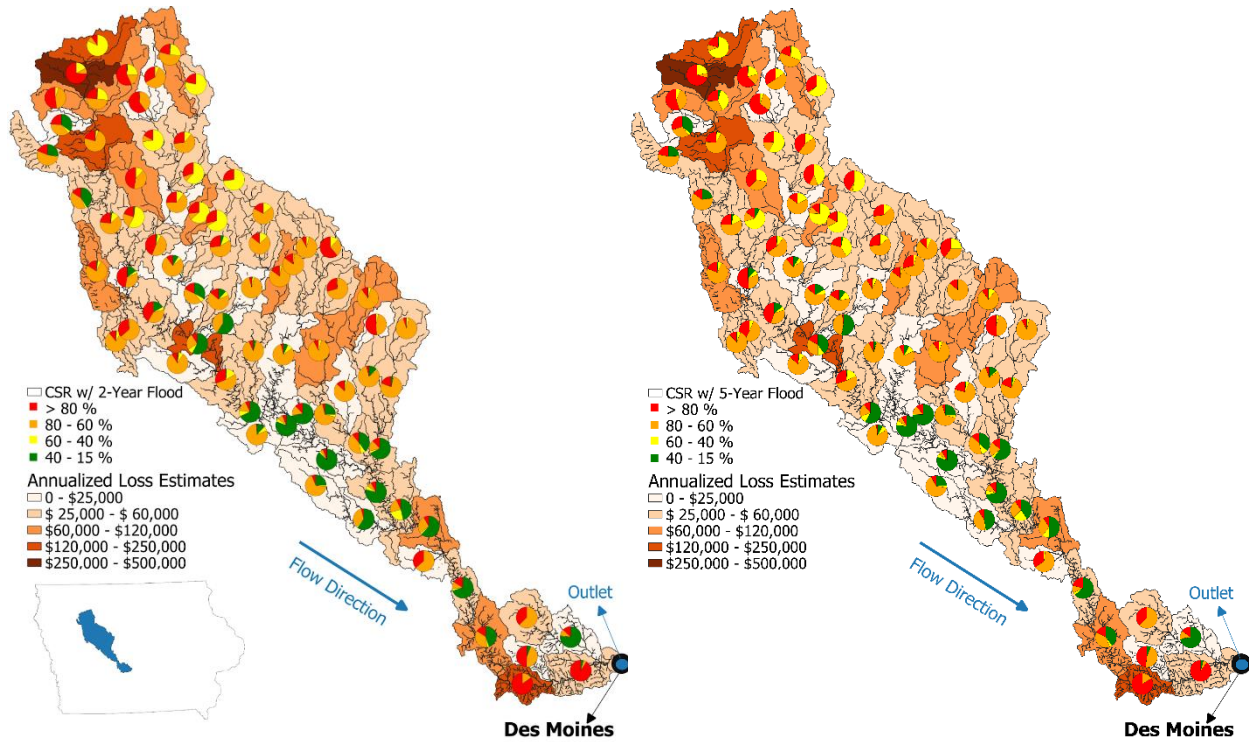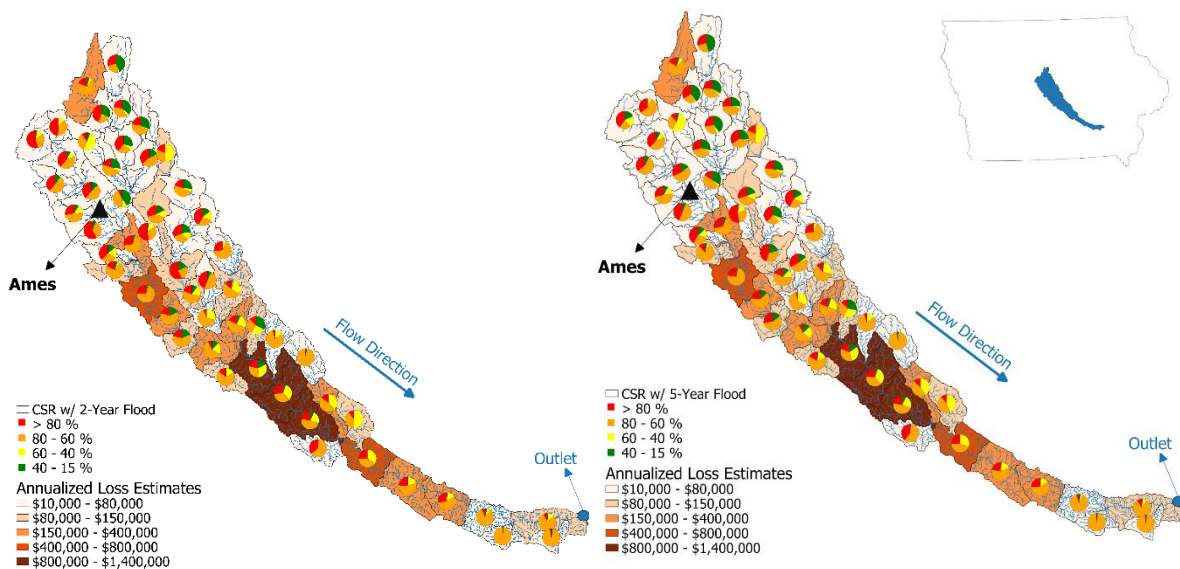

Figure 7. Distribution of CSR for 2- and 5- year flood scenario in North Racoon watershed
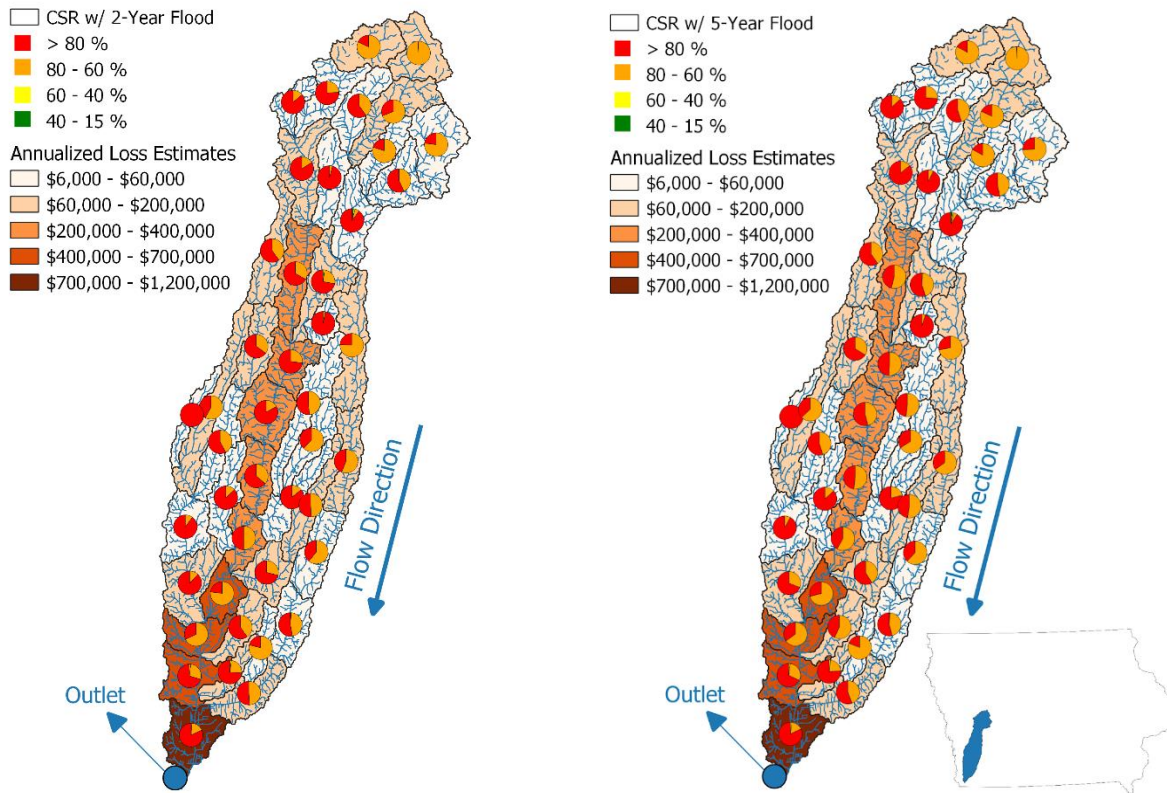
Figure 8. Distribution of CSR for 2- and 5- year flood scenario in Skunk River (Top) and West Nishnabotna (Bottom) watershed

Overall, the most vulnerable watershed regions show a promising potential for flood reduction efforts. However, these efforts must be carefully studied to evaluate the benefits and costs of the mitigation. On the other hand, fertile regions within the flood zones should be considered for flood protection measures to maintain sustainable food production. The potential impact of flood protection measures must be investigated to avoid further loss downstream.

3.4. DEM-based Flood Map Evaluation

Terrain-based flood model outputs were generated for a pilot region located in southeastern Iowa using a client-side rapid inundation mapping system (Hu and Demir, 2021; Li and Demir, 2021) based on Height Above Nearest Drainage (HAND) model. The model outputs were generated based on 100-year and 500-year return period flood scenarios. The pilot region has seventy-seven HUC-12 scale watersheds. Soybean is selected to estimate the inundation area using the HAND data. Then, the correlation coefficient for the whole region and the error rates for each HUC-12 are estimated with reference to FEMA outputs (See Figure 9). Overall, 0.93 and 0.94 correlations are estimated for the 100-year and 500-year scenarios, respectively. On a watershed scale, HAND outputs performed with a low error rate (between 10% to -10%) in the majority of the watersheds. However, the error rate is estimated to be higher for the outer regions, with up to a 40%

overestimation and a 60% underestimation. It is important to note that the estimated inundation areas for those regions are small (10–100 acres) in both data sources. Due to lower requirements, we found that terrain-based flood models are cost-efficient and reliable ways to assess flood impact for agricultural regions.
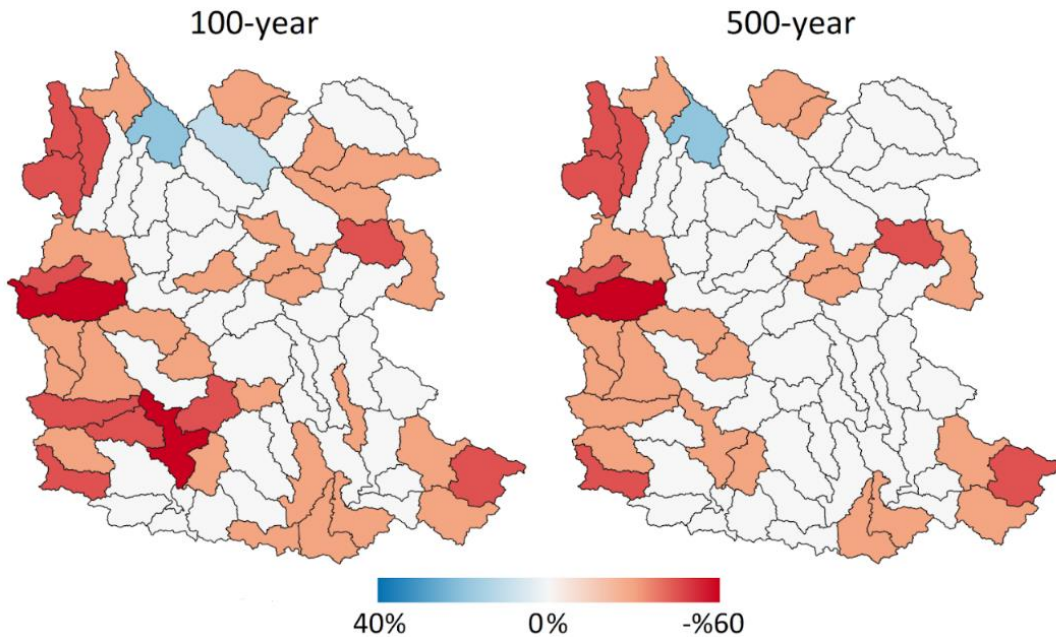

Figure 9. Error rates of HAND model output with reference to the FEMA maps for inundated area estimation of soybean fields

4. Conclusion

In this study, we present a comprehensive agricultural flood impact assessment in the state of Iowa. The assessment employed large-scale datasets such as statewide flood inundation maps, the most up-to-date agricultural land use data, corn suitability rate raster, and crop frequency layers. Our analysis suggests that nearly 450,000 acres of farmland are located in the 2-year flood zone, frequently prone to flood losses. The total ratio of the inundation area stays the same for each crop type and all years. The study reveals a slight variance in flood loss concerning seasons (i.e., 2016, 2017) and certain regions (i.e., HUC-8 watershed). The highest AAL is estimated for corn crops, and it is followed by soybeans. The crop frequency analysis shows that these crop types (e.g., corn, soybeans) will remain under flood threat for a while without mitigation efforts. We identified the Middle Cedar, Skunk River, North Racoon, and West Nishnabotna watersheds as the most vulnerable regions for the studied crop types (i.e., corn, soybeans, and alfalfa).

The study provides significant insights into the agricultural flood vulnerability of the state where agricultural practice is one of the core driving economic factors. The study also emphasized the importance of future mitigation assessments to ensure food security, protect jobs, and reduce potential flooding impacts for the state's urban regions. Our analysis reveals that potential flood reduction may be possible for major communities such as Des Moines, Cedar Falls, Cedar Rapids,

and Waterloo. Contrarily, the study also suggests corn-productive regions (e.g., West Nishnabotna), located in flood-prone regions, may need a protective measure for flooding to maintain high production. This research emphasizes the importance of the downstream impacts of possible mitigation efforts. The study also tested the terrain-based flood model (HAND) performance by estimating the inundation area, which performed well with a correlation of 0.93 for the 100-year scenario and 0.94 for the 500-year scenario.

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