Flooded Fields

Title: A Real-time Modeling System of Croplands Affected by Extreme Flooding
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Project Repository: https://github.com/SAliHossaini/FloodedFields

Abstract

a. Thesis statement:
Under changing climatic conditions, extreme rainfall leads to extreme flooding, and many acres of cropland are entirely prevented from planting due to accumulating water. As climate change makes weather events more extreme, GIS can be used very effectively in agricultural land use / land cover analysis as well as damage assessment because of floods and other extreme weather events. This project builds a real-time modeling system that can estimate the number of acres flooded out on a per crop basis each year across the Midwest, particularly croplands affected by extreme flooding in 2019. We follow a Python-based approach for creating a landscape classification, identifying croplands and wetlands using supervised and unsupervised methods, retrieving real-time statistics about the impacts of flooding on agriculture on a per crop basis, and exporting statistics to CSV file and all geospatial data into Geo-Tiff which can be used for future processing in a GIS software like ArcGIS. This report concludes with a discussion about comparison of our pixel-based classification results with USDA data, economic impacts of weather-damaged cropland, depressional wetlands, and opportunities for future work with the material presented in this project for precision agriculture.

b. Keywords: #cropland #flood_impact #GIS #classification #precision_agriculture

Introduction

For much of the United States, 2019 was a record year for spring precipitation. According to National Oceanic and Atmospheric Administration (2019), a bomb cyclone over Colorado and unusually high precipitation led to nearly the entire country having above average precipitation, and it was the wettest year recorded for the country as a whole. With extreme precipitation came extreme floods. 42 locations across the Midwest, especially around the Missouri River, set record river levels (figure 1) and many other areas experienced severe flooding (Erdman, 2019).

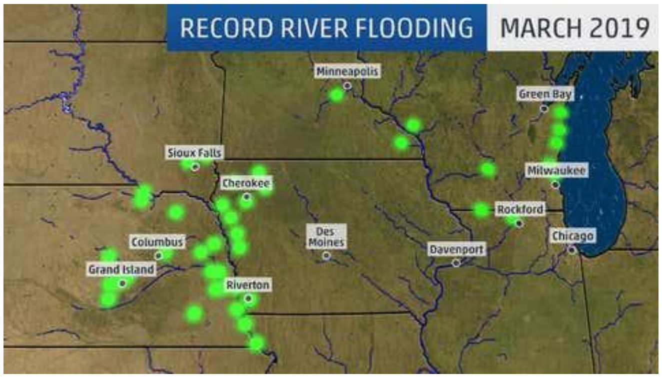

Figure 1. Locations with record river levels

Flooding impacted states throughout the Midwest: 11 states had to seek federal disaster funds used in more than 400 counties, and 14 million people were affected in total (Almukhtar et al., 2019). It led to striking images of extreme flooding, and a lot of news coverage for places like Nebraska and Iowa. While not the most impacted state, Minnesota also experienced extreme precipitation. Southwestern Minnesota was especially impacted: by mid-April, much of the southwestern counties had experienced precipitation almost twice has high as normal (Minnesota Department of Natural Resources). As these are rural counties with considerable agriculture, extreme precipitation during the timespan when corn and soy are planted (University of Minnesota Extension) led to huge impacts on Minnesota's crops.

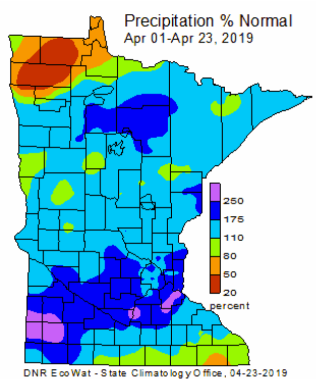

Figure 2. Minnesota's percentage of precipitation above normal in 2019

The recently glaciated landscape of southwest Minnesota gives it a particular hydrology, called “prairie potholes.” In this very flat landscape, water has no clear path of drainage through which to leave the landscape. Instead, water accumulates in low-lying depressions, forming wetlands called “potholes”. These “pothole” wetlands were eventually drained with tile drainage systems to make use of the region’s valuable agricultural soils (Environmental Protection Agency, 2020). As such, there are few wetlands extant in the region and these depressional areas are used as cropland. However, the low areas where water would collect remain, and can still be inundated if water accumulating outpaces the water drained away. This fact was illustrated clearly in 2019, in which the Midwest saw the wettest 12-month period in history (NOAA News and Features, 2019). Extreme rainfall led to extreme flooding, and many acres of cropland were entirely prevented from planting due to accumulating water (Newton, 2019).

Benefitting from National Agriculture Imagery Program (NAIP) imagery taken before and immediately after the flooding, we can create a striking map of cropland that was flooded in 2019. From that map we can quantify the areas impacted: from calculating the total amount of land kept out of agriculture, down to showing individual depressions within fields that farmers could not plant. While this map is interesting in itself to understand the catastrophic severity of this flood event, it can also help illustrate interesting general ideas about agriculture in the region. Events like this one, which impact the harvest for farmers, are very expensive: farmers are reimbursed the value of their lost earnings (Newton, 2019). Given these costs, it can be argued that the farming of marginal lands (like those that are susceptible to flooding) should be disincentivized, as the land is not worth farming in the long-term. As Minnesota is expected to become wetter with climate change and extreme events like the flooding in 2019 could become more common (Minnesota Pollution Control Agency, 2019), this map can help explore whether all current farmland in the region is truly viable as cropland.

To understand just how much agriculture in Minnesota was impacted by flooding during 2019, we compared classified imagery from 2019 to classified imagery in 2017 and identified areas that could not be planted due to flooding through a real-time modeling system.

Datasets

We used the 2017 and 2019 NAIP imagery for the state of Minnesota for our classification. It has high spatial resolution of 1 meter suitable for identifying regions within fields, a temporal resolution with images from before and immediately after the flooding at the same point in the growing season, and spectral bands useful for differentiating between vegetation and bare earth or water (visible and near-infrared). Supplementary data to our classification include JRC monthly water history dataset and USDA CDL crop dataset like acreage planted compared to previous years and crop prices (to calculate costs related to flood impacts).

The JRC Monthly Water History dataset contains maps of the location and temporal distribution of surface water with 30 m resolution from 1984 to 2020 and provides statistics on the extent and change of those water surfaces. Each pixel was individually classified into water / non-water using an expert system and the results were collated into a monthly history for the entire time-period and two epochs (1984-1999, 2000-2020) for change detection. Thus, it is useful for wetland classification in this project.

The Cropland Data Layer (CDL) dataset is created by United States Department of Agriculture (USDA). It provides a raster, geo-referenced, crop-specific land cover map for the continental United States. This dataset is a crop-specific land cover data layer created annually using moderate resolution satellite imagery and extensive agricultural ground truth. We used this dataset for cropland classification as well as finding flooded fields on a per crop basis.

First, we identified the areas of Minnesota with the most extreme precipitation in 2019 to choose our area of interest. We concluded floods mostly impacted the southwest region of Minnesota and chose to focus on Jackson County for its size (for ease of processing) and extent of agriculture (no major towns), although the programming workflow we developed is capable to process the extent for the whole state.

Then, we defined a clipping geometry to the NAIP imagery in Google Earth Engine for 2017 and 2019. We used the near-infrared, false-color images for classification because of its ability to clearly distinguish bare earth, water, and vegetation. Then, we used NDVI, NDWI, and barren indices to extract vegetation and water bodies of the region.

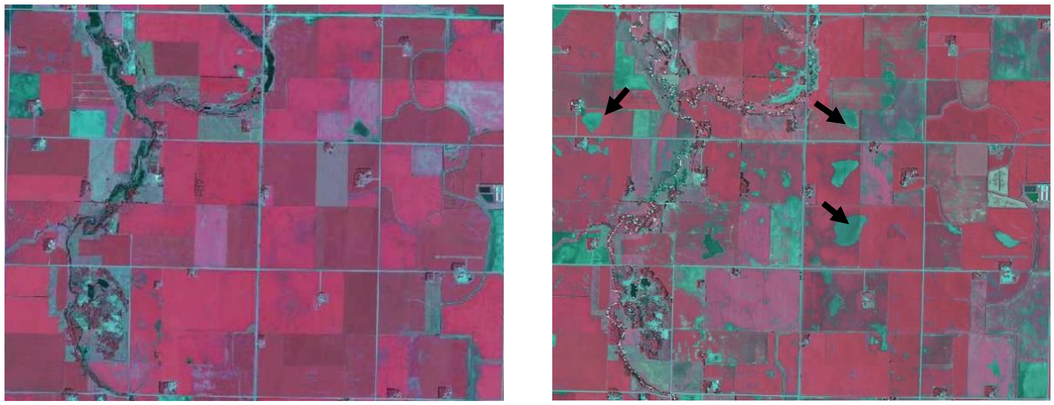

Figure 1. An example of what we identify with NAIP. The images show a section of Renville County, Minnesota in false-color composite. The 2017 image (left) shows the area without significant flooding, and the 2019 image shows the area (right) with significant bare earth scars due to flooding (highlighted).

Methods

I. Project Preparation

We created a real-time modeling system for land-cover classification map of both 2017 and 2019, with the classes agriculture (broken into individual crops), water, and other. We distinguish these classes (most importantly agriculture from bare earth and surface water) by using vegetation indices like NDVI, NDWI, barren, or visible color and NIR bands (figure 2). This is done with a pixel-based given the high-resolution of NAIP imagery. Noise within fields (like pixels with slightly lower NDVI and higher NDWI) is classified as flood-impact using pixel-based methods. However, object-based methods can better discriminate using clear differences in shape and size for agriculture and flood impacts: farm fields have large, square shapes compared to the smaller, irregularly circular depressions that were flooded. Since we use pixel-based interpretation due to time constraints, the small scale at which depressional areas are visible make the creation of training data very time consuming. However, we tested using both supervised and unsupervised methods in our pixel-based approach.

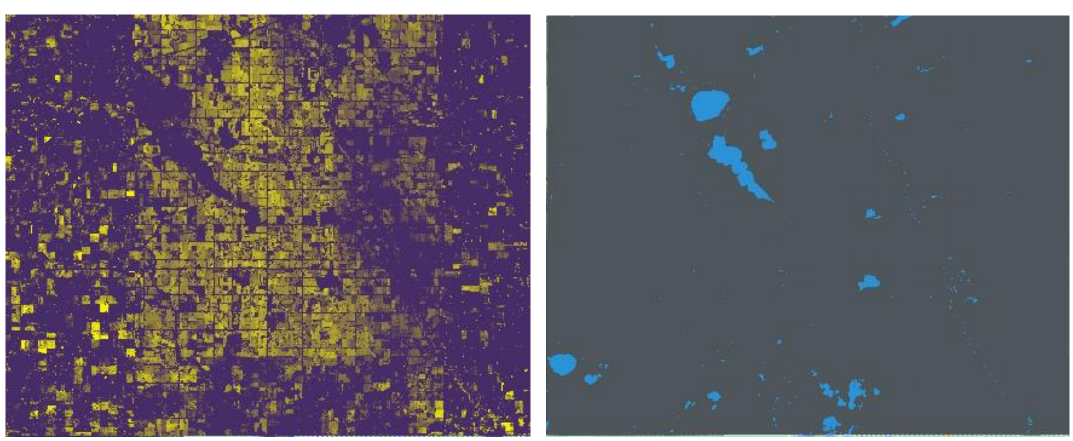

Figure 3. NDVI (left) and NDWI (right) indices.

II. Geoprocessing

To identify the best classification method, we clipped the study area of Jackson County and classified it with different approaches, then checked them for accuracy against known landcover using the USDA Crop Data Layer (2019). We tested various numbers of classes and compared a pixel-based for supervised and unsupervised classifications. We chose to do a supervised pixel-based classification with at least 5000 random training points per class and 3 classes: vegetated, water, and non-vegetated. We chose this method because it gave satisfying results without significant processing time. While these classes are broad, we care specifically about vegetated cropland that became barren or water. We can get to these specific changes and avoid confusion (forests being included in the vegetated classification, urban areas being included in the barren classification, etc.) by masking our results to only include agricultural land with the USDA Crop Data Layer. Figure 3 demonstrates the final data flow diagram for the supervised classification of 2017 and 2019 NAIP imagery.

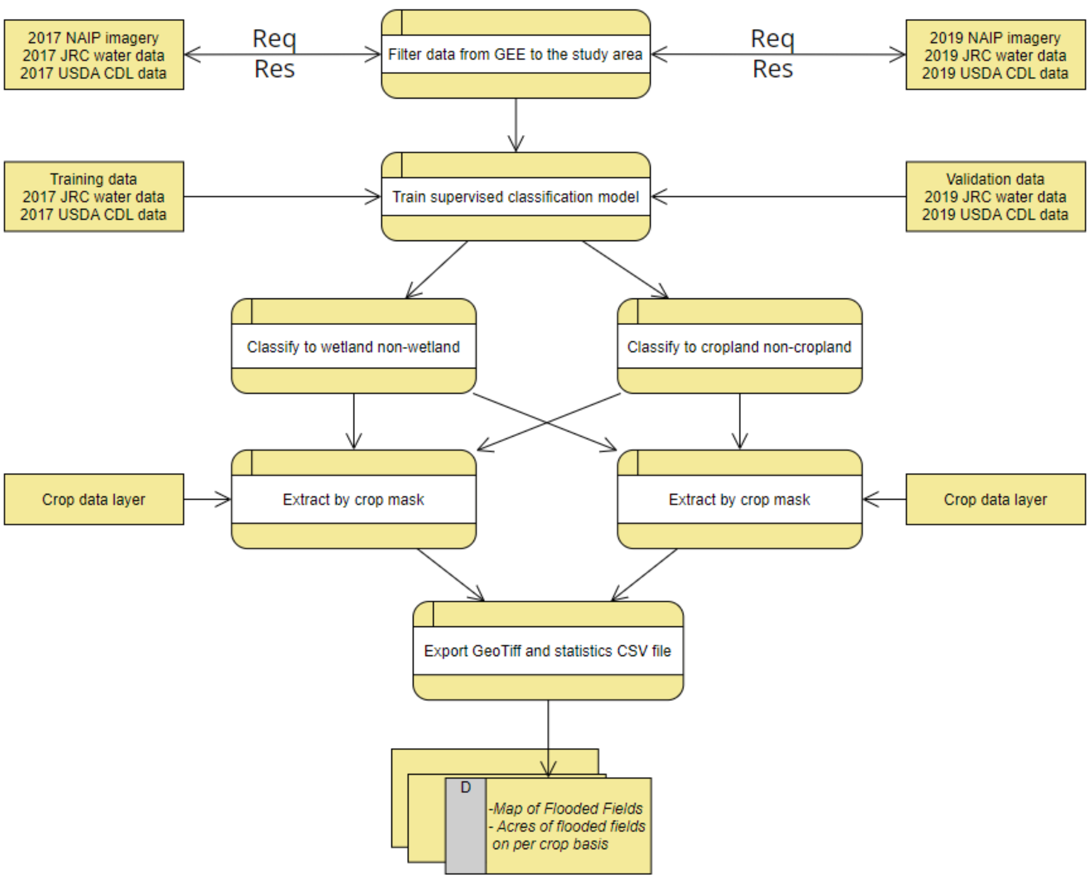

Figure 4. Data flow diagram

Regarding the statewide and county extents of the project, we required high-performance computing (HPC) equipment. Hence, we planned to apply the Google Earth Engine (GEE) which provides a plethora of datasets and HPC resources. We used the cropland data provided by USDA for the year 2017 and 2019 to generate random training and validation datasets.

To perform the cropland and wetland classification analysis we experimented the K-Means as an unsupervised ML classification algorithm and a few supervised ML algorithms including Classification and Regression Tree (CART), and Random Forest (RF) as supervised classification algorithms. After evaluating the results of these methods, RF generated the highest accuracy. Thus, we chose RF as the classification method for this project.

The k-means algorithm is a simple iterative method to partition a given dataset into a user specified number of clusters, k (Wu et al., 2008). The basic principle of k-means clustering is finding a partition of the data set into k groups, such that the sum of squared deviations of the partitions is minimized (Kriegel, 2017). A decision tree is a type of supervised learning algorithm that is mostly used for classification problems. In this algorithm, we split the population into two or more homogeneous sets. The CART stands for Classification and Regression Trees. A CART decision tree is a binary recursive partitioning procedure capable of processing continuous and nominal attributes both as targets and predictors (Wu et al., 2008). The CART mechanism is intended to produce not one, but a sequence of nested pruned trees, all of which are candidate optimal trees.

The Random Forest algorithm is based on tree classifiers and grows many classification trees (Kulkarni, 2016). To classify a new feature vector, the input vector is classified with each of the trees in the forest. Each tree gives a classification, and we say that the tree "votes" for that class. The forest chooses the classification having the most votes over all the trees in the forest. Among many advantages of Random Forest, the significant ones are unexcelled accuracy among current algorithms, efficient implementation on large data sets, and an easily saved structure for future use of pre-generated trees (Breiman, 2001 & Gislason et al., 2006).

We built an RF model with a number of 10 decision trees. For generating the cropland and wetland raster for 2017 we passed imagery for the period of 2017-01-01 to 2018-01-01. Similarly, regarding the year 2019, we used visible and NIR bands of NAIP bands imagery for the period of 2019-01-01 to 2020-01-01.

After classification, we made masks of the three most significant crops in southwest Minnesota (corn, soybeans, and wheat) using the USDA's Crop Data Layer. The crop data mask we used for 2019, made from the USDA Crop Data Layer noting that the most common crops in southwest Minnesota are corn and soy. We extracted our classification by the crop masks to quantify amounts of non-vegetated pixels to specific crops. We measured the amount of barren and ponded land within each crop type in 2017 and compared it to the same in 2019. This way, we could see the growth of wet areas as a result of flooding and the decrease in actually vegetated area for each crop type.

To export the resulting raster, we generalized the resulting raster to 1 m resolution and defined a task for GEE to export the raster in Geo-Tiff format. This step was done using the geemap.ee_export_image_to_drive function in the Python programming workflow to reduce the computational load of exporting tasks and address the GEE limitations. After exporting each zone as a separate TIFF file, we applied the MosaicToNewRaster() function of ArcGIS Pro to mosaic all zones and generate a single statewide (or county level) flooded field map. The resulting maps for both 2017 and 2019 are shown in figure 3. Finally, since in this project we were interested in the acres of agricultural lands impacted by flooding in the study area, we reclassified the final output to only keep the flooded fields.

III. Accuracy Assessment

To evaluate the accuracy of the results of the developed ML model, we generated the confusion matrices for training and validation data separately and calculated the consumer's accuracy (reliability) of a confusion matrix, and overall accuracy of the model. In machine learning, the sum of the diagonal elements of a confusion matrix is widely used to measure the success of a classification based on an algorithm in comparison with a “true” measurement such as classification by an expert.

The main idea is that an algorithm forms its own hidden equivalence classes of the data and is forced to assign the classes to the categories given by the true measurement (Düntsch, 2019). The confusion matrix determines the accuracy of the classification models for each process. It is an N x N matrix used for evaluating the performance of a classification model, where N is the number of target classes (Bhandari, 2020). The matrix compares the actual target values with those predicted by the machine learning model. This gives us a holistic view of how well our classification model is performing and what kinds of errors it is making.

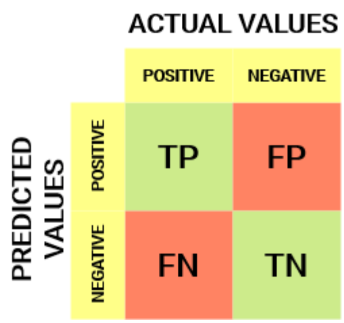

Figure 5. A 2 x 2 confusion matrix.

In figure 5, the target variable has two values of positive or negative and the columns represent the actual values of the target variable. The rows represent the predicted values of the target variable. Precision tells us how many of the correctly predicted cases actually turned out to be positive. This would determine whether our model is reliable or not. Recall tells us how many of the actual positive cases we were able to predict correctly with our model. And here’s how we can calculate Precision and Recall reaching the accuracy for our model:

$$\begin{aligned} precision &= \frac{TP}{TP + FP} \\ recall &= \frac{TP}{TP + FN} \\ accuracy &= \frac{TP + TN}{TP + FN + TN + FP} \\ specificity &= \frac{TN}{TN + FP} \end{aligned}$$

Figure 6. Evaluation formula for the implemented ML model

In the formulas presented in figure 6 TP indicates the true positive rate, FP shows the false positive rate, TN stands for true negative rate, and lastly, FN represents the false-negative rate in the results.

Results

We created classification maps for 2017 and 2019 with three classes: vegetated, non-vegetated, and water. We noted that there are significantly more contiguous areas of vegetated pixels in 2017, and that many of those same areas are broken up by bare earth or water in 2019. The pixels that switched from vegetated cropland to barren or water in 2019 are how we quantify acres impacted by flooding. The confusion matrix of supervised classifications shows a high accuracy of 98% for wetland classification and an accuracy of 86% for cropland classification.

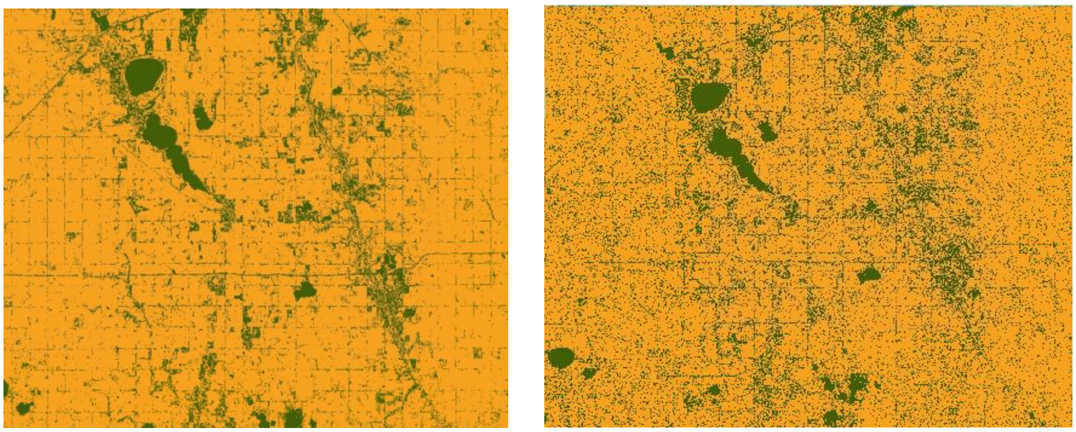

Figure 7. Cropland classification results for 2017 (left) and 2019 (right)

Considering the 30 m resolution of USDA Crop Data Layer mask, each pixel is 900 square meters for the count of pixels classified to each type. According to the, there should be 366,938 acres of cropland in 2017. Within these areas identified as cropland, we identified 319,474 acres as vegetated, 40,445 as barren, and 6,794 acres as wet. Much less land was in production in 2019, and a lower proportion of cropland was identified as vegetated in 2019. 246,831 acres of what should be cropland according to the USDA was identified as vegetated, but 88,473 acres were identified as barren, and 1,340 acres had standing water. Table 1 is a demonstration of acre statistics about extracted cultivated areas and flooded fields within them on a crop basis (Corn, Soybeans, Wheat).

Crop type	USDA acres 2017	USDA acres 2019	cropland acres 2017	cropland acres 2019	wetland acres 2017	wetland acres 2019	Non-cropland acres 2017	Non-cropland acres 2019
Corn	191475	177228	174779	122378	6787	847	10900	54003
Soybeans	175685	159,533	144663	124451	896	492	29516	34590
Wheat	1838	1698	1615	1429	24	8	199	261
Total	414177	336644	366938	246831	6794	1340	40445	88473

Table 1. acres of extracted cultivated areas and flooded fields within them on a crop basis

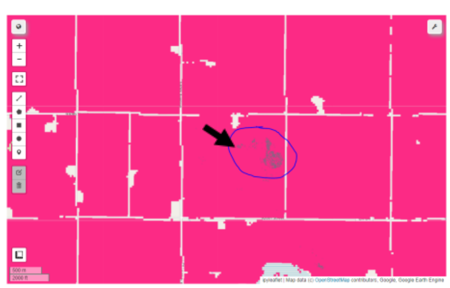

Figure 8. Wetlands within fields as a result of 2019 flooding in Jackson County

Discussion & Conclusion

According to the USDA's official statistics of planted and prevented-plant acres, approximately 10% of all croplands in Jackson County was prevented from planting: 339,436 acres were planted, and 31,894 were filed as prevent-plant (US Department of Agriculture, 2019). We predict a significantly larger area as prevent plant, but this is likely due to using a pixel-based classification. While prevent-plant claims are filed on a field-by-field basis, our classification identifies the specific pixels within fields. The pixels we identified may not have been enough to cause prevented planting but were still quantified in classification. Further, small differences in collection date in the NAIP seemed to catch some areas too early after planting to identify them as vegetated. As such, while we get a detailed picture identifying the specifically affected parts of fields, we couldn't identify the correct total area without additional data.

Our results suggest that corn was the more impacted crop, as a more significant proportion of corn cropland was classified as barren or wet in 2019 than soy. This disproportionately high impact on corn is confirmed by the USDA. According to the USDA, approximately 153,000 acres in Jackson County were planted with corn, and ~28,000 acres of this corn was filed as prevent-plant (18%) (US Department of Agriculture, 2019). In comparison, while a similar acreage of soy was planted in Jackson County (~139,000 acres), only 3,000 acres of soy were filed as prevent-plant (2%) (US Department of Agriculture, 2019). This disproportionately high impact on corn yields may be due to an earlier planting period for corn. Corn is planted from mid-April until the end of May, while soy is planted from early May to mid-June (University of Minnesota Extension); this means corn had less time for the land to dry out after severe precipitation in early spring.

Minnesota saw 27x more acres prevented from planting in 2019 than there were in 2017. This trend of high crop loss in 2019, especially for corn, was not an isolated to Jackson County. Of the 21 million acres of cropland in Minnesota in 2019, 1.2 million were prevented from planning. 1 million of these prevented acres were corn, and only 161,246 acres were soybean, despite approximately equal total acreage for corn and soy (US Department of Agriculture, 2019). While these prevent-plant acres are only ~5% of the total cropland in Minnesota, this is a relatively catastrophic amount: Minnesota saw 27x more acres prevented from planting in 2019 than there were in 2017 (US Department of Agriculture, 2019).

Weather-damaged cropland like what we identified has a significant economic impact. Farmers prevented from planting their cropland are able to claim special insurance payments specifically for "prevented planting," which is based on the market value for the crop they would have planted. According to the Congressional Research Service, these payment amounts were $270.13 per acre for corn, and $200.48 per acre for soy (Schnepf, 2020). This means that for the state of Minnesota alone, the value of prevent-plant claims paid out was $302.5 million (Schnepf, 2020). It also had larger impacts on the agricultural market as a whole:

Many of these low spots in the landscape that flooded and prevented fields from being planted were once depressional wetlands, where water would collect on the landscape. However, they were drained for agriculture and plowed over. Extreme flood events like the spring of 2019 illustrate where these wetlands once were, as these same areas tend to pond again when agricultural drainage is overwhelmed by the volume of precipitation. As climate change makes weather events more extreme and precipitation events like 2019 become more likely (National Oceanic and Atmospheric Administration, 2019), perhaps some land currently farmed should be restored to wetland. Identifying such depressions that were once wetland, and perhaps should become wetland again to prevent agricultural loss, have been identified in the Restorable Wetlands Inventory produced by Ducks Unlimited. By restoring these low areas that require considerable drainage to be plowed, and that can easily prevented from planting with extreme precipitation, agricultural loss could be minimized and greater amounts of land could be conserved.

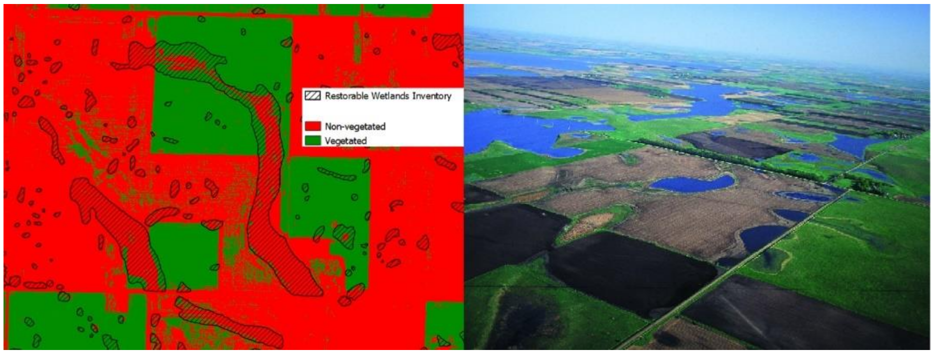

Figure 9. A comparison of our classification results to the Restorable Wetlands Inventory (by Ducks Unlimited) (left) showing how many of the places unable to be planted due to flooding were previously depressional wetlands. An example of such depressional wetlands (called prairie potholes) is to the right.

Acknowledgements

Audrey Lothspeich

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